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Measuring Potential Growth with an Estimated DSGE Model of Japan's Economy*

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In this paper, we calculate the potential output and the output gap using a Bayesian-estimated DSGE model of Japan's economy. For bridging the gap with conventional measures, we define our measure of potential output as a component of the efficient output generated only by persistent growth rate shocks. Our potential growth displays a high degree of smoothness and moves closely with conventional measures. Moreover, the output gap from our measure of potential output shows better forecasting performance for inflation—in particular, at short horizons—than other measures of output gap.

JEL Codes: E32, E37, O41, O47.

1. Introduction

It has been widely acknowledged that estimated dynamic stochastic general equilibrium (DSGE) models are able to fit the data as well as do reduced-form vector autoregression (VAR) models, as shown by Smets and Wouters (2003), Christiano, Eichenbaum, and Evans (2005), and Levin et al. (2006). A recent trend in developing DSGE

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models is to pursue their ability to "tell stories" in a policymaking context (Edge, Kiley, and Laforte 2008). For monetary and fiscal policy discussions, empirically plausible and theoretically coherent explanations for model-based estimates of potential output and output gap would be invaluable and essential.

Despite their conceptual importance in a policymaking context, measures of potential output and output gap from DSGE models are controversial.[1] In general, model-based measures of potential output, which estimate an efficient level of output without pressure for inflation to either accelerate or decelerate, tend to be more volatile than conventional measures based on the production function approach or on statistical smoothing methods (e.g., the Hodrick-Prescott (HP) filter) which try to capture medium-term growth trends of output. This tendency reflects a significant difference in views between modelers and policymakers on which types of shocks drive the short-run macroeconomic fluctuations. While DSGE models attribute a substantial fraction of the fluctuations to fundamental shocks such as temporary technology shocks, policymakers' traditional views implicitly assume that "animal spirit" expenditure shocks play a central role in the short-run fluctuations and that an efficient level of output is driven mainly by permanent technological changes.

The aim of this paper is to bridge the gap between the conventional and model-based measures of potential output using a Bayesian-estimated DSGE model of Japan's economy.[2] Our model shares many similar features with recent New Keynesian DSGE models in the literature and those practically used in central banks. A key feature of our model is that it takes into account persistent growth rate shocks, so that we can estimate directly the growth trend of output without detrending the data.[3] Based on this model, we

[1]For instance, Mishkin (2007) and Basu and Fernald (2009) discuss the characteristics of several measures and concepts of potential output.

[2]The model is a variant of the Medium-scale Japanese Economic Model (M-JEM), which was developed at the Bank of Japan's Research and Statistics Department.

[3]Many DSGE models of Japan's economy are estimated or calibrated using detrended data. For instance, Sugo and Ueda (2008) use the data detrended with kinked linear trends, and Ichiue, Kurozumi, and Sunakawa (2013) use those detrended by potential output based on the production function approach. Hirose and Kurozumi (2012) consider technology growth rate shocks but use the output gap based on the production function approach in the estimation.

define our measure of potential output as a component of the efficient (flexible-price) level of output *generated only by persistent growth rate shocks*. This "*long-run* efficient output," which corresponds to the long-run balanced growth path of the economy, displays a high degree of smoothness and moves closely with conventional measures of potential output, while the normally defined (short-run) efficient output in our model, which would be observed in the absence of nominal rigidities and shocks to price and wage markups, moves closely with the actual output and thus is more volatile than the conventional measures. We bridge the gap between the conventional and model-based measures of potential output by incorporating into our model-based measure the policymakers' views that an efficient level of output is driven mainly by permanent technological changes.

Apart from its compatibility with the policymakers' views, the long-run efficient output has some practical advantages over the short-run efficient output. First, the long-run efficient output may be more informative about short-term inflationary pressure than the short-run efficient output. We compare the predictability of inflation across several measures of output gap, which is defined as the deviation of the actual output from a measure of potential output. According to our results, the gap from the long-run efficient output shows better forecasting performance—in particular, at short forecast horizons—than the gap from the short-run efficient output and the conventional measures of output gaps. Second, the long-run efficient output is less sensitive to the specification or structural interpretation of the model.[4] This feature is practically important because recent New Keynesian DSGE models are becoming more complex, and many aspects of them are controversial among researchers. Indeed, in those complex models, it is not necessarily straightforward to theoretically determine which measure of potential output represents a truly efficient level of output and which measure of output gap is most relevant to short-term inflationary pressure. Under these circumstances, the sensitivity to the details of models is a great concern for users of model-based measures.

[4]In our working paper version (Fueki et al. 2010), we show that the long-run efficient output in our model is robust with respect to the specification of monetary policy rules and identifications of labor supply shocks, price and wage markup shocks, and measurement errors in prices and wages.

Moreover, our model has a two-sector production structure in which the final goods are explicitly divided into the consumption goods produced by a slow-growing sector and the investment goods produced by a fast-growing sector, so that the long-run efficient output in our model can be decomposed into the economy-wide and investment-specific technology growth rate shocks in addition to an exogenous population growth. This structure not only enhances the model's empirical performance[5] but also allows us to tell simple and plausible stories about the long-run growth trends of Japan's economy: while the investment-specific technology growth rate shock has constantly raised the potential growth during the sample period since the 1980s, the economy-wide technology growth rate shock has reduced the potential growth since the 1990s.

A closely related analysis on DSGE model-based measures of potential output and output gap was conducted by Kiley (2013). He shows that the deviation of the U.S. actual output from its long-run stochastic trend (Beveridge-Nelson cycle) estimated from a DSGE model used at the Federal Reserve Board (the Estimated, Dynamic, Optimization-based, or EDO, model) is similar to the output gap based on the production function approach (the one calculated by the Congressional Budget Office). This result is similar to ours although the long-run efficient output in our model is a different concept from the Beveridge-Nelson stochastic trend. Meanwhile, some other recent studies investigate the cyclical properties and theoretical background of model-based measures of potential output and output gap. Sala, Söderström, and Trigari (2010) show that the output gap and the labor wedge are closely related in their estimated DSGE model, but the estimates are sensitive to the structural interpretation of shocks to the labor market. Justiniano, Primiceri, and Tambalotti (2013) show that the output gap in their model is procyclical and often quite large, but the policy trade-off between the stabilization of output gap and that of price and wage inflation is fairly weak on condition that the exogenous movements in the

[5]The two-sector production structure in our model reflects the secular trends in relative prices and different trends in categories of real expenditure apparent in the Japanese data. Moreover, this structure can generate empirically plausible co-movement between consumption and investment in response to investment-specific technology shocks.

competitiveness of the labor market are not a fundamental driver of macroeconomic fluctuations. Compared with their measures of potential output, the long-run efficient output in our model is less sensitive to the structural interpretation of labor market shocks.

The remainder of the paper is organized as follows. Section 2 describes our model. Section 3 explains the estimation procedures and shows the estimation results. In section 4, we calculate our measure of potential growth and compare it with alternative measures. In section 5, we calculate the several corresponding measures of output gap and compare the predictability of inflation across those measures. Section 6 concludes.

2. The Model

In this section, we provide an overview and a brief description of our model.[6]

2.1 Overview

Our model is a two-sector growth model that takes into account persistent growth rate shocks including investment-specific technological progress.[7] There are two final goods in the model: the consumption goods produced by the slow-growing sector and the investment goods produced by the fast-growing sector. We assume that the former goods are purchased by households and the government and that the latter goods are purchased by capital owners and foreign countries (net exports). The two-sector production structure with differential rates of technological progress across sectors induce different trends in categories of real expenditure and secular trends in relative prices, which are both apparent in the Japanese data.[8]

[6] More details of the model, including the equilibrium conditions, stationary equilibrium conditions, and log-linearized system, are provided in appendix A of our working paper version (Fueki et al. 2010).

[7] Our model closely follows the Federal Reserve Board's EDO model (Edge, Kiley, and Laforte 2007; Chung, Kiley, and Laforte 2010). The two-sector representation of the investment-specific technological progress is also described by Whelan (2003), Ireland and Schuh (2008), and others.

[8] In our data set from 1981 to 2009 (explained in section 3), the average annual growth rate of the real value added of the slow-growing sector is 1.86 percent, and

Meanwhile, our model shares many similar features with recent New Keynesian DSGE models in the literature, such as monopolistic competition, sticky prices and wages, adjustment costs, habit persistence, etc. The goods are produced in two stages by intermediate- and then final-goods-producing firms in each sector. The final-goods-producing firms aggregate differentiated sector-specific intermediate goods. The intermediate-goods-producing firms combine the aggregate labor inputs with utilized capital and set prices of their differentiated output. The capital owners rent their capital to the intermediate-goods-producing firms in both sectors. Households supply differentiated labor forces to the intermediate-goods-producing firms in both sectors. In what follows, we describe the decisions made by each of the agents in our economy.

2.2 Final Goods Producers

Final goods producers in the slow-growing sector (sector c) produce the consumption goods X_t^c, and those in the fast-growing sector (sector k) produce the investment goods X_t^k. They face competitive markets and produce the final goods, X_t^s, $s \in \{c, k\}$, by combining a continuum of s sector-specific intermediate goods, $X_t^s(j)$, $j \in [0, 1]$, according to the following Dixit-Stiglitz type technology.

$$X_t^s = \left(\int_0^1 X_t^s(j)^{\frac{\Theta_t^{x,s}-1}{\Theta_t^{x,s}}} dj \right)^{\frac{\Theta_t^{x,s}}{\Theta_t^{x,s}-1}}, \quad s = \{c, k\}, \tag{1}$$

where $\Theta_t^{x,s}$ is the elasticity of substitution between the differentiated intermediate goods input. Letting $\theta_t^{x,s}$ be the log-deviation from its steady-state value, we assume that $\theta_t^{x,s}$ follows an ARMA(1,1) process.[9]

$$\theta_t^{x,s} = \rho^{\theta_{x,s}} \theta_{t-1}^{x,s} + \epsilon_t^{\theta,x,s} - \rho^{\theta_{x,s},ma} \epsilon_{t-1}^{\theta,x,s}, \tag{2}$$

that of the fast-growing sector is 2.81 percent, while the price of the investment goods relative to the consumption goods has declined at 1.75 percent per year on average.

[9]Smets and Wouters (2007) assume that the price and wage markup shocks follow ARMA(1,1) processes to capture the high-frequency fluctuations in price and wage inflations.

where $\epsilon_t^{\theta,x,s}$ is an i.i.d. shock process. This stochastic elasticity of substitution introduces transitory markup shocks into the pricing decisions of intermediate goods producers. Subject to the above aggregation technology, a final goods producer in each sector chooses the optimal level of each intermediate goods to minimize the cost of purchasing them, taking their prices as given.

2.3 Intermediate Goods Producers

Intermediate goods producers in both sectors face the monopolistically competitive market and produce the sector-specific intermediate goods $X_t^s(j)$, $s \in \{c, k\}$ with the following production function.

$$X_t^s(j) = \left[K_t^{u,s}(j)\right]^{\alpha} \left[A_t^m Z_t^m A_t^s Z_t^s L_t^s(j)\right]^{1-\alpha}, \tag{3}$$

where $K_t^{u,s}(j)$ and $L_t^s(j)$ are the effective capital input and the labor input of a firm j, respectively. Letting $U_t^s(j)$ be the capital utilization rate in sector s, the effective capital input is written as $K_t^{u,s}(j) \equiv K_t^s(j) \times U_t^s(j)$. Further, the labor input of a firm j is the composite of the differentiated labor input, $L_t^s(j) = [\int_0^1 L_t^s(i,j)^{(\Theta_t^l-1)/\Theta_t^l} di]^{\Theta_t^l/(\Theta_t^l-1)}$, where Θ_t^l is the elasticity of substitution, and its log-deviation θ_t^l follows an ARMA(1,1) process. This stochastic elasticity of substitution introduces transitory wage markup shocks into households' labor supply decisions.

$A_t^m Z_t^m$ is the economy-wide technology shock and $A_t^k Z_t^k$ is the fast-growing (investment-goods-producing) sector-specific technology shock. In order to reduce the number of shocks in the model, we presume that the slow-growing (consumption-goods-producing) sector does not have the sector-specific shock ($A_t^c = Z_t^c = 1$). We assume that each of the technology shocks contains two separate stochastic components: one (A_t^n) is stationary in levels and the other (Z_t^n) is stationary in growth rates, where $n \in \{m, k\}$.

$$\ln A_t^n = \ln A_*^n + \epsilon_t^{a,n} \tag{4}$$

$$\ln Z_t^n - \ln Z_{t-1}^n = \ln \Gamma_t^{z,n} = \ln(\Gamma_*^{z,n} \times \exp[\gamma_t^{z,n}]) = \ln \Gamma_*^{z,n} + \gamma_t^{z,n} \tag{5}$$

$$\gamma_t^{z,n} = \rho^{z,n} \gamma_{t-1}^{z,n} + \epsilon_t^{z,n}, \tag{6}$$

where $\epsilon_t^{a,n}$ and $\epsilon_t^{z,n}$ are i.i.d. shock processes, and A_*^n and $\Gamma_*^{z,n}$ are the constant technology level and growth rate, respectively. (Hereafter, variables with subscript $*$ represent the variables at steady state.)

An intermediate goods producer j in sector $s \in \{c, k\}$ maximizes the discounted future profit,

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{\Lambda_t^c}{P_t^c} \left\{ P_t^s(j) X_t^s(j) - MC_t^s(j) X_t^s(j) \right.$$
$$\left. - \frac{100 \cdot \chi^p}{2} \left(\frac{P_t^s(j)}{P_{t-1}^s(j)} - \eta^p \Pi_{t-1}^{p,s} - (1-\eta^p)\Pi_*^{p,s} \right)^2 P_t^s X_t^s \right\}, \quad (7)$$

subject to the final goods producers' demand schedule,

$$X_t^s(j) = \left(\frac{P_t^s(j)}{P_t^s} \right)^{-\Theta_t^{x,s}} X_t^s, \quad (8)$$

taking as given the marginal cost of production, $MC_t^s(j)$, the aggregate price level for its sector, $P_t^s = \{\int_0^1 [P_t^s(j)]^{(\Theta_t^s - 1)/\Theta_t^s} dj\}^{\Theta_t^s/(\Theta_t^s - 1)}$, and households' valuation of a unit nominal income in each period, Λ_t^c / P_t^c, where Λ_t^c is the marginal utility of consumption. The second line in (7) represents the quadratic price adjustment cost as in Rotemberg (1982), where $\Pi_t^{p,s} = P_t^s / P_{t-1}^s$ and $\Pi_*^{p,s}$ is the time-invariant trend inflation. Since the cost is imposed on the deviation of the optimum price inflation from the past inflation, the equilibrium inflation as well as the price response to the marginal cost becomes sticky.

2.4 Capital Stock Owners

Capital stock owners provide the capital service to the intermediate goods producers in both sectors, receive the rental cost of capital in exchange, and accumulate the investment goods. Each capital stock owner k chooses investment expenditure, $I_t(k)$, the amount and utilization of capital in both sectors, $K_t^c(k)$, $U_t^c(k)$, $K_t^k(k)$, and $U_t^k(k)$, to maximize its discounted profit,

$$E_0 \sum_{t=0}^{\infty} \beta^t \frac{\Lambda_t^c}{P_t^c} \left[R_t^c U_t^c(k) K_t^c(k) + R_t^k U_t^k(k) K_t^k(k) - P_t^k I_t(k) \right], \quad (9)$$

subject to the capital evolution process with quadratic investment adjustment cost and the costs from higher utilization rates,

$$K_{t+1}(k) = (1-\delta)K_t(k) + I_t(k) - \frac{100 \cdot \chi}{2}\left[\frac{I_t(k)A_t^{\varphi} - I_{t-1}(k)\Gamma_t^{z,m}\Gamma_t^{z,k}}{K_t}\right]^2 K_t - \sum_{s=c,k}\kappa\left[\frac{\left(Z_t^U U_t^s(k)\right)^{1+\psi} - 1}{1+\psi}\right]K_t^s, \tag{10}$$

where $K_t(k) = K_t^c(k) + K_t^k(k)$. The third term (in the second line) of the right-hand side is the quadratic investment adjustment cost, where A_t^{φ} is a stochastic variation in the adjustment cost that is assumed to be unity at the steady state and to follow an AR(1) process. The last term of the right-hand side is the utilization cost, which presumes that higher capital utilization leads to faster capital depreciation, as in Greenwood, Hercowitz, and Krusell (1997). Z_t^U is a stochastic variation in the utilization cost that is assumed to be common in both sectors and to follow an AR(1) process. We set κ so that the utilization rate is unity at the steady state.

2.5 Households

Each household i chooses its purchase of consumption goods, $C_t(i)$, its holdings of bonds, $B_t(i)$, its wages for both sectors, $W_t^c(i)$ and $W_t^k(i)$, and supply of labor consistent with each wage, $L_t^c(i)$ and $L_t^k(i)$, given the demand schedule for the differentiated labor supply, $L_t^c(i) = (W_t^c(i)/W_t^c)^{-\Theta_t^l}L_t^c$ and $L_t^k(i) = (W_t^k(i)/W_t^k)^{-\Theta_t^l}L_t^k$, to maximize the utility function,

$$E_0\sum_{t=0}^{\infty}\beta^t\Xi_t^{\beta}\left\{\varsigma^c\ln\left(C_t(i) - hC_{t-1}(i)\right) - \varsigma^l\frac{\left[\left(L_t^c(i) + L_t^k(i)\right)/\Xi_t^l\right]^{1+\nu}}{1+\nu}\right\}, \tag{11}$$

subject to its budget constraint,

$$\frac{1}{R_t}B_{t+1}(i) = B_t(i) + \sum_{s=c,k} W_t^s(i)L_t^s(i) + \Omega_t(i) - P_t^c C_t(i)$$
$$- \sum_{s=c,k} \frac{100 \cdot \chi^w}{2} \left\{ \frac{W_t^s(i)}{W_{t-1}^s(i)} - \eta^w \Pi_{t-1}^{w,s} - (1-\eta^w)\Pi_*^{w,s} \right\}^2$$
$$\times W_t^s L_t^s - \frac{100 \cdot \chi^l}{2} \left(\frac{L_*^c}{L_*^c + L_*^k} W_t^c + \frac{L_*^k}{L_*^c + L_*^k} W_t^k \right)$$
$$\times \left(\frac{L_t^c(i)}{L_t^k(i)} - \eta^l \frac{L_{t-1}^c}{L_{t-1}^k} - (1-\eta^l)\frac{L_*^c}{L_*^k} \right)^2 \frac{L_t^k}{L_t^c}. \tag{12}$$

In the utility function, Ξ_t^β is the *inter*temporal preference shock, Ξ_t^l is the labor supply shock (*intra*temporal preference shock), ς^c and ς^l are scale parameters that determine the ratio between the household's consumption and leisure, and h is the degree of the habit persistence of the household. We assume that the log-deviation of the intertemporal preference shock follows an AR(1) process and that the labor supply shock is non-stochastic ($\Xi_t^l = 1$) to properly identify the wage markup shock.[10] In the budget constraint, R_t is the nominal interest rate on the bonds and $\Omega_t(i)$ is the household's capital and profits income. The fifth term (in the second line) of the right-hand side is the quadratic wage adjustment cost imposed on the deviation of the wage growth from the past wage inflation, $\Pi_{t-1}^{w,s}$, and from the trend wage inflation, $\Pi_*^{w,s}$. With this formulation, the wage inflation as well as the wage level becomes sticky. The last term of the right-hand side is the labor reallocation cost, which helps to generate realistic sectoral co-movement of labor inputs during business cycles.

2.6 Real GDP Growth and GDP Deflator Inflation

Since the trend growth rate is different in each sector, we aggregate the real GDP as a divisia index, following Whelan (2003) and Edge, Kiley, and Laforte (2007). This divisia-index aggregation allows us

[10] We consider the case of stochastic labor supply shock in section 6.2 of our working paper version (Fueki et al. 2010).

to avoid the base-year bias of the deflator and to mimic the SNA data compiled with the chain-index aggregation. The growth rate of the real GDP is calculated as

$$H_t^{gdp} = \left[\left(\frac{X_t^c}{X_{t-1}^c} \right)^{P_*^c X_*^c} \left(\frac{X_t^k}{X_{t-1}^k} \right)^{P_*^k X_*^k} \right]^{\frac{1}{P_*^c X_*^c + P_*^k X_*^k}} . \qquad (13)$$

The inflation rate of the GDP deflator, $\Pi_t^{p,gdp}$, is implicitly defined by

$$\Pi_t^{p,gdp} H_t^{gdp} = \frac{P_t^{gdp} X_t^{gdp}}{P_{t-1}^{gdp} X_{t-1}^{gdp}} = \frac{P_t^c X_t^c + P_t^k X_t^k}{P_{t-1}^c X_{t-1}^c + P_{t-1}^k X_{t-1}^k}. \qquad (14)$$

2.7 Monetary Authority

Following Chung, Kiley, and Laforte (2010), we assume that the monetary authority sets the short-term nominal interest rate following a Taylor-type feedback rule with interest rate smoothing.

$$R_t = (R_{t-1})^{\phi^r} (\bar{R}_t)^{1-\phi^r} \exp(\epsilon_t^r) \qquad (15)$$

$$\bar{R}_t = R_* \left(\tilde{X}_t \right)^{\phi^{h,gdp}} \left(\frac{\tilde{X}_t}{\tilde{X}_{t-1}} \right)^{\phi^{\Delta h,gdp}} \left(\frac{\Pi_t^{p,gdp}}{\Pi_*^{p,gdp}} \right)^{\phi^{\pi,gdp}} , \qquad (16)$$

where ϕ^r is the degree of interest rate smoothing, ϵ_t^r is the interest rate shock, and $\phi^{h,gdp}$, $\phi^{\Delta h,gdp}$, and $\phi^{\pi,gdp}$ are the degrees of responsiveness in the policy rule. $\tilde{X}_t$ is the deviation of real GDP, which is calculated as a divisia index similarly to its growth rate (13), from its efficient level (the short-run efficient output defined in section 4.)[11]

2.8 Market Clearing

Before closing the model, we assume that government expenditure, G_t, and net exports, F_t, are produced by the slow-growing sector

[11]We consider the case of the monetary policy rule that responds to the output gap from the long-run efficient output in section 6.1 of our working paper version (Fueki et al. 2010).

and fast-growing sector, respectively. Both factors are stochastic and obey AR(1) processes as follows.

$$\ln G_t - \ln\{Z_t^m (Z_t^k)^\alpha (Z_t^c)^{1-\alpha}\} = \ln \tilde{G}_t = \rho^g \ln \tilde{G}_{t-1} + \epsilon_t^g \tag{17}$$

$$\ln F_t - \ln\{Z_t^m Z_t^k\} = \ln \tilde{F}_t = \rho^f \ln \tilde{F}_{t-1} + \epsilon_t^f \tag{18}$$

At the symmetric equilibrium, each market clears.

$$\begin{aligned} X_t^c = &\int_0^1 C_t(i)di + G_t + \frac{100 \cdot \chi^w}{2}\left[\Pi_t^{w,c} - \eta^w \Pi_{t-1}^{w,c} - (1-\eta^w)\Pi_*^w\right]^2 \\ &\times W_t^c L_t^c + \frac{100 \cdot \chi^p}{2}\left[\Pi_t^{p,c} - \eta^p \Pi_{t-1}^{p,c} - (1-\eta^p)\Pi_*^{p,c}\right]^2 P_t^c X_t^c \\ &+ \frac{100 \cdot \chi^l}{2}\left(\frac{L_*^c}{L_*^c + L_*^k} W_t^c + \frac{L_*^k}{L_*^c + L_*^k} W_t^k\right) \\ &\times \left\{\frac{L_t^c}{L_t^k} - \eta^l \frac{L_{t-1}^c}{L_{t-1}^k} - (1-\eta^l)\frac{L_*^c}{L_*^k}\right\}^2 \frac{L_t^k}{L_t^c} \end{aligned} \tag{19}$$

$$\begin{aligned} X_t^k = &\int_0^1 I_t(k)dk + F_t + \frac{100 \cdot \chi^w}{2}\left[\Pi_t^{w,k} - \eta^w \Pi_{t-1}^{w,k} - (1-\eta^w)\Pi_*^w\right]^2 \\ &\times W_t^k L_t^k + \frac{100 \cdot \chi^p}{2}\left[\Pi_t^{p,k} - \eta^p \Pi_{t-1}^{p,k} - (1-\eta^p)\Pi_*^{p,k}\right]^2 P_t^k X_t^k \end{aligned} \tag{20}$$

$$L_t^s(i) = \int_0^1 L_t^s(i,j)dj, \quad \forall i \in [0,1], \ s \in \{c,k\} \tag{21}$$

$$\int_0^1 U_t^s(k) K_t^s(k)dk = \int_0^1 K_t^{u,s}(j)dj, \quad s \in \{c,k\} \tag{22}$$

3. Model Estimation

3.1 Estimation Procedures

We solve the model and estimate its structural parameters using Bayesian methods. Since persistent growth rate shocks in the system make some of the endogenous variables non-stationary, we divide the non-stationary variables by the corresponding I(1) trends and stationarize the model. We then log-linearize the set of equilibrium conditions, solve the linear rational expectations system, and obtain the transition dynamics of the whole system.

$$\hat{\zeta}_t = G(\vartheta)\hat{\zeta}_{t-1} + H(\vartheta)\hat{\varepsilon}_t, \tag{23}$$

where $\hat{\zeta}_t$ is a properly defined $k \times 1$ vector of stationarized and log-linearized endogenous variables, $\hat{\varepsilon}_t$ is the $n \times 1$ vector of exogenous i.i.d. disturbances, and ϑ is the $p \times 1$ vector of structural unknown coefficients. $G(\vartheta)$ and $H(\vartheta)$ are the conformable matrices of coefficients that depend on the structural parameters ϑ.

To estimate the model, we specify the observation equation,

$$x_t = J\hat{\zeta}_t + \mu, \tag{24}$$

where x_t is the observed data described in the next subsection and μ is the vector of constant terms. Since the variables in our model $\hat{\zeta}_t$ include persistent growth rate shocks, we do not detrend or demean any data series, while some of the data are transformed into log-differences. Also, we do not incorporate measurement errors into the observation equation.[12]

Letting x^T be a set of observable data, the likelihood function $L(\vartheta, x^T)$ is evaluated by applying the Kalman filter. We combine the likelihood function $L(\vartheta, x^T)$ with priors for the parameters to be estimated, $p(\vartheta)$, to obtain the posterior distribution, which is proportional to $L(\vartheta, x^T)p(\vartheta)$. Since we do not have a closed-form solution of the posterior, we rely on Markov chain Monte Carlo (MCMC) methods using Dynare. Draws from the posterior distribution are generated with the Metropolis-Hastings algorithm.[13] We obtain the posterior median estimates and posterior intervals

[12]This is an important difference from the Federal Reserve Board's EDO model, which incorporates measurement errors in most variables in the observation equation. As we discuss in section 6.3 of our working paper version (Fueki et al. 2010), where some alternative models with measurement errors in prices and wages are estimated, measurement errors can drastically affect the estimation results and complicate structural interpretation of shocks.

[13]A sample of 800,000 draws was created (neglecting the first half of these draws). Our selected step size for the jumping distribution in the Metropolis-Hastings algorithm results in an acceptance ratio of 0.39. The resulting sample properties are not sensitive to the step size. To test the stability of the sample, we use the convergence diagnostic based on Brooks and Gelman (1998).

of unobservable model variables, including the efficient output, by applying the Kalman smoother.

3.2 Data

The model is estimated using ten key macroeconomic quarterly Japanese time series from 1981:Q1 to 2009:Q4 as observed data:[14] nominal value added of the slow-growing sector, nominal value added of the fast-growing sector, nominal household consumption, nominal business investment, deflator of the slow-growing sector, deflator of the fast-growing sector, compensation of employees, total hours worked, short-term nominal interest rate (call rate),[15] and capital utilization rate (operating ratio). All the variables, except for the last two, are transformed into log-differences. None of them, however, are detrended or demeaned.

The nominal value added of the slow-growing sector is the sum of nominal household consumption (including residential investment) and nominal government expenditure. The nominal value added of the fast-growing sector is the sum of nominal business (non-residential) investment and nominal net exports. Those GDP components are transformed into a per-capita base (divided by the population over fifteen years old).

Our model has two price indices for the slow-growing and the fast-growing sectors. In order to match the SNA data with our theoretical model, we construct the chain index of the real value added of each sector and calculate the implicit deflator, following Whelan (2003).[16]

3.3 Estimation Results

The model's calibrated parameters are presented in table 1, and the estimated parameters are reported in table 2. Referring to previous

[14]The GDP data are the second preliminary quarterly estimates released in March 2010.

[15]The sample period includes the period after the short-term nominal interest rate effectively hit the zero lower bound. However, the estimation results using the data up to 1998:Q4, just before the Bank of Japan started the zero interest rate policy, are not much different from the baseline results using the full sample data.

[16]More details of the data are summarized in appendix B of our working paper version (Fueki et al. 2010).

Table 1. Calibrated Parameter Values

$\boldsymbol{\alpha}$	$\boldsymbol{\beta}$	$\boldsymbol{\delta}$	$\boldsymbol{\Theta_*^{x,c}}$	$\boldsymbol{\Theta_*^{x,k}}$	$\boldsymbol{\Theta_*^{x,l}}$	$\boldsymbol{\Gamma_*^{z,m}}$	$\boldsymbol{\Gamma_*^{z,k}}$
0.30	0.99	0.02	6.00	6.00	6.00	1.002	1.004

studies, we set six structural parameter values such as households' subjective discount rate, capital share, capital depreciation, and elasticity of substitution. We also set the steady-state values based on historical averages of the data.[17] Meanwhile, we estimate fourteen structural parameters as well as the parameters that characterize thirteen shock processes. In general, most of our posterior estimates of the structural parameters are consistent with previous studies.[18]

Next we report the variance decompositions in table 3. It shows the posterior mean estimates of forecast error variance decompositions of output (real GDP) growth, consumption growth, investment growth, and GDP deflator inflation at forecast horizon $T = 1$ and 100. The output fluctuations, both in the short and in the long run, are mainly caused by the technology shocks (economy wide and investment specific), the investment adjustment cost shocks, and the intertemporal preference shocks. The contributions of the investment-specific technology shocks are smaller than those of the economy-wide technology shocks, as in Hirose and Kurozumi (2012). The investment adjustment cost shocks contribute substantially to the investment fluctuations, and the intertemporal preference shocks contribute substantially to the consumption fluctuations. Meanwhile, the inflation fluctuations are mainly caused by the consumption goods price markup shocks. The investment-specific technology shocks and the intertemporal preference shocks also have large contributions to the long-run fluctuations in inflation.

Finally, we report the impulse responses of key variables to the economy-wide and investment-specific technology shocks in figure 1.

[17]Although the GDP growth rate has declined during the sample period, we set the steady-state growth rates to its full sample average. The estimation results using the data from 1991:Q1, when Japan's "lost decade" started, are not much different from the baseline results using the full sample data.

[18]Prior and posterior distributions of the model parameters are shown in figure 1 of our working paper version (Fueki et al. 2010).

Table 2. Estimated Parameter Values (Prior and Posterior Distributions)

Param.	Prior Distribution	Prior Mean	Prior S.D.	Posterior Distribution		
				Mean	5th Percentiles	95th Percentiles
h	Beta	0.6	0.15	0.49	0.39	0.59
v	Gamma	2	1	0.31	0.06	0.55
χ^p	Gamma	4	2	13.85	8.21	19.26
η^p	Beta	0.5	0.15	0.16	0.05	0.26
χ^w	Gamma	4	2	11.49	7.56	15.37
η^w	Beta	0.5	0.15	0.16	0.05	0.26
χ^l	Gamma	2	1	1.90	0.40	3.37
η^l	Beta	0.5	0.15	0.51	0.26	0.75
χ	Gamma	2	1	1.24	0.47	1.99
ϕ^r	Beta	0.7	0.15	0.92	0.90	0.94
$\phi^{\pi,gdp}$	Normal	1.5	0.5	1.16	0.76	1.57
$\phi^{h,gdp}$	Normal	0.5	0.5	0.16	0.08	0.23
$\phi^{\Delta h,gdp}$	Normal	0	0.5	1.13	0.67	1.59
ψ	Normal	1	1	3.14	2.09	4.19
$\rho^{z,k}$	Normal	0.98	0.01	0.97	0.96	0.99
$\rho^{z,m}$	Normal	0.98	0.01	0.97	0.95	0.98
$\rho^{\theta_{x,c}}$	Beta	0.5	0.15	0.83	0.75	0.91
$\rho^{\theta_{x,k}}$	Beta	0.5	0.15	0.44	0.25	0.63
ρ^{θ_l}	Beta	0.5	0.15	0.26	0.08	0.42
ρ^{φ}	Beta	0.7	0.15	0.65	0.47	0.82

(*continued*)

Table 2. (Continued)

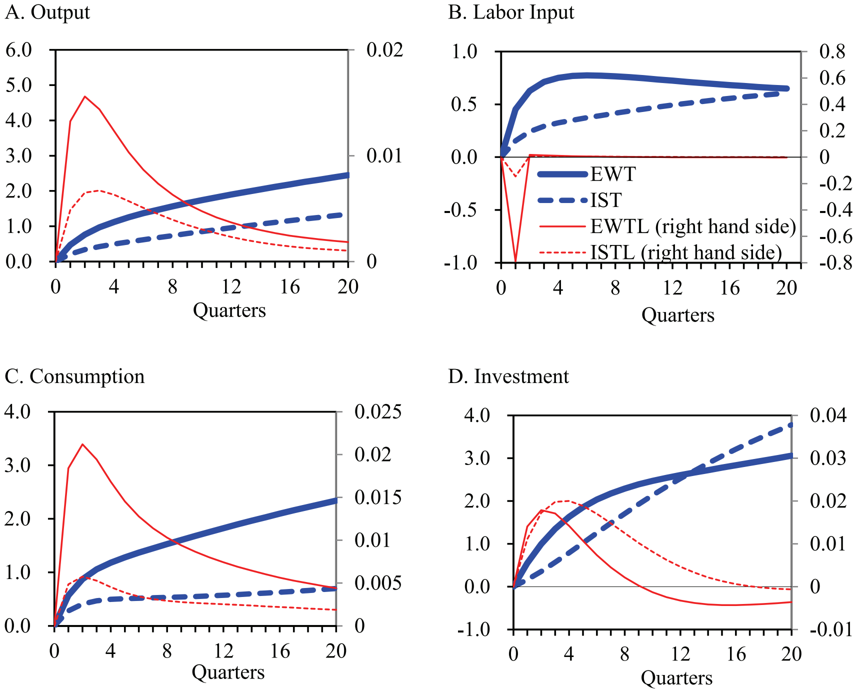
Param.	Prior Distribution	Prior Mean	Prior S.D.	Posterior Distribution		
				Mean	**5th Percentiles**	**95th Percentiles**
ρ^{g}	Beta	0.5	0.15	0.93	0.90	0.97
ρ^{f}	Beta	0.5	0.15	0.87	0.82	0.92
$\rho^{\xi,\beta}$	Beta	0.8	0.15	0.96	0.93	0.98
ρ^{U}	Beta	0.7	0.15	0.91	0.86	0.97
$\rho^{\theta_{x,c},ma}$	Beta	0.5	0.15	0.70	0.55	0.86
$\rho^{\theta_{x,k},ma}$	Beta	0.5	0.15	0.50	0.33	0.67
$\rho^{\theta_{l},ma}$	Beta	0.4	0.15	0.39	0.27	0.51
σ^{r}	Inverse Gamma	0.1	2	0.10	0.09	0.11
$\sigma^{z,k}$	Inverse Gamma	0.5	2	0.23	0.12	0.34
$\sigma^{z,m}$	Inverse Gamma	0.5	2	0.16	0.10	0.22
$\sigma^{\theta_{x,c}}$	Inverse Gamma	0.5	5	0.42	0.33	0.50
$\sigma^{\theta_{x,k}}$	Inverse Gamma	1.5	5	2.77	2.35	3.18
$\sigma^{\theta,l}$	Inverse Gamma	0.5	5	3.10	1.90	4.28
$\sigma^{\alpha,k}$	Inverse Gamma	2	5	1.12	0.53	1.71
$\sigma^{\alpha,m}$	Inverse Gamma	5	5	1.08	0.94	1.21
σ^{φ}	Inverse Gamma	3	5	9.88	3.47	16.09
σ^{g}	Inverse Gamma	1	5	1.52	1.35	1.69
σ^{f}	Inverse Gamma	0.5	5	0.24	0.22	0.27
$\sigma^{\xi,\beta}$	Inverse Gamma	5	5	4.67	3.19	6.08
σ^{U}	Inverse Gamma	1	2	1.56	1.38	1.74

Table 3. Variance Decomposition

	Output	Consumption	Investment	Inflation
$T = 1$				
Monetary Policy Shock	3.15	2.6	1.24	0.07
Economy-Wide Technology Shock	27.66	30.48	3.34	0.04
Investment-Specific Technology Shock	5.51	5.77	0.68	0.59
Price Markup Shock (Consumption Goods)	2.57	6.82	0.01	95.92
Price Markup Shock (Investment Goods)	4.52	2.63	17.21	0.64
Wage Markup Shock	0.05	0.04	0.21	1.09
Investment Adjustment Cost Shock	39.62	0.11	76.38	0.1
Government Expenditure Shock	0.14	0.11	0.09	0
Net Export Shock	2.46	0.18	0.25	0
Intertemporal Preference Shock	13.34	49.82	0.44	1.32
Capital Utilization Adjustment Cost Shock	0.97	1.45	0.14	0.21
$T = 100$				
Monetary Policy Shock	1.89	1.85	1	0.16
Economy-Wide Technology Shock	36.24	41.44	3.92	0.26
Investment-Specific Technology Shock	14.15	6.32	7.03	10.93
Price Markup Shock (Consumption Goods)	2.55	9.2	0.04	74.4
Price Markup Shock (Investment Goods)	3.65	2.77	13.08	0.96
Wage Markup Shock	0.07	0.05	0.18	2.33
Investment Adjustment Cost Shock	31.99	2.6	73.63	0.6
Government Expenditure Shock	0.36	0.08	0.08	0.01
Net Export Shock	2.02	0.12	0.38	0
Intertemporal Preference Shock	6.53	34.61	0.53	10.04
Capital Utilization Adjustment Cost Shock	0.56	0.95	0.13	0.3

Note: Each table shows variance decompositions of the output growth rate, the consumption growth rate, the investment growth rate, and the inflation rate.

Figure 1. Responses to Structural Shocks



Notes: Each graph shows the impulse responses to a shock equal to one standard deviation. All impulse responses are reported as percentage deviations from non-stochastic steady state. EWT: the economy-wide technology shock (persistent growth rate shock); IST: the investment-specific technology shock (persistent growth rate shock); EWTL: the economy-wide technology shock (in level); ISTL: the investment-specific technology shock (in level).

The persistent technology *growth rate* shocks, either economy wide or investment specific, increase output and labor input, while the technology *level* shocks decrease labor input.[19] This relates to the following result that our measure of potential output (long-run efficient output) driven by persistent *growth rate* shocks moves procyclically. Meanwhile, the economy-wide and investment-specific technology shocks, either in growth rate or in level, increase both

[19] Christiano, Trabandt, and Walentin (2010) discuss this point in detail.

consumption and investment.[20] The notable result here is that the investment-specific technology shocks increase consumption as well as investment, which is hard to obtain in a one-sector model. An important advantage of our two-sector model is that it generates empirically plausible co-movement between consumption and investment.[21]

4. Potential Growth

In this section, we calculate our measure of potential growth and compare it with alternative measures.

4.1 Several Measures of Potential Output

First, we calculate the (short-run) efficient output, which is usually considered a DSGE model-based measure of potential output. It is defined as the level of output in an environment without nominal rigidities in goods and labor markets and without shocks to price and wage markups.[22] Figure 2 shows the year-on-year growth rate of the above-defined efficient output,[23] which moves closely with the actual output (real GDP). This implies that a substantial fraction of the actual economic fluctuations is viewed as efficient in our model.

As discussed in the introduction, many policymakers' traditional views implicitly assume that the short-run fluctuations are inefficient and that an efficient level of output is driven by permanent

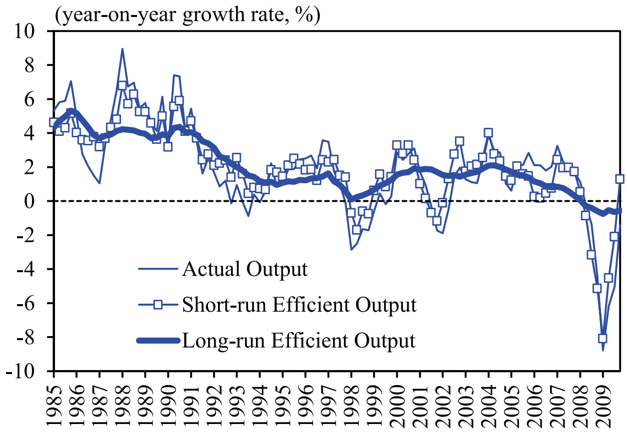
[20] The responses of consumption and investment are generally consistent with those in the VAR results of Braun and Shioji (2007).

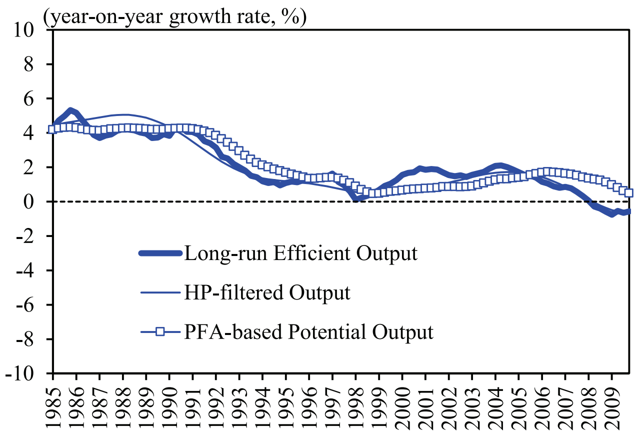
[21] Guerrieri, Henderson, and Kim (2010) discuss this point in detail.

[22] We calculate in this paper the "unconditional" efficient output based on the state variables in the counterfactually efficient allocation from the past to the future. In our working paper version (Fueki et al. 2010), we also show the "conditional" efficient output (Adolfson et al. 2011) calculated using the actual values of the state variables and assuming that the allocation becomes unexpectedly efficient (prices and wages become flexible) today and is expected to remain efficient in the future, which does not qualitatively affect our discussion below.

[23] We show the total efficient output in the figure by multiplying the per-capita efficient output by the population over fifteen years old. The per-capita efficient output we calculate is the Kalman-smoothed posterior median. The year-on-year growth rate is calculated as the sum of the quarter-on-quarter growth rates for a year.

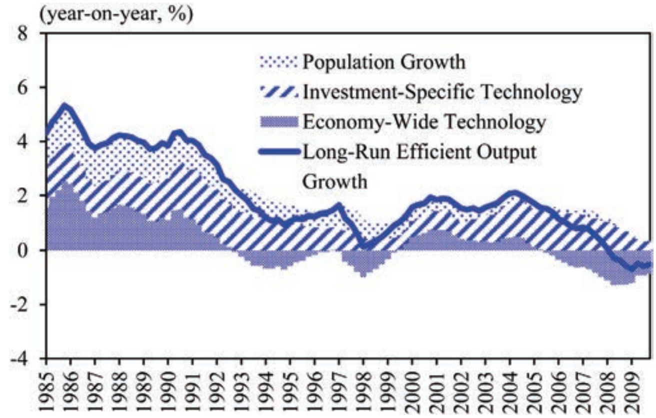
Figure 2. Potential Growth





technological changes. In order to bridge the gap between model-based measures and conventional measures of potential output, we define our measure of potential output (*long-run* efficient output) as a component of the efficient output *generated only by persistent growth rate shocks*. The year-on-year growth rate of this long-run efficient output, which corresponds to the long-run balanced growth path of the economy, is also shown in figure 2 together with the short-run efficient output and the actual output. Compared with the growth rate of the short-run efficient output, our measure of potential growth displays a higher degree of smoothness. In the

Figure 3. Decomposition of Potential Growth



lower panel of figure 2, we compare the year-on-year growth rate of the long-run efficient output with the HP-filtered output and the potential output based on the production function approach (PFA) by Hara et al. (2006). Our measure of potential growth moves closely with those conventional measures of potential growth.

4.2 Decomposition of Potential Growth

In figure 3 we decompose the year-on-year growth rate of the long-run efficient output into component parts generated by each source. Since the persistent growth rate shocks we consider in our model are the economy-wide and investment-specific technology shocks, our measure of potential growth can be decomposed into those two types of technology growth rate shocks in addition to the exogenous population growth. While the investment-specific technology growth rate shock has constantly raised the potential growth during the sample period,[24] the economy-wide technology growth rate shock has reduced the potential growth since the 1990s, except in the early 2000s when information technology (IT) propagated

[24]Braun and Shioji (2007) show that the investment-specific technological progress sustained the potential growth of Japan's economy, even in the 1990s, by calibrating a neoclassical growth model.

through the economy.[25] This widening of the difference in the pace of technological progress between the two sectors could result in sluggish reallocation or misallocation of resources in the labor and financial markets, which in turn could lead to further decline in the economy-wide technology growth. This decomposition makes different but somewhat related stories from those in the PFA-based "growth accounting," in which the capital inputs and the total factor productivity have raised the potential growth while the labor inputs have reduced it.[26]

5. Output Gap

Based on several measures of potential output discussed in the previous section, we can calculate the several corresponding measures of output gap, which is defined as the deviation of the actual output from a measure of potential output. In this section, we compare several measures of output gap.

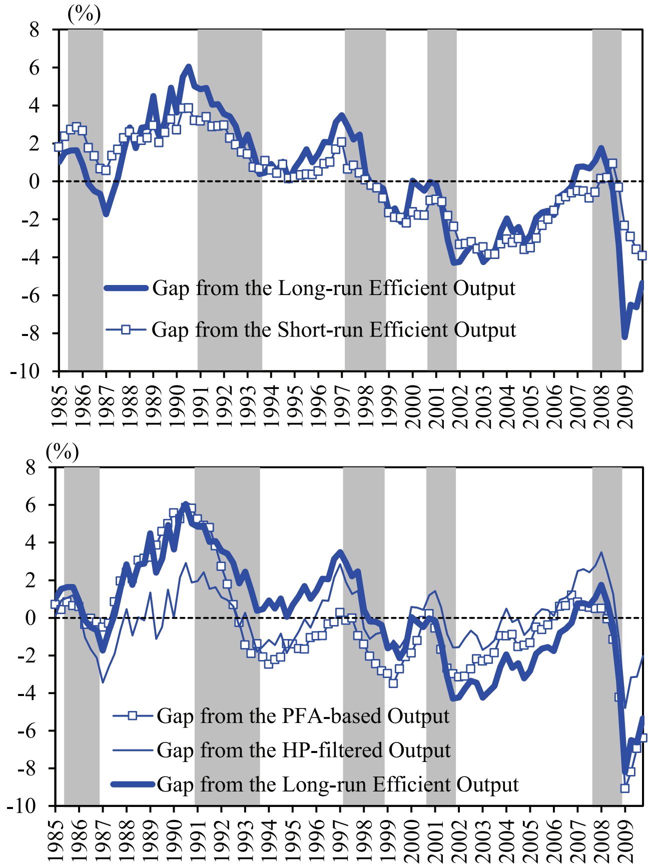
5.1 Several Measures of Output Gap

The upper panel of figure 4 shows the output gaps from the short-run and long-run efficient outputs. The former is less volatile than the latter, because the short-run efficient output moves more closely with the actual output than the long-run efficient output as shown in figure 2. These model-based output gaps move procyclically in

[25] Fueki and Kawamoto (2009) suggest the possibility that Japan experienced IT-driven pickup in productivity growth in the 2000s, which occurred not only in the investment-goods-producing sector but also in the consumption-goods-producing sector.

[26] Hayashi and Prescott (2002) show that Japan's "lost decade" in the 1990s can be explained by the fall in the growth rate of total factor productivity and by the reduction of the workweek length, using the growth accounting and a one-sector neoclassical growth model. They conjecture that the low productivity growth was the result of policy-induced misallocation in which inefficient firms and declining industries were subsidized. Caballero, Hoshi, and Kashyap (2008) discuss the possibility that Japanese banks' lending to otherwise insolvent firms ("zombies") had distorting effects on healthy firms and played an important role in the productivity slowdown in the lost decade.

Figure 4. Output Gap



Note: Shaded regions show the ESRI recession dates.

accordance with the expansion and recession dates determined by the Economic and Social Research Institute (ESRI).

The lower panel of figure 4 shows the output gap from the long-run efficient output together with the gaps from the HP-filtered output and the PFA-based potential output. The gaps from these conventional measures of potential outputs are as volatile as the gap from the long-run efficient output and they move closely with each other.

5.2 Predictability of Inflation

The conventional measures of output gap discussed above have been widely used for forecasting future inflation. Meanwhile, within the New Keynesian theoretical framework, the gap from the short-run efficient output should be a relevant measure that indicates inflationary pressure.[27] The gap from the long-run efficient output, which moves closely with the conventional measures, may also have some theoretical relevance to inflationary pressure and predictive ability for actual inflation. We compare the predictability of inflation across those several measures of output gap.

We evaluate the predictability of inflation by comparing bivariate models of output gap and inflation with an univariate autoregressive (AR) model of inflation, following Coenen, Smets, and Vetlov (2009). The general specification of the bivariate models is as follows:

$$\pi^h_{t+h} = a + b(L)\pi_t + c(L)x_t + \epsilon^h_{t+h}, \tag{25}$$

where π^h_{t+h} is the annualized h-period percent change in GDP or consumption goods deflator, π_t is the annualized one-period inflation $(= \pi^1_t)$, x_t is each measure of output gap, and $b(L)$ and $c(L)$ are finite polynomials of order p and q selected by the Schwarz information criteria. Parameters are estimated by ordinary least squares on rolling samples from 1985:Q1 to 1999:Q1 through 1985:Q1 to 2009:Q4. We then calculate the mean squared forecast errors (MSFE) of the bivariate models (25) and a univariate autoregressive model of inflation at forecast horizons (h) of one, four, and eight quarters ahead. The results are summarized in table 4. Judging from the MSFE of the bivariate models relative to that of the univariate AR model, the measures of output gap we consider generally have forecasting power for inflation when they are included in the bivariate models in addition to the lagged inflation. The comparison of the forecasting power across those measures of output gap reveals that our measure of output gap, the gap from the long-run efficient output, shows better performance—in particular, at short forecast horizons—than

[27] In a somewhat complex New Keynesian DSGE model including ours, however, the relationship between the output gap and inflation is not necessarily straightforward due to the existence of wage rigidity, capital accumulation, and so on.

Table 4. Analysis of Forecast Accuracy

	MSFE			**Relative to AR**		
	Horizon 1q	**Horizon 4q**	**Horizon 8q**	**Horizon 1q**	**Horizon 4q**	**Horizon 8q**
GDP Deflator						
GAP from the PFA-Based Output	2.98	0.74	0.65	0.78	0.96	1.40
GAP from the HP-Filtered Output	3.33	0.38	0.18	0.87	0.49	0.39
GAP from the Short-Run Efficient Output	2.73	0.69	0.41	0.72	0.89	0.88
GAP from the Long-Run Efficient Output	2.63	0.41	0.35	0.69	0.53	0.76
GAP from the Alternative Efficient Output 1	2.70	0.61	0.38	0.71	0.79	0.81
GAP from the Alternative Efficient Output 2	3.32	0.73	0.42	0.87	0.95	0.90
AR	3.81	0.77	0.47	1.00	1.00	1.00
Consumption Goods Deflator						
GAP from the PFA-Based Output	1.74	0.76	0.55	0.72	0.64	1.20
GAP from the HP-Filtered Output	2.31	1.00	0.39	0.96	0.84	0.85
GAP from the Short-Run Efficient Output	2.51	1.27	0.54	1.04	1.07	1.16
GAP from the Long-Run Efficient Output	1.60	0.87	0.53	0.67	0.73	1.14
GAP from the Alternative Efficient Output 1	2.43	1.11	0.50	1.01	0.93	1.09
GAP from the Alternative Efficient Output 2	2.60	1.26	0.52	1.08	1.06	1.13
AR	2.41	1.19	0.46	1.00	1.00	1.00

other measures. For the GDP deflator, our measure of output gap gives the best performance at the one-quarter horizon, while the gap from the HP-filtered output gives the best performance beyond the four-quarter horizon. For the consumption goods deflator, our measure again gives the best performance at the one-quarter horizon, while the gaps from the PFA-based potential output and from the HP-filtered output give the best performance at the four-quarter and eight-quarter horizons, respectively. Meanwhile, the gap from the short-run efficient output shows consistently poorer performance than the gap from the long-run efficient output.

A disadvantage of the conventional measures of output gap, the gaps from the HP-filtered output and from the PFA-based potential output, in forecasting inflation is that they are calculated without using information on the actual inflation. The inflation data in Japan, either the GDP deflator or consumption goods deflator, have been persistently driven by many structural factors, including deregulation and import competition, and accordingly have a clear downward trend from the 1990s to the 2000s, but those factors cannot be considered in calculation of the conventional measures of output gap. Our measure of output gap is calculated using all information in the model and, as a result, moves more closely with the actual inflation than the conventional measures: for example, it was higher than the conventional measures in the 1990s while lower than the conventional measures in the 2000s, as shown in the lower panel of figure 4. Moreover, our measure also captures high-frequency movements in many temporary shocks, including price markup shocks that explain most of the short-run fluctuations in inflation according to the model's variance decomposition shown in table 3, which is related to the better forecasting performance of our measure especially at short forecast horizons.[28]

Meanwhile, the relatively poor performance of the gap from the short-run efficient output may imply some misspecification or misinterpretation in our model. In order to investigate the background

[28]At longer forecast horizons such as four quarters and eight quarters, the forecast performances of the univariate AR models are much better than those at the one-quarter horizon, which makes the advantages of our measure of output gap mentioned above relatively marginal when included in the bivariate models in addition to the lagged inflation.

of this result, we consider some alternative measures of efficient output. For instance, as a midpoint between the short-run and long-run efficient outputs, we can define a component of the efficient output generated by the technology shocks (both in level and growth rate), the investment adjustment cost shocks, the capital utilization adjustment cost shocks, and the intertemporal preference shocks as an alternative measure of efficient output. The gap from this variant of efficient output includes not only the inefficient response of output caused by nominal rigidity and the markup shocks but also the efficient (flexible-price) response of output to the monetary policy shocks, the government expenditure shocks, and the net export shocks. As shown in table 4, the gap from this "alternative efficient output 1" gives comparable forecasting performance to the short-run efficient output gap that includes only the inefficient response caused by nominal rigidity and the markup shocks. In the meantime, the long-run efficient output gap that includes the output response, either efficient or inefficient, to all kinds of temporary shocks shows in most cases substantially better forecasting performance than the above alternative gap as well as the short-run efficient output gap. These results may imply that our model has some misspecification or misinterpretation with respect to the efficient response to temporary shocks—in particular, the level technology shocks, the investment adjustment cost shocks, the capital utilization adjustment cost shocks, and the intertemporal preference shocks.[29]

Moreover, the difference between the gaps from the short-run and long-run efficient output in the period from 2008 to 2009, when the global financial crisis affected Japan's economy, may suggest that a possible candidate of the above-mentioned misspecification or misinterpretation in our model would be the efficient response of output to the investment adjustment cost shocks. As shown in the upper panel of figure 4, while the gap from the long-run efficient output declined sharply in the above period, the gap from the short-run efficient output did not decline so much. This large

[29]The "alternative efficient output 2" in table 4 is the short-run efficient output in a model where the wage markup shock is replaced with a temporary labor supply shock. The gap from this alternative efficient output shows in most cases poorer forecasting performance than both the short-run and long-run efficient outputs in our benchmark model, which may imply that the wage markup shock in our model cannot be interpreted as the labor supply shock.

difference between the two gaps was mainly explained by the different contributions of the investment adjustment cost shocks.[30] While the long-run efficient output gap includes the efficient as well as inefficient response of output to these shocks, the short-run efficient output gap includes only the inefficient response caused by nominal rigidity. The efficient response to the investment adjustment cost shocks in the above period, however, might actually capture some inefficiencies related to frictions other than nominal rigidity, such as financial frictions, which are not explicitly specified in our model. This possibility implies that the gap from the short-run efficient output would under-estimate the negative inflationary pressure in the period after the global financial crisis.

6. Concluding Remarks

In this paper, we have calculated the potential output and the output gap using a Bayesian-estimated DSGE model of Japan's economy. For bridging the gap with conventional measures, we define our measure of potential output as a component of the efficient output generated only by persistent growth rate shocks. Our potential growth displays a high degree of smoothness and moves closely with conventional measures. Moreover, the output gap from our measure of potential output shows better forecasting performance for inflation—in particular, at short horizons—than other measures of output gap.

The short-run efficient output calculated from our model is more volatile and shows poorer forecasting performance for inflation than our measure, which may imply that a substantial fraction of the actual economic fluctuations is, somehow mistakenly, viewed as efficient in our model. Some recent DSGE models, however, consider various kinds of real frictions in the financial market, the labor market, and the open economy so that the models can generate

[30] While the long-run efficient output gap was lower than the short-run efficient output gap by 3.08 percentage points on average from 2008:Q3 to 2009:Q4 (the end of our sample period), the difference in the contributions of the investment adjustment cost shocks to the two gaps in the same period was 2.71 percentage points on average.

substantially inefficient fluctuations. Developing those kinds of models would be another way of bridging the gap with conventional measures of potential output. That will be an important future task.

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A Forecasting Metric for Evaluating DSGE Models for Policy Analysis*

Abhishek Gupta

This paper evaluates the strengths and weaknesses of a dynamic stochastic general equilibrium (DSGE) model from the standpoint of its usefulness in doing monetary policy analysis. The paper isolates cross-correlations among one-step-ahead forecast errors as the most relevant feature for practical monetary policymaking and uses the diagnostic tools of posterior predictive analysis to evaluate them. The paper accounts for the observed flaws in the model with regards to these features using the correlation structure among the estimated shocks. This corresponds to testing and rejecting the over-identifying restriction of no correlation among the structural shocks in the model. The paper attributes this correlation among the estimated structural shocks to model misspecification.

JEL Codes: C11, C52, E1, E58.

1. Introduction

As recent events make all too clear, building models to understand how monetary and fiscal policy may impact the economy is an important goal of the macroeconomics profession. Kydland and Prescott (1982) turned the profession to a new class of models, known as dynamic stochastic general equilibrium (DSGE) models, as they demonstrated that a small DSGE model could match a few simple features of the macro data set. However, it was the pioneering work of Smets and Wouters (2003) that showed that these DSGE models

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can forecast as well as standard atheoretical benchmarks that led to these models becoming an important part of the toolkit at central banks for forecasting and policy analysis. Still, there remains much disagreement about the reliability of these models. This paper looks at the strengths and weaknesses of these DSGE models to check if they are getting better at doing policy analysis.

In particular, this paper provides new diagnostic tools for evaluating the adequacy of DSGE models for the intended purpose of monetary policymaking. These new tools form a part of the growing literature on the New Macroeconometrics that estimates DSGE models using Bayesian techniques.[1] Much work in the area of evaluating these models has focused solely on their overall fit. The most notable among these is the analysis suggested by Del Negro et al. (2007), in which they form a Bayesian comparison of the DSGE model to a general time-series model. They show that the degree to which the data shifts the posterior plausibility mass along a continuum from a fully articulated structural model to a general model with no causal interpretability reflects the degree of misspecification in the structural model. In addition, their approach also helps in assessing the effects of various shocks even in a misspecified model. In contrast, this paper offers tools for diagnosing the dimensions in which a given model suffers from misspecification. Besides this, a number of papers have looked at the out-of-sample forecasting performance of these DSGE models and have reported encouraging results.[2]

In this paper, we take the view that current DSGE models are misspecified in some known and some unknown dimensions and yet may still offer valuable insights for the policy process. We argue that evaluating flawed models using an overall fit metric, though insightful in informing us about the overall likelihood of different competing models, is uninformative about the specific nature of misspecification. Tiao and Xu (1993), Kydland and Prescott (1996), and Hansen (2005) have argued that models should be designed and evaluated for a specific question. Therefore, we evaluate these models for their

[1]For a review of this literature see Fernández-Villaverde, Guerrón-Quintana, and Rubio-Ramírez (2010).

[2]Some of these papers are Smets and Wouters (2004), Adolfson et al. (2007), and Edge, Kiley, and Laforte (2009).

specific usefulness in the task of monetary policymaking. In particular, we argue that monetary policymaking at central banks can be characterized as interpreting the structural sources of unexpected outcomes in the observed data and accordingly acting upon it. We then show how to assess a DSGE model with regards to certain selected features of interest for policy analysis. Finally, we apply the diagnostic tools developed by Faust and Gupta (2012) to link the discrepancies between the model and the data with regards to these features to specific structural misspecifications in the model.

In the present context this amounts to checking whether the model-implied structure of the one-step-ahead (where a step is one decision-making period) forecast errors is consistent with the observed data on two counts: (i) forecast accuracy as reflected by the standard deviations of the one-step-ahead forecast errors (FEs) and (ii) the cross-correlations among the FEs that are crucial to understanding the correct source of the structural shocks causing the economy to deviate from its efficient path. To draw an analogy with the sport of endurance horse racing, these two requirements of the DSGE models are akin to speed and skill. If the jockey focuses only on developing speed and not skill, then he might not be prepared to jump over natural obstacles such as creeks and ditches and very likely might fall into one. We, therefore, want to emphasize that this paper is not only about a horse race for achieving a better overall fit and that it differs significantly from the existing literature that focuses on the forecast accuracy of DSGE models. This underlines the main contribution of this paper, that is, to apply new diagnostic tools to evaluate these models in a way that highlights the structural misspecifications in the model.

We illustrate our approach using the Smets and Wouters (2007) DSGE model, henceforth SW. We find that the consistency of the model with the data requires a non-zero cross-correlation among the smoothed structural shocks of the model: a gross violation of the model assumption. This finding is closely related to an argument of Chari, Kehoe, and McGrattan (2007). They measure certain wedges, which are closely related to our one-step-ahead forecast errors. They note that if two wedges (or one-step errors) are positively correlated, then it must be that at least one structural shock moves both wedges in the same direction. If there is no such shock, then the model can only accommodate the correlated forecast errors by finding that the underlying structural shocks are correlated. Another alternative is to simply suspend the assumption of no correlation of the structural shocks. Cúrdia and Reis (2010) explore this option and allow for disturbances to be dynamically correlated in the SW model. They find that this resolves some of the conflicts between estimates from DSGE models and those from vector autoregressions. This correlation might either be estimated as a diagnostic, in which case it is similar in spirit to what we are doing,[3] or it might be taken to be a serious structural alternative. Our main intent is to provide a diagnostic check and not to advocate a particular new structure. In general, however, we think that if there are certain systematic channels that would lead structural shocks to be correlated, then it makes more sense to model these channels explicitly than to posit a correlation of shocks.

Faust and Gupta (2012) develop the diagnostic tools used in this paper and show, using the same tools, that DSGE models are highly unlikely to produce recessions similar to the ones observed in the post-War U.S. sample. We believe that analysis like this and like that illustrated in this paper can be highly informative for policymakers, who—in lieu of an immediate fix—can judgmentally allow for these models in policymaking.

The rest of the paper is organized as follows: section 2 describes the diagnostic tools of posterior predictive analysis, section 3 discusses the application to the SW model, and section 4 concludes.

2. Model Evaluation Purpose and Tools

In this section, we provide a characterization of model-based monetary policy analysis that suggests model diagnostics that are particularly illuminating in highlighting certain policy relevant deficiencies in these models. In the following sections we also provide a simple example of how these diagnostic tools can help us improve upon these models in their ongoing development to aid in the monetary policymaking process.

[3]Note one clear difference. In our work the sample correlation we are detecting came as a surprise to the agents, who believe that the underlying shocks are uncorrelated. Thus, the model is exploiting not only a systematic correlation but also a systematically surprising correlation.

2.1 Policy Analysis

Policymakers meeting at time t do the following things: they observe new data since the last meeting at $t-1$ (thus, t is measured as the index of meetings); set the policy rate for the current meeting, $i_{t|t}$; and make a forecast for the policy rate for the next meeting, $i_{t+1|t}$.[4] Thus, on an ongoing basis policymakers come into the meeting at time t with the anticipated policy decided at the previous meeting, $i_{t|t-1}$, and at the meeting they decide how to update that view of optimal policy in light of information that has arrived since the last meeting. Under time consistency at least, policymakers will deviate from their expected policy path, $i_{t|t-1}$, only if they have observed new data that is not consistent with their expectations.

Practical policymaking at central banks is thus characterized as interpreting the structural sources of the news in the observed data and accordingly acting upon it. In the DSGE context, the news is entirely reflected in the one-step-ahead forecast errors for the observable variables, Z_t:

$$\nu_t = Z_t - Z_{t|t-1}.$$

Let us suppose that policy is given by a simple Taylor rule (any linear policy rule will do here),

$$i_{t|t} = a + b\pi_{t|t} + cy_{t|t},$$

where $\pi_{t|t}$ is the assessment of inflation at t given time-t information and $y_{t|t}$ is a view of the output gap at t given information at t. As written, the value of these two variables at t is not perfectly observed at t. Although inflation is measured pretty well later, the gap between actual and efficient output remains imprecisely measured indefinitely.

The update in policy rule is written as

$$i_{t|t} - i_{t|t-1} = b(\pi_{t|t} - \pi_{t|t-1}) + c(y_{t|t} - y_{t|t-1}).$$

---

[4] In a forward-looking model, forming the expectations about the future path of policy is an inherent part of setting policy today.

The crucial idea is that the update on these two latent variables under the linear and Gaussian structure of a DSGE model is given by the Kalman filter as a linear function of the news:

$$\begin{bmatrix} \pi_{t|t} - \pi_{t|t-1} \\ y_{t|t} - y_{t|t-1} \end{bmatrix} = \Gamma \nu_t = \Gamma (Z_t - Z_{t|t-1}).$$

Thus, policy analysis, in this simple structure, is a matter of computing the news in the observables. The structural interpretation of this news is given by the interrelationship among the structural shocks in the model, and the Kalman gain, Γ, reflects the implication of this interrelationship for the latent variables.

To see a simple version of this, consider a simple textbook aggregate demand/aggregate supply (AS/AD) framework where the observables are output and some indicator of inflation. The basic idea is that if output and prices come in higher than expected, then we might infer that a positive AD shock has shifted the AD curve outward, which would raise both output and inflation, and warrant a higher interest rate. If on the other hand, inflation comes in higher than expected but the output indicator is lower than expected, then we might infer a negative supply shock has shifted the AS curve inward, which would reduce output and raise inflation. The optimal policy response in this case might be to leave rates approximately unchanged if, say, the fall in output is the efficient response to the adverse supply shock.

This stylized account of policy suggests that we analyze the structure of news according to the model. In particular, the model will imply a correlation matrix for one-step-ahead forecast errors. Given a sample data, we can ask whether the forecast errors estimated by the model on this observed data have a similar correlation structure to that estimated on model-simulated data. This is a different question from pure forecast accuracy. We are not asking "are the errors small?" We are asking "do the errors have the right interrelationships?" In other words, the focus is on evaluating how well the estimated DSGE model is able to characterize the structural source of the unexpected news.

2.2 Diagnosis of the One-Step-Ahead Forecast Errors: A Simple Example

Consider a simple model[5] in which the data are generated by two supply shocks, both of which push output growth and inflation in the opposite direction:

$$\begin{bmatrix} y_t \\ \pi_t \end{bmatrix} = A \begin{bmatrix} y_{t-1} \\ \pi_{t-1} \end{bmatrix} + C\varepsilon_t,$$

where $\varepsilon_t \sim$ i.i.d. $N(0, I)$, and the first row of the shock impact matrix, C, is negative and the second row is positive, e.g.,

$$C = \begin{bmatrix} -2 & -2 \\ 1 & 2 \end{bmatrix}.$$

Setting aside small sample issues, the FEs are given by

$$\nu_t = C\varepsilon_t.$$

We denote the variance-covariance matrix of FEs, ν_t, by Ω and that is given by

$$\begin{aligned} \Omega &= CE(\varepsilon_t \varepsilon_t')C' \\ &= CC' \\ &= \begin{bmatrix} 8 & -6 \\ -6 & 5 \end{bmatrix}. \end{aligned} \tag{1}$$

The FE covariance for output growth and inflation generated by this simple model is negative: both shocks move output and prices in opposite directions.

Suppose the true model driving the data is as stated above except that there is one demand shock and one supply shock. The demand shock moves both output and inflation in the same direction, while the supply shock moves them in the opposite direction as before. This can be captured in the above model if we replace C with

$$\tilde{C} = \begin{bmatrix} -2 & 2 \\ 1 & 2 \end{bmatrix}.$$

[5] This is a numerical example and not found on any model or calibration.

Now the analyst is using a misspecified model that has two different supply shocks, but in reality the data are generated by a process with one supply and one demand shock. Since both models have the same A, which we assume for simplicity is known, the optimal forecasts of the two models are identical. The choice of C and $\tilde{C}$ is such that the variance of the two FEs for the true model is the same as that for the misspecified model. This is to emphasize the difference between the diagonal elements of the variance-covariance matrix of the FEs that tell us about the univariate accuracy of forecast errors, and the off-diagonal elements that tell us about the interrelationship among the FEs.

Suppose we observe a large sample of data generated according to the true model driven by A, $\tilde{C}$, and i.i.d. $N(0, I)$ shocks. The FEs estimated on this large realized sample will then have the variance-covariance matrix approximately equal to $\tilde{C}\tilde{C}'$, and in particular the FE covariance between the two variables will be positive:

$$\begin{aligned} \hat{\Omega} &= \tilde{C}\tilde{C}' \\ &= \begin{bmatrix} 8 & 2 \\ 2 & 5 \end{bmatrix}. \end{aligned} \tag{2}$$

Note that the diagonal elements of the variance-covariance matrix of FEs given by the true model in the above equation are equal to those given by the misspecified model in equation (1).

If one is working with the misspecified model, then all errors would be interpreted as supply shocks, and policy would be chosen to be the optimal response to the observed mix of supply shocks. The only misspecification one would observe is that the covariance of forecast errors estimated on the realized sample would be different from that predicted by the model (the off-diagonal elements in (1) and (2)).

We can diagnose the above symptom to provide a structural analysis of the misspecified model that would help us in figuring out the true model. In particular, any estimate of the FEs, $\hat{\nu}_t$, will imply an estimate of the structural shocks, $\hat{\varepsilon}_t$. Under the model, we know that

$$\hat{\nu}_t = C\hat{\varepsilon}_t.$$

The estimate of the variance-covariance matrix of FEs implied by the misspecified model on the realized sample is then given by

$$\begin{aligned} \hat{\Omega} &= CE(\hat{\varepsilon}_t \hat{\varepsilon}_t')C' \\ &= C\hat{\Sigma}C' \\ \Rightarrow \hat{\Sigma} &= C^{-1}\hat{\Omega}C'^{-1}, \end{aligned} \tag{3}$$

where $\hat{\Sigma}$ is the sample variance-covariance matrix of the estimated structural shocks under the misspecified model. For our example values,

$$\hat{\Sigma} = \begin{bmatrix} 17 & -12 \\ -12 & 9 \end{bmatrix}.$$

Thus, the structure of this misspecified model reflected in C, along with the realized variance-covariance matrix of the FEs, $\hat{\Omega}$, implies a realized value for the variance-covariance matrix of the structural shocks that does not obey the assumptions of the model. In other words, the estimated structural shocks on the realized sample turn out to be correlated to accommodate the misspecification in the model.

The symptom of misspecification we observe is that our estimate of the realized supply shocks on the observed sample—that is, the $\hat{\varepsilon}'$'s—has a negative sample correlation. The intuition: in the misspecified model both shocks move output and inflation in different directions, but in the realized sample output and inflation surprises tend to move in the same direction. In order to reconcile the misspecified AS/AD model with the realized sample, we need the two supply shocks to work together in just the right way. That is, we need just the right mix of negative correlation between the two structural shocks. Working with our numerical example, this is delivered if the two supply shocks have different signs, and the first shock dominates.[6] In this very simple case, when observing that the model "needed" the two supply shocks to be negatively correlated to explain the sample, we quickly deduce that what we need is a shock

[6]For example, one can work with a magnitude of 4x for the first shock and –3x for the second shock.

that moves output and inflation in the same direction—a demand shock. In the next section we show how to apply this analysis in the case of a more complex DSGE model.

2.3 Diagnosis of the One-Step-Ahead Forecast Errors in the DSGE Context

The analysis works the same in a larger and more complex DSGE model, but given higher dimensions, the diagnosis is a bit more subtle. The diagnosis of the one-step-ahead forecast errors in the DSGE context focuses on three additional subtleties we abstracted from in the simple case: (i) sampling fluctuation in estimated parameters and sample variance-covariance matrices, (ii) the model may be misspecified in terms of the conditional mean, which was not the case above, and (iii) the DSGE models generally imply a vector autoregression moving-average (VARMA) structure.

We will take into account issue (i), sampling fluctuations, using posterior predictive analysis as discussed in the next section. Issue (ii), misspecified conditional mean, adds no real problems and simply adds to the list of problems we may detect. Issue (iii) requires a bit more discussion.

Regarding (iii), standard DSGE models imply a VARMA process for the data instead of a pure vector autoregression as assumed in the simple example above. In the VAR case, conditional on initial conditions we observe the ε's, but this is not the case with MA components. Thus, we must work with our best estimate of the ε's, which will be implied by the Kalman filter and/or Kalman smoother. Therefore, rather than working with ε_t, we can work with the updated structural shocks, $\hat{\varepsilon}_{t|t}$, that reflect only the information up to period t, or the smoothed structural shocks, $\hat{\varepsilon}_{t|T}$.[7] To see the effects of the MA terms, write the MA representation[8] of the observables as

[7]This paper reports the results using updated shocks. However, one might want to look at the smoothed shocks to reflect on how the model relates to the full-information case. The results are not noticeably different for the two cases.

[8]The VARMA representation is assumed to be stationary in the DSGE context, which is a trivial assumption for most economic applications.

$$Z_t = \sum_{i=0}^{\infty} C_i \varepsilon_{t-i},$$

where C_i denotes the coefficients for the MA parts and C_0 is the lag-zero impact matrix equivalent to C in the previous section. Taking expectations conditional on information available at time $t-1$, we get

$$Z_{t|t-1} = \sum_{i=1}^{\infty} C_i \hat{\varepsilon}_{t-i|t-1}.$$

The one-step-ahead forecast errors, ν_t, are then defined by the following identity that must hold under the DSGE model for all versions (partial information or full information) of estimated shocks:

$$\nu_t = C_0 \varepsilon_t + \sum_{i=1}^{\infty} C_i (\varepsilon_{t-i} - \hat{\varepsilon}_{t-i|t-1}).$$

This paper focuses on the partial-information case, the updated structural shocks ($\hat{\varepsilon}_{t|t}$), in order to be consistent with the one-step-ahead decision-making problem of the policymakers. The forecast errors are then given by

$$\nu_{t|t} = C_0 \varepsilon_{t|t} + \underbrace{\sum_{i=1}^{\infty} C_i (\hat{\varepsilon}_{t-i|t} - \hat{\varepsilon}_{t-i|t-1})}_{err},$$

where the *err* term includes the revision to the ε's due to the new information made available this period relative to the previous period.[9] In practice, this *err* term turns out to be small in the DSGE context when the data used for estimation belongs to a single-vintage as opposed to a real-time data set. Table 1 reports the correlations

[9] In the full-information case of smoothed structural shocks, $err = \sum_{i=1}^{\infty} C_i (\hat{\varepsilon}_{t-i|T} - \hat{\varepsilon}_{t-i|t-1})$. In this case the revision to the ε's reflects the new information available due to the full sample relative to the forecasting period, and this is likely to be small for the recent periods in the sample relative to periods far back in the sample since the information gap is likely to be small for recent periods. Moreover, the importance of the error terms far back in the past declines exponentially due to the declining magnitude of the associated MA coefficients. Effectively, the *err* term turns out to be small even in the case of smoothed structural shocks.

Table 1. Relationship between $\nu_{t|t}$ and $C_0\varepsilon_{t|t}$, at Posterior Mode

	Partial-Information Case ($\|t$)		Full-Information Case ($\|T$)	
	Correlation	R-Square	Correlation	R-Square
	$(\nu_{t\|t}, C_0\varepsilon_{t\|t})$	$(\nu_{t\|t} = \alpha + \beta C_0\varepsilon_{t\|t} + \gamma)$	$(\nu_{t\|t}, C_0\varepsilon_{t\|T})$	$(\nu_{t\|t} = \alpha + \beta C_0\varepsilon_{t\|T} + \gamma)$
ΔGDP	0.9997	0.9995	0.9823	0.9649
ΔC	0.9995	0.9990	0.9714	0.9435
ΔI	1.0000	0.9999	0.9888	0.9777
Hours	0.9998	0.9996	0.9930	0.9861
ΔW	0.9999	0.9999	0.9993	0.9986
Inflation	0.9999	0.9998	0.9944	0.9889
Interest Rate	0.9999	0.9994	0.9947	0.9893

between $\nu_{t|t}$ and $C_0\varepsilon_{t|t}$ and the variance in $\nu_{t|t}$ that is explained by $C_0\varepsilon_{t|t}$ (r-square) for the iconic Smets and Wouters (2007) DSGE model's observed variables. These results confirm that the *err* term can be safely ignored in the case of a single-vintage data set, as the additional information available in each new data point is not informative enough to cause a significant revision in our estimates of the shocks. More generally, one could also work with real-time data where, in each period, there are substantial revisions to the previous period's data as reported in the provisional estimates and advanced estimates in addition to the benchmark revisions. Under that scenario the new information set available in each period could result in significant revisions to the estimates of the shocks based on previous information sets. The *err* term in this case could be substantial, thereby making the mapping between ν_t and ε_t more complicated. This analysis is beyond the scope of this paper but, nevertheless, remains an important exercise for future research.

In the simple VAR example we didn't have this additional *err* term, and the estimated variance-covariance matrix of the forecast errors, $\hat{\Omega}$, were linked to the estimated variance-covariance matrix of the structural shocks, $\hat{\Sigma}$, via the lag-zero impact matrix C_0. This paper analyzes the single-vintage case, and given that the *err* term is small, the simple VAR relationship holds approximately between $\hat{\Omega}$ and $\hat{\Sigma}$:

$$\hat{\Omega} \approx C_0 \hat{\Sigma} C_0',$$

where the C_0 matrix reports the impact effect of one unit shock and not one standard deviation shock. In order to estimate the conditional contribution of a shock pair correlation such as (α, β) to the elements of $\hat{\Omega}$, we first define a matrix $D^{\alpha,\beta}$ as follows[10]:

$$D^{\alpha,\beta}_{i,j} = \begin{cases} \hat{\Sigma}_{i,j} & \text{if } i = \alpha,\ j = \beta \text{ and vice-versa} \\ 0 & \text{otherwise.} \end{cases}$$

Now the conditional contribution of correlated shock pair (α, β) to the forecast error correlation (FEC) of variables such as (a, b) is given by

[10] If $\alpha = \beta$, then this represents the contribution of the shock variance instead of the shock pair correlation.

$$FEC((a,b)|\hat{\Sigma}_{\alpha,\beta}) = \left(\frac{C_0 D^{\alpha,\beta} C_0'}{\sqrt{\hat{\Omega}_{a,a}}\sqrt{\hat{\Omega}_{b,b}}} \right)_{a,b}. \quad (4)$$

2.4 Describing Posterior Predictive Analysis

The literature on prior and posterior predictive analysis was popularized by Box (1980) and has since been extended by many others, including Gelman, Meng, and Stern (1996), Bayarri and Berger (1999), and Geweke (2007). Even though the basic analytics of this predictive analysis are all well established in the statistics literature, these have received little application in the DSGE context. An and Schorfheide (2007) and Smets and Wouters (2007) have used posterior predictive checks for evaluation of "descriptive" sample moments. A complete description of this prior and posterior predictive analysis as applied to the DSGE context is provided in Faust and Gupta (2012). We provide a brief description here for the sake of completeness.

Posterior predictive analysis relies on a simple idea: if the available sample is collectively an outlier from the standpoint of the model+posterior, then perhaps the model or prior should be refined. It provides formal tools for judging the degree to which relevant features of a sample are "freakish" from the standpoint of the model+posterior. If the realized value is too surprising, then that calls into question the practical validity of the model in exercises related to those specific features.

In a standard Bayesian estimation approach, we have an economic model (the DSGE model) that describes the full joint distribution of observed variables, Y, in terms of unobservable parameters, θ. We define a descriptive feature, $h(Y)$, as one that can be described as a function of Y alone. However, this paper considers only structural features, $h(Y, \theta)$, that depend upon θ in addition to the sample. The structural features considered here are the correlations of the optimal one-step-ahead model consistent forecast errors and the correlations among the updated structural shocks, $\varepsilon_{t|t}$.

Any feature when evaluated on the realized sample (i.e., the observed data), Y^r, is referred to as the realized value of the feature. When talking about realized features, an important difference arises between a descriptive feature and a structural feature. While the former is defined completely by the realized sample at hand, Y^r, the latter is not, because of the dependence on the unknown θ.

Due to the dependence of the realized value of the feature on θ, computing the p-value is slightly more complex for the structural features. However, conditional on a fixed θ^*, one can compute the realized value of the structural feature, $h(Y^r, \theta^*)$, and therefore the probability that the value for this feature in repeated sampling will be greater than the realized value for a fixed θ^* is given by

$$pr(h(Y^{rep}, \theta^*) > h(Y^r, \theta^*)),$$

where Y^{rep} denotes a replication sample drawn according to the model at the posterior parameter vector θ^* and Y^{rep} is of the same size as Y^r.

In order to compute the posterior predictive p-value, one can now integrate out the dependence on θ using the posterior distribution for the parameters to get the p-value as follows:

$$pr(h(Y^{rep}, \theta^{rep}) > h(Y^r, \theta^{rep})),$$

where (Y^{rep}, θ^{rep}) are drawn according to the full posterior distribution.

In practical terms, computing the pair $h(Y^{rep}, \theta^{rep})$, $h(Y^r, \theta^{rep})$ for enough values of (Y^{rep}, θ^{rep}) drawn from the model+posterior will allow us to characterize the posterior predictive distribution for the structural feature and the posterior distribution for the realized sample value. To analyze these two distributions jointly, we can look at a contour plot[11] with $h(Y^r, \theta^{rep})$ on the horizontal axis and $h(Y^{rep}, \theta^{rep})$ on the vertical axis. The p-value described above is then simply the smaller share of points on either side of the 45-degree line in this contour plot. Summarizing a distribution with a single number such as a p-value can hide

[11]For example, figure 1 (column 1, row 1) plots the contour cloud of the standard deviation of output growth, with the posterior for the realized sample value on the x-axis and the posterior predictive values on the y-axis. The three rings of decreasing intensity moving outward cover 50, 75, and 95 percent of the mass, respectively. The contour clouds are smoothed as in Eilers and Goeman (2004).

a lot of information. Such crude summaries should, therefore, be used with caution, and we will largely report the entire predictive density. Still, at times, p-values provide a convenient and compact summary.

If the realized structural feature is not surprising from the standpoint of model+posterior, then one should expect most of the contour cloud to lie around the 45-degree line. On the other hand, if the entire contour cloud lies either mostly above or mostly below the 45-degree line, then it says that for essentially no value of the posterior parameter is the model able to produce a value similar to that observed on the realized sample. This implies that either the realized sample is freakish from the standpoint of the DSGE model and we will almost never observe a sample like that again, or that the DSGE model is misspecified with regards to that feature.

For example, take as our structural feature the sample one-step-ahead forecast error correlation between hours and wage growth. Figure 3, panel A graphs the contour plot for this feature in which each point represents a joint draw of a θ and a replication sample. For each such draw we compute and plot the pair $(h(Y^r, \theta), h(Y^{rep}, \theta))$—the feature on the realized and on the predictive sample, respectively. We plot these pairs as a contour plot with the realized value on the horizontal axis and the predictive sample on the vertical axis. In this case we note that the entire contour plot lies above the 45-degree line and the associated p-value is 0.00, indicating discrepancy between the model and the data with regards to this feature.

It should be noted that the diagnostic tools of posterior predictive analysis discussed in this paper are, however, not in themselves Bayesian in nature. Posterior predictive analysis takes into account both parameter and sampling uncertainty and is, strictly speaking, neither Bayesian nor frequentist in approach. This is in contrast to the Bayesian approach that only accounts for parameter uncertainty and the frequentist approach that looks at only sampling uncertainty. Faust and Gupta (2012) discuss this frequentist vs. Bayesian debate and provide a justification for the use of posterior predictive tools in the non-standard DSGE context and defend its use against standard criticisms.

3. Application

In this section, we evaluate the iconic SW DSGE[12] model for the task of monetary policy analysis using the diagnostic tools of posterior predictive analysis as described in the previous section. We chose this model over many other competing models because this was the first model that was shown to forecast as well as certain atheoretical benchmarks like Bayesian VARs. It introduces a rich set of frictions and as many structural shocks as observed variables, most of which have meaningful economic interpretations. In addition, this is one of the best-known medium-scale DSGE models available for policy analysis.[13] In this section we discuss the results of the posterior predictive evaluation of this model and their implications for model assessment.

3.1 Variance-Covariance Matrix of One-Step-Ahead Forecast Errors

Having motivated the relevant features as the elements of the variance-covariance matrix of FE's, Ω, and the elements of the variance-covariance matrix of the estimated structural shocks, Σ, we evaluate the SW model, in this section, on these features. We compare the posterior distributions of the elements of Ω and Σ estimated on the realized sample with the corresponding posterior predictive distributions.[14]

To begin with, we provide a comparison of the point estimates at the posterior mode of the elements of matrix Ω broken down into the diagonal elements, the standard deviations of the one-step-ahead FEs (FESTDs), and the normalized off-diagonal elements,

[12]The paper uses the same data, model, and posterior draws of the estimated parameters as reported in Smets and Wouters (2007). The files containing the original data, model code, and nearly 250,000 posterior draws of the estimated parameter vector were provided by the authors, who were extremely gracious in extending help.

[13]A brief description of the model is provided in the appendix.

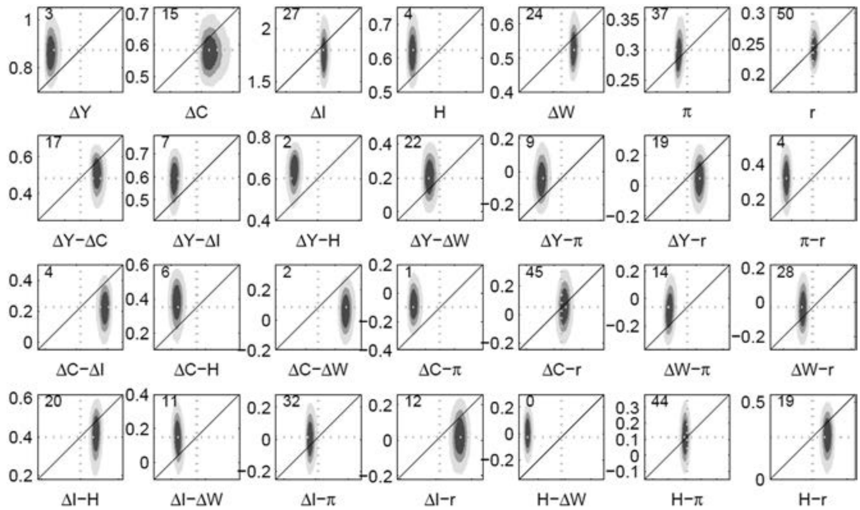
[14]All computations are done using the software Dynare (see Adjemian et al. 2011). For posterior predictive distributions, the model simulated sample size is taken to be the same as that of the realized sample. The distributions are based on the full posterior distribution of the estimated parameter vector θ in Smets and Wouters (2007) as provided by the authors.

Table 2. Ω, Variance-Covariance Matrix of FEs, ν_t, at Posterior Mode

Variables	Standard Deviations	
	Population	**Realized Sample**
ΔGDP	0.85	0.75
ΔC	0.56	0.62
ΔI	1.75	1.85
Hours	0.61	0.54
ΔW	0.52	0.56
Inflation	0.29	0.28
Interest Rate	0.24	0.24
Correlations		
ΔGDP, ΔC	0.50	0.58
ΔGDP, ΔI	0.59	0.50
ΔGDP, Hours	0.63	0.49
ΔGDP, ΔW	0.19	0.14
ΔGDP, Inflation	−0.05	−0.16
ΔGDP, Interest Rate	0.04	0.14
ΔC, ΔI	0.22	0.39
ΔC, Hours	0.38	0.23
ΔC, ΔW	0.04	0.27
ΔC, Inflation	−0.08	−0.28
ΔC, Interest Rate	0.05	0.07
ΔI, Hours	0.41	0.48
ΔI, ΔW	0.14	0.04
ΔI, Inflation	0.01	−0.03
ΔI, Interest Rate	0.03	0.13
Hours, ΔW	−0.01	−0.29
Hours, Inflation	0.12	0.11
Hours, Interest Rate	0.29	0.38
ΔW, Inflation	−0.09	−0.20
ΔW, Interest Rate	−0.03	−0.09
Inflation, Interest	0.31	0.17

the one-step-ahead FE correlations (FECs). However, these are only meant to provide a benchmark reference point, and we later look at the full posterior distributions. Table 2 compares these point estimates of the elements of Ω estimated on the realized sample

Figure 1. Elements of the Ω Matrix



Notes: The figure shows contour plots for the standard deviations and correlations of the FEs, ν_t. The first row plots the standard deviations; remaining rows plot the correlations. The horizontal axis plots the posterior values for the realized sample; the vertical axis plots the posterior predictive values. The number in the upper left gives the smaller share of points on either side of the 45-degree line.

to their corresponding population value. For the FESTDs evaluated at the posterior mode, the population values implied by SW are "close" to estimated values on the realized sample. This closeness in point estimates is confirmed by the posterior distributions around these point estimates. The first row in figure 1 graphs the contour plots of the FESTDs. These contour plots provide a natural way to compare the posterior density on the realized sample (horizontal axis) with the posterior predictive density (vertical axis) for these structural features. For instance, for the FESTD of interest rates (figure 1, row 1, column 7), the contour cloud centers on the 45-degree line. This says that a typical sample drawn according to the model+posterior will have its interest rate FESTD similar to that estimated on the realized sample. Except for output growth and hours (for which the contour cloud lies mainly over the 45-degree line), this is true for all the other observed variables. The p-values reported on the upper left corner for the panels for the FESTD of output growth and hours indicates that the model+posterior produces much higher volatility in these variables than what it estimates on the realized sample. Overall, it is not surprising to observe that the SW model does well with regards to matching the forecast error accuracy since the DSGE models over time have been tailored to match these dimensions.

The second half of table 2 compares the point estimates of the FECs at the posterior mode for the realized sample to their corresponding population value. SW performs poorly with regards to some key FECs such as FEC($\Delta Y, Hours$), FEC($\Delta Y, \pi$), FEC(π, r), FEC($\Delta C, \Delta I$), and FEC($Hours, \Delta W$), among others. The contour plots corresponding to these point estimates depicting the full posterior distributions are graphed in rows 2, 3, and 4 in figure 1. Some of these contour plots lie entirely on either side of the 45-degree line, and that highlights the misspecifications within the model. As argued earlier, the structural interpretation of these conditional FECs is crucial to monetary policymaking. Any incorrect interpretation regarding the source of the FECs translates into an incorrect understanding of the structural shock hitting the economy, and that can translate into an inefficient policy recommendation.

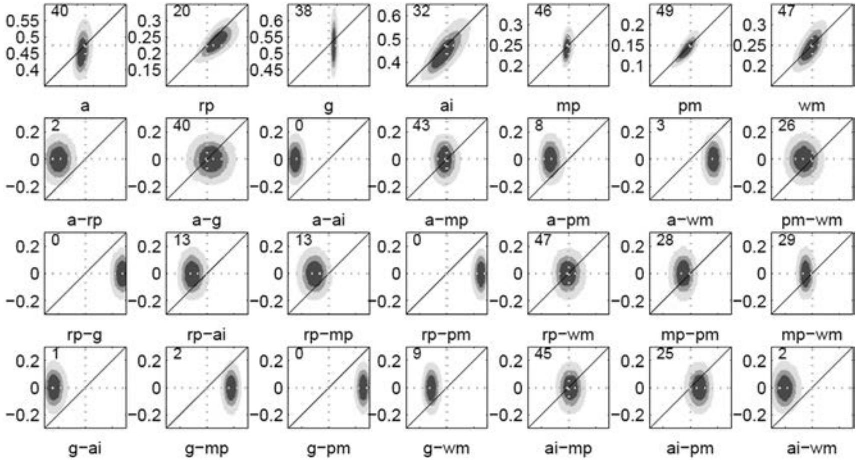
To focus on the structural interpretation of these conditional FECs, we look at the point estimates of the elements of the variance-covariance matrix of the structural shocks, Σ, as a benchmark comparison in table 3 and then analyze the full posterior distributions in figure 2. With regards to the standard deviations of the structural shocks, we find that the estimated posterior mode values are "close" to the corresponding values estimated on the realized sample. Further, the contour plots depicting the posterior distributions around these point estimates (figure 2, row 1) also confirm this. With regards to the correlations of the structural shocks that are assumed to be uncorrelated in the structural model, we find certain pairs of shocks to be correlated on the realized sample. If one believes the realized sample to be the only available sample as a description of the economy, then these correlated structural shock pairs indicate the dimensions in which the model is misspecified. For instance, the contour plot of sample correlation between productivity and investment-specific technology shocks (figure 2, row 2,

Table 3. Σ, Variance-Covariance Matrix of Structural Shocks, $\varepsilon_{t|t}$, at Posterior Mode

	Standard Deviations	
Shocks	**Population**	**Realized Sample**
Productivity	0.45	0.46
Risk Premium	0.24	0.26
Govt. Spending	0.52	0.54
Investment	0.45	0.47
Monetary Policy	0.24	0.24
Price Markup	0.14	0.14
Wage Markup	0.24	0.25
Correlations (Population = 0)		
Productivity, Risk Premium		−0.20
Productivity, Govt. Spending		0.03
Productivity, Investment		−0.26
Productivity, Monetary Policy		−0.02
Productivity, Price Markup		−0.14
Productivity, Wage Markup		0.18
Risk Premium, Govt. Spending		0.27
Risk Premium, Investment		−0.11
Risk Premium, Monetary Policy		−0.11
Risk Premium, Price Markup		0.26
Risk Premium, Wage Markup		−0.03
Govt. Spending, Investment		−0.22
Govt. Spending, Monetary Policy		0.18
Govt. Spending, Price Markup		0.25
Govt. Spending, Wage Markup		−0.13
Investment, Price Markup		0.01
Investment, Inflation		0.06
Investment, Wage Markup		−0.20
Monetary Policy, Price Markup		−0.05
Monetary Policy, Wage Markup		−0.06
Price Markup, Wage Markup		−0.07

column 3) shows this shock pair to be negatively correlated on the realized sample. This indicates that a positive productivity shock is systematically accompanied by a negative technology shock to the investment function. We are not aware of a "conventional" story

Figure 2. Elements of the Σ Matrix

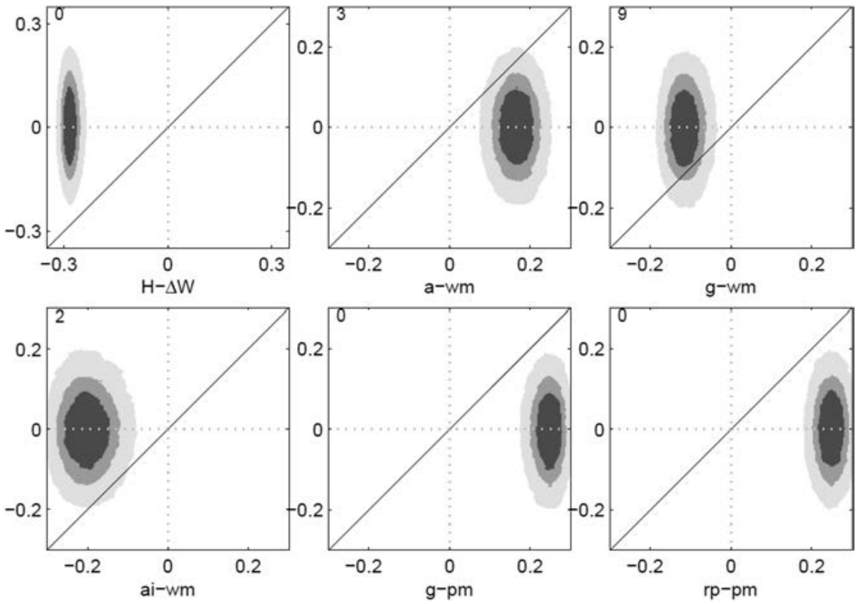


Notes: The figure shows contour plots for the standard deviations and correlations of the structural shocks, $\varepsilon_{t|t}$. The first row plots the standard deviations; remaining rows plot the correlations. The horizontal axis plots the posterior values for the realized sample; the vertical axis plots the posterior predictive values. The shock labels are as follows: a: productivity; ai: investment productivity; rp: risk premium; pm: price markup; wm: wage markup; g: government spending; mp: monetary policy. The number in the upper left gives the smaller share of points on either side of the 45-degree line.

of why investment productivity shocks come in high when general productivity are low. The model requires this shock pair to be correlated in this theoretically unmotivated manner to probably account for some of the discrepancies between the data and model with regards to certain FECs as highlighted above. The accounting framework provided in equation (4) tells us that the posterior mode value for this estimated negative correlation between general and investment productivity shocks contributes positively to FEC($\Delta Y, \pi$) and FEC($\Delta I, \pi$) while lowering FESTD(ΔY), among others.

In the next two sections we explore two key FECs (FEC($Hours, \Delta W$), FEC($\Delta Y, \pi$)) where the SW model performs poorly and use the accounting framework discussed earlier to assign the misspecification with regards to these features to certain correlated shock pairs.

Figure 3. Contour Plot Accounting for FEC($\boldsymbol{Hours, \Delta W}$)



Notes: The upper left graph plots the forecast error correlation between hours and wage growth; remaining graphs plot the correlated shock pairs that account for the negative values of this correlation on the realized sample (see table 4). The horizontal axis plots the posterior density for the realized sample; the vertical axis plots the posterior predictive values. The shock labels are as follows: a: productivity; ai: investment productivity; rp: risk premium; pm: price markup; wm: wage markup; g: government spending. The number in the upper left gives the smaller share of points on either side of the 45-degree line.

3.1.1 FEC($Hours, \Delta W$)

The upper left graph in figure 3 plots the contour plot for FEC($Hours, \Delta W$).[15] The posterior predictive values (on the vertical axis) are centered around zero, whereas the posterior values estimated on the realized sample (on the horizontal axis) show a negative correlation centered around -0.29.

[15]The point estimate for this correlation, given in table 2, is –0.01 for the posterior mode value relative to –0.29 for the realized value.

In order to be consistent with the observed negative FEC($Hours, \Delta W$) on the realized sample, the model would need a shock that moves wages and hours in opposite directions on impact. Productivity and wage markup shocks are potential candidates in the SW model, but these fail to generate a quantitatively significant negative correlation between hours and wage growth. Similar to Galí (1999), a positive productivity shock in this model increases a firm's markup as sticky wages stall the rise in wages until the next period of optimization. This creates a wedge between the marginal productivity of labor and real wages that decreases over time as real wages optimally adjust to a higher value over time. The intertemporal substitution effect, therefore, causes households to reduce their labor supply contemporaneously. Further, due to sticky prices, real balances and aggregate demand remains unchanged and the same output is produced using fewer hours. Also, as argued in Francis and Ramey (2005), real rigidities such as habit formation and investment adjustment costs cause hours to decline in response to a productivity shock. Consumption and investment being highly persistent results in the extra resources being spent on the only available alternative, that is, leisure. However, the presence of sticky wages prevents a substantial rise in wages that limits the negative correlation between hours and wage growth due to the productivity shock.

On the other hand, the wage markup shock bypasses the wage stickiness and increases real wages on impact but has a limited negative impact on hours worked, as the negative wealth effect is countered by the positive substitution effect. Overall, whatever little negative correlation is generated by the productivity and wage markup shocks is countered by positive correlation generated between hours and wage growth by other shocks and pairs of shocks.

The model, therefore, requires certain pairs of shocks estimated on the realized sample to be correlated in order to produce the negative value of realized FEC($Hours, \Delta W$). For instance, a positive correlation between the productivity and wage markup shocks causes wages to rise and hours to fall on impact. Similarly, the other major correlated shock pairs impacting FEC($Hours, \Delta W$) are discussed in table 4, which provides a quantitative accounting for the negative realized value of FEC($Hours, \Delta W$) using (4).[16] The graphs that follow the upper left

[16] The lag-zero shock impact matrix at the posterior mode is provided in table 6.

Table 4. Accounting for Realized Value of FEC(*Hours*, ΔW), at Posterior Mode

Main Correlated Shock Pairs	Shock Correlation	Contribution to FEC(*Hours*, ΔW)
(Productivity, Wage Markup)	0.18	−0.07
(Govt. Spending, Wage Markup)	−0.13	−0.06
(Investment, Wage Markup)	−0.20	−0.08
(Govt. Spending, Price Markup)	0.25	−0.08
(Risk Premium, Price Markup)	0.26	0.07

FEC($Hours$, ΔW) with uncorrelated shocks = −0.01.
FEC($Hours$, ΔW) with correlated shocks = −0.29.

graph in figure 3 show the posterior distributions of these correlated shock pairs.

The wage markup shock tends to be negatively correlated with the spending and investment shocks. A positive wage markup shock raises wages and is accompanied by negative spending and investment shocks that lower hours worked. This explains a substantial amount of the negative $\text{FEC}(Hours, \Delta W)$ on the realized sample. The spending and price markup shocks are positively correlated, and this again generates a negative $\text{FEC}(Hours, \Delta W)$, as a positive spending shock raises hours worked and a positive price shock lowers the real wages. Lastly, the positive correlation between the risk premium and price markup shock generates a positive $\text{FEC}(Hours, \Delta W)$, as a positive risk premium shock lowers consumption and investment demand, thereby causing a decline in hours worked, and at the same time a positive price markup shocks lowers real wages.

This diagnosis tells us that the SW DSGE model+posterior under the structural assumption of uncorrelated shocks is highly unlikely to produce samples with a negative value for $\text{FEC}(Hours, \Delta W)$. This symptom of misspecification then tells us that the model needs a shock that raises wages and lowers hours worked at the same time and does so in a quantitatively significant way. A leisure preference shock could do the trick. But to say that employees take a voluntary vacation during recessions is rather unsatisfactory.[17] The exploration of other potential channels to account for this observed discrepancy, such as the role of labor market frictions and efficiency wages, however, is beyond the scope of this paper. The focus and the contribution of this paper is to apply a set of diagnostic tools to identify the strengths and weaknesses of these structural models rather than developing new models that can account for these identified weaknesses. Nevertheless, the results from this paper can prove to be highly useful for modeling experts in the development of new models.

3.1.2 FEC($\Delta Y, \pi$)

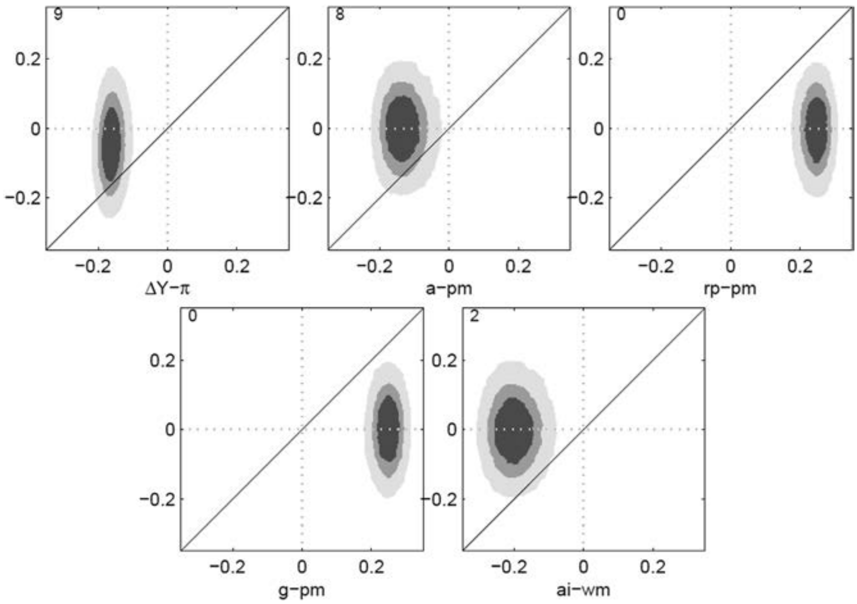
Figure 4 and table 5 provide a similar accounting analysis for the realized value of FEC($\Delta Y, \pi$). The upper left graph in figure 4 plots the contour plot for FEC($\Delta Y, \pi$).[18] The posterior predictive values (on the vertical axis) are not significantly different from zero, whereas the posterior values estimated on the realized sample (on the horizontal axis) show a negative correlation centered around -0.16. The remaining graphs of figure 4 plot the correlated pairs of structural shocks that account for this negative realized value of FEC($\Delta Y, \pi$).

As was shown in our simple example in section 2.2, it is important for the model to get right not only the standard deviation of the FEs in output growth and inflation, but more importantly how these two forecast errors are correlated. Output growth and inflation are the two key policy variables and, given that the model produces an estimate of FEC($\Delta Y, \pi$) that is at odds with the data, one should be highly cautious in using such a model for analyzing the structural source of the forecast errors. The main correlated shock pairs that contribute to a negative FEC($\Delta Y, \pi$) include a positive correlation between the price markup and risk premium shock, a negative correlation between price markup and productivity shock, and a negative correlation between investment spending and wage markup shock. On the other hand, a positive correlation

[17]Edge, Kiley, and Laforte (2009) include a leisure shock in an estimated DSGE model for the U.S. economy that amounts to a negative labor supply shock causing wages to increase and hours to fall.

[18]The point estimate for this correlation, given in table 2, is –0.05 for the posterior mode value relative to –0.16 for the realized value.

Figure 4. Contour Plot Accounting for FEC($\Delta Y, \pi$)



Notes: The upper left graph plots the forecast error correlation between output growth and inflation; remaining graphs plot the correlated shock pairs that account for the negative values of this correlation on the realized sample (see table 5). The horizontal axis plots the posterior density for the realized sample; the vertical axis plots the posterior predictive values. The shock labels are as follows: a: productivity; ai: investment productivity; rp: risk premium; pm: price markup; wm: wage markup; g: government spending. The number in the upper left gives the smaller share of points on either side of the 45-degree line.

between government spending and price markup shock contributes to a positive FEC($\Delta Y, \pi$).

With regards to the structural model, productivity and markup shocks are the only potential candidates that can generate a negative FEC($\Delta Y, \pi$). However, that is countered by the positive correlation generated by the demand shocks and the policy shock. The problem here seems to be that the model+posterior is putting too much emphasis on demand shocks and in order to counteract this effect, the model requires a combination of positive and negative correlations among the various structural shocks as discussed above. Faust and Gupta (2012) highlight that the model+prior in the SW model

Table 5. Accounting for Realized Value of FEC($\Delta Y, \pi$), at Posterior Mode

Main Correlated Shock Pairs	Shock Correlation	Contribution to FEC($\Delta Y, \pi$)
(Productivity, Wage Markup)	−0.14	−0.06
(Risk Premium, Price Markup)	0.26	−0.13
(Investment, Wage Markup)	−0.20	−0.05
(Govt. Spending, Price Markup)	0.25	0.14

FEC($\Delta Y, \pi$) with uncorrelated shocks = −0.05.
FEC($\Delta Y, \pi$) with correlated shocks = −0.16.

Table 6. Lag-Zero Shock Impact Matrix, C at Posterior Mode*

Variables → Shocks ↓	ΔY	ΔC	ΔI	Hours	ΔW	π	Interest Rate
Productivity	0.33	0.07	0.32	−0.28	0.07	−0.05	−0.07
Risk Premium	−0.42	−0.51	−0.35	−0.29	−0.04	−0.02	−0.11
Govt. Spending	0.50	−0.06	−0.12	0.34	0.01	0.01	0.03
Investment	0.37	−0.04	1.64	0.25	0.03	0.04	0.04
Monetary Policy	−0.19	−0.19	−0.28	−0.13	−0.03	−0.04	0.18
Price Markup	−0.12	−0.05	−0.23	−0.05	−0.28	0.24	0.06
Wage Markup	−0.03	−0.08	−0.07	−0.06	0.43	0.13	0.04

*Impact effect of a one-standard-deviation shock.

heavily leans towards a bigger role for the demand shocks. In light of that result, to fix this issue at hand, one could either change the prior or think of a new model specification that has a larger role for supply shocks in these models. However, since we are looking at a general equilibrium model, it is not certain how this would affect the overall likelihood of the model. This analysis, nevertheless, provides a starting point for future model refinement, as it highlights a crucial weakness of the model.

Smets and Wouters (2007) show that the model fares well in matching the unconditional correlation function between output growth and inflation using posterior predictive analysis. Two remarks are in order. First, their use of posterior predictive analysis is limited to a descriptive feature of the data, whereas we are analyzing a structural feature that in addition to depending on the data also depends on the model parameters. Second, with regards to monetary policy analysis, as argued earlier, the important feature to consider is $\text{FEC}(\Delta Y, \pi)$ and not the unconditional correlation function between these variables.

Other discrepancies with regards to the off-diagonal elements of the Ω matrix (see figure 1) can similarly be analyzed to shed light on the structure of the model. The most notable among these are $\text{FEC}(\Delta Y, Hours)$, $\text{FEC}(\Delta Y, \Delta I)$, $\text{FEC}(r, \pi)$, and $\text{FEC}(\Delta C, Hours)$, where the model generates too high a positive correlation relative to what is observed on the realized sample; $\text{FEC}(\Delta C, \Delta W)$, where the model generates no significant correlation as opposed to a significant positive correlation seen on the realized sample; $\text{FEC}(\Delta C, \pi)$, where the model generates no significant correlation as opposed to a significantly negative correlation observed on the realized sample; and $\text{FEC}(\Delta C, \Delta I)$, where the model generates too low a positive correlation relative to what is observed on the realized sample.[19]

4. Conclusion

This paper characterizes monetary policy analysis as being divided into two steps: first, estimating the variance-covariance matrix of the FEs and, second, filtering the structural implications of these forecast errors using the shock impact matrix, C, and the realized value of the estimated structural shocks. The paper illustrates the application of these tools to the SW model, highlighting the model's strengths and weaknesses. The model+posterior does reasonably well on the FESTDs but performs poorly with regards to certain key FECs. The paper also highlights specific misspecifications in the model with regards to the structural shocks. We show that the model is highly over-identified and the only way it can accommodate the realized sample is by assigning non-zero cross-correlations to structural shocks estimated on the realized sample. This suggests

[19] Accounting analysis for these other forecast error correlations at the posterior mode similar to the ones presented in table 4 and table 5 is available from the author on request.

that the structural model to a certain degree, to the extent of the non-zero cross-correlations among the structural shocks, is akin to a more atheoretical model with no causal interpretability. The evaluation tools discussed in this paper diagnose the problem areas in these models at a structural level and highlight what pairs of shocks in these models are the trouble areas. We strongly encourage the use of these tools in evaluating other models, particularly from the standpoint of monetary policymaking.

Appendix. DSGE Model: Smets and Wouters (2007)

SW is an extension of the standard DSGE model with sticky wages and sticky prices, largely based on Christiano, Eichenbaum, and Evans (2005).[20] This model allows for sticky nominal wage and price settings with backward inflation indexation. Other features include habit formation in consumption, investment adjustment costs, variable capacity utilization, and fixed costs in production. The model introduces seven orthogonal structural shocks that include productivity, investment, risk premium, government spending, wage and price markup, and monetary policy shocks.

Households maximize a non-separable utility function in consumption and labor. Consumption depends on the previous period's consumption, and the degree of habit formation is given exogenously. Labor is differentiated, so households have some market power over wages. Due to wage rigidity à la Calvo (1983), households set their optimized wages only periodically, and the households that do not optimize partially index the wages to the previous period's inflation. Households own the capital stock and rent it out to firms. They decide how much to invest given the investment adjustment costs and also determine the rate of capital utilization in order to minimize costs. Labor aggregator firms purchase the differentiated labor input from the households and transform it into aggregate labor. A continuum of intermediate firms purchase this aggregated labor and rent capital from households and produce differentiated goods that are sold to the final producers. Similar to households, intermediate firms face nominal rigidities and set prices à la Calvo (1983).

[20] Readers are referred to Smets and Wouters (2007) for a thorough explanation of the model equations and frictions.

Prices that are not optimized are partially indexed to the previous period's inflation. The final goods firm then takes the prices of these intermediate goods as given and transforms them into a composite good sold to consumers, investors, and the government. The model is closed with a Taylor-type monetary policy reaction function, where the interest rate is adjusted gradually in response to the output gap and inflation.

This model has been estimated with Bayesian techniques using quarterly U.S. data for seven key macroeconomic variables from 1966 to 2004: real GDP growth, real consumption growth, real investment growth, inflation, real wage growth, hours worked, and the nominal interest rate. GDP, personal consumption expenditure, and private fixed investment are all deflated using the GDP price deflator and divided by a population index, thus making them real per capita variables. Hours worked is computed by multiplying civilian employment with the average weekly hours worked by all persons in the non-farm business sector. This is divided by the population index to make the series per capita. Real wage is computed by deflating the hourly compensation of all persons in the non-farm business sector by the GDP deflator. Inflation is defined as the log-difference in the GDP deflator, and the nominal interest rate used is the quarterly effective federal funds rate. All growth rates are computed using quarter-to-quarter log-differences.

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What Determines the Credibility of the Central Bank of Israel in the Public Eye?*

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In line with the rational expectations approach, economists emphasize transparency as a key factor for central banks' credibility. In this paper, a psychological approach yields different results: trust in the banks' policy is associated with the professionalism and independence of the bank and *not* with its transparency. It is a subtle difference: transparency is indeed a positive factor in the overall perception of the bank as trustworthy, but a statistical analysis shows that not all aspects of perception are relevant to trust in the bank's credibility in its inflationary policy.

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1. Introduction

Central banks cannot function in the absence of trust. Other branches of the government need trust too, but for the central bank it is crucial because trust has replaced the gold standard as the anchor of the world's monetary system. Following the demise of the Bretton Woods monetary regime, price stability is dependent upon the fiscal and monetary policy of the government, and the trust in those policies experienced by economic agents. In essence, it consists of the belief that the central bank is in control of the money supply, and that current monetary policy is adequate for

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maintaining price stability.[1] The recent proliferation of inflation-targeting regimes (Fouejieu and Roger 2013, Salle 2013) formalizes this trust through the attempt to influence the public inflationary expectations. The central bank has a formal or informal inflation target, most often around 2 percent per year, which attempts to anchor inflationary expectations.

Israel is a fine example of the success of inflation targeting: it managed to complete its disinflation process, starting at a hyperinflation rate of 445 percent in 1984, going through around 10 percent in the 1990s, and settling at its current inflation rate, which is in the low one-digit range. This success hinges upon the ability of the Bank of Israel to persuade the public that it adheres to its inflation target—between 1 and 3 percent per year—even though it often missed it.[2] The anchoring of inflationary expectations is important per se, but it also allows the Bank to pursue anti-cyclical monetary policy: easing the money supply in times of economic slowdown. If the inflationary expectations are firmly anchored, the public does not interpret this move as a signal that inflation is returning, but rather as a real increase in the money supply and credit.

The acquired reputation of the central bank is a solution to the well-known "time-inconsistency problem" introduced by Prescott and Kydland: policymakers sometimes have an incentive to say one thing, but later do something else. One solution is for policymakers to develop a reputation for credibility and recognize that the long-term benefits of having a reputation for reliability exceed the short-run costs involved (Gomme 2006, Rogoff 1985).

Central bank credibility means price and wage setters will be more willing to exercise restraint if they believe the central bank is firmly committed to price stability (Krugman 2012). A high level of central bank credibility should lead to various economic advantages such as less costly disinflation—when the bank operates to lower inflation rates. It also prevents random shocks in prices and causes less fluctuation in inflationary expectations (Herrendorf and

[1]The OECD targeted trust in government as one of the subjects the organization wants to address in the aftermath of the current crisis, and it stressed the need to use tools from behavioral economics and psychology in this endeavor (OECD 2013).

[2]It is easy to gauge inflationary expectations in Israel as the difference between the interest rates on indexed and non-indexed government bonds.

Lockwood 1997). Further, it enables the bank to make tactical changes in monetary policy without inducing fear in the financial markets. Lastly, even when the bank acts as lender of last resort or has to protect the local currency against speculators, the required policies won't necessarily lead to an increase in inflationary expectations, provided the bank enjoys a good reputation (Blinder 2000).

The above explains why efforts to attain and measure credibility are valuable. Notions like "credibility"—which, like most abstract concepts, are somewhat nebulous—must be defined precisely (Gomme 2006). Very often, credibility is measured by the difference between medium-/long-term public expectations regarding the bank's target and the target itself. Since public expectations about inflation constitute one of the key factors that determine actual inflation, the interest of the bank in this measure is clear. However, this measure is not a clean indicator of the basic credibility of the bank, the basis of the inflation-targeting regime. This is because inflationary expectations are a combination of the analysis of economic conditions together with the bank's powers and intentions. The measure which we develop in this paper is designed to gauge the latter only: how people view the ability and intentions of the bank.

We measured the credibility of the Bank of Israel by asking respondents how much confidence they have in the Bank's inflationary forecasts and also growth forecasts. We then combined these measures with perceptions of laypeople regarding the Bank, in order to determine what creates the Bank's credibility in the public eye.

The Bank of Israel's forecasts are made by the Bank's research department and its reports are published twice a year (Bank of Israel 2011). We chose this item because the Bank places much emphasis on these forecasts. It makes an effort to convince the public that its forecasts are objective and reliable, by detailing the procedure and the models underlying them. The forecasts are one of the tools that the Bank uses to convince the public that it is serious about its commitment to control inflation and to confine it within its target. While our measure of credibility is tightly linked to the inflation forecasts, it focuses on the *confidence* that the public has in the Bank's forecasting abilities, rather than in the *outcome* of its actions.

In an attempt to determine what factors affect a central bank's credibility, Blinder (2000) asked eighty-four central bank governors to rate the variables that make a central bank credible. "A history of living up to its word" and "independence from the political system" were found to be the most important factors (with no significant difference between them). A history of fighting inflation and transparency followed, in terms of importance (again, no significant difference between them), while low fiscal deficit, clear rules, and incentives to the bank's governor ranked last.

However, the governors' views do not necessarily represent those of the public at large. Indeed, this would be unlikely, as their position and experience endows them with a thoroughly atypical perspective. It is important to study the attitudes of laypeople, since they are those who by their economic behavior affect prices through expectations. Expectations regarding future prices affect today's purchases, which in turn affect today's prices, and this means that laypeople's expectations regarding prices are critical for the control of inflation (Gaffeo and Canzian 2011). Due to the complexity of causal relations in economics, it seems doubtful that the public grasps the nature of the central banks' actions and their purpose, and indeed, it may well fail to understand the very function of central banks. As Arthur (2005) stresses, economics is inherently difficult. Professional arguments relating to the central bank's credibility are exceedingly technical. If the public tries to evaluate its activity, it must perforce impose some simpler structure and rely on heuristics (Leiser and Aroch 2009) to decide how much credence to give to the bank's pronouncements.

Much is already known about what may happen when comprehension is challenged. Psychologists distinguish two modes of mental functioning, and these map onto two qualities of trust: trust based on either cognitive-rational processes or on automatic-affective ones (Castelfranchi and Falcone 2010; Gangl et al. 2012). The differentiation in cognitive-rational and automatic-affective trust echoes a distinction made in various theoretical and empirical contexts, such as the dual models of Darlow and Sloman (2010); Epstein and Pacini (1999), or the Elaboration Likelihood Model (Petty and Cacioppo 1986) and the Heuristic Systematic Model (Chen and Chaiken 1999), both of which describe persuasion and attitude change.

We draw on Castelfranchi and Falcone's (2010) conceptualization of trust, and differentiate between reason-based and implicit trust. Reason-based trust represents the result of a rational argumentative decision (Castelfranchi and Falcone 2010). For our purposes, we will focus on the two main factors affecting the decision. The trustor evaluates the other's competence and willingness regarding the successful achievement of a specific goal. Competence means that the other is perceived as being capable of successfully achieving a certain goal. Willingness results from the assessment of the other's motivation, intention, and persistence to achieve a specific goal. The rational evaluation of these components combined with the costs, benefits, and dangers involved determine the degree of reason-based trust.

Reason-based trust therefore corresponds to trust definitions assuming a rational agent who trusts the other if it can be expected that he will forgo opportunistic goals (Coleman 1994). As we noted above, this is precisely what the reputation of a central bank relies on to achieve its goal despite the "time-inconsistency problem." By contrast, implicit trust is defined as an automatic, unintentional, and unconscious reaction to stimuli (Castelfranchi and Falcone 2010). The automatic reaction originates from associative and conditioned learning processes and memory. It is related to social trust (Welch et al. 2005) and to affective trust, as conceptualized by Jones (1996). Both qualities of trust—reason-based trust and implicit trust—are relevant to the perception of the central bank. One purpose of this study is to evaluate the relative importance of the two sets of processes (the reason-based and the implicit factors) in the evaluation of the central bank's credibility.

2. Method

Using social networks, e-mails, forums, and content sites, we publicized an online questionnaire that contained three sets of questions: (i) demographics; (ii) questions measuring the judged credibility in the economic predictions of the Bank of Israel, as compared with other major economic institutions; and (iii) questions regarding the respondents' assessment of the Bank's performance.

Data collection was concentrated in the period between May 16 and July 14, 2011. During this period, the most prominent global economic features were the continued decline in global markets and further deterioration of the European debt crisis. Meanwhile, Israel's economy experienced continued growth, leading to the strengthening of the shekel (the local currency) against the U.S. dollar, as well as a continued rise in housing prices. The inflation rate (twelve months ending in July 2011) was 4.1 percent, higher than the upper limit of the inflation target (3 percent), while inflationary expectations derived from markets stood at 2.9 percent (Bank of Israel interest rate press release, July 2011).

2.1 Materials

Our online questionnaire consisted of four sections and was constructed in a way that its average time of completion would not exceed eight to nine minutes. Therefore, the number of questions was kept small. Its sections were as follows: In the first, an overview of the task was given to participants and it was emphasized that filling in the questionnaire was voluntary; respondents could leave the questionnaire at any stage and information given by them would strictly be kept in confidence. The second section collected sociodemographic information.

In the third section, our operational goal was the extent to which our survey respondents believed that the Bank's forecasts will materialize. Each respondent rated, on a nine-point scale (ranging from 1 = "Definitely not" to 9 = "Definitely"), the level of trust they give to the forecasts on inflation and economic growth of the central bank. We then compared them with the forecasts of five major economic institutions which we used as reference. For each institution, we used the indicator it is mostly identified with, in the same way that central banks are associated with inflation and growth forecasts. The five institutions are (i) Bank Hapoalim, the largest commercial bank in Israel, (ii) the international investment bank Goldman-Sachs, (iii) the Israeli Ministry of Finance, (iv) the Manufacturers' Association of Israel, and (v) Teva, a global pharma company and the largest firm in Israel. To ensure that we measured trust in the institutions' forecasts, rather than forecasts about the current economic situation, all questions were formulated hypothetically, the time involved was left undefined, and the predicted values exceeded current estimates by 20 percent to 100 percent. The following will serve to illustrate the questions we asked:

> Assume the Bank of Israel expects the CPI to rise in a particular year between 5 and 6 percent. Please rate on a scale of 1 to

9, to what extent do you believe that the Bank's forecast will be realized and will the CPI will indeed fall in this range?

The last section measured respondents' perceptions regarding the Bank. Respondents rated, on a six-point scale (1 = "Not at all" to 6 = "Very much"), the extent of their agreement with fifteen statements regarding the Bank of Israel. Some of the statements were formulated as positive, others as negative. Two additional statements were formulated as "semantic differential" scales—a method in which participants are asked to declare their positions regarding a phrase on a scale between two bipolar adjectives, as for example: "The Bank of Israel is a *political/professional* institution." In general, all statements were relevant to the role and reputation of the central bank. Questions were adapted from statements used by Vigoda (2000) and Vigoda and Mizrahi (2010), who studied public trust in the Israeli public sector, to which we added questions about topics not covered by them and required for our study. The order of the questions in each section was modified randomly for each participant, to control for order effects. Table 1 presents all the statements dealing with preferences, functions, and performance of the Bank as a fair, transparent, independent, professional, and trustworthy institution.

2.2 Participants

When publicizing the questionnaire, we endeavored to reach all socioeconomic levels of the Israeli population, with a wide range of age, professions, and educational level. The distribution procedure yielded 1,083 responses, of which 50 percent (542) completed the questionnaire. We excluded partially completed questionnaires and questionnaires completed by respondents with an academic degree in economics, leaving us with laypeople only. We further excluded forms bereft of variance (e.g., all answers were rated 6) as indicating respondents who were only interested in glancing at the questions or to reach the questionnaire's end. The final sample consists of 481 respondents (mean age = 39.9, SD = 13.7), of which 249 were female and 232 male, who had no (288) or little (193) formal training in economics. Among the respondents, 98 had no college education, 274 were undergraduates, and 168 were studying for or had completed their graduate studies. When asked to rate their socioeconomic

Table 1. Statements and Encoding

No.	Statement	Encoding	Aspect
1	When the Bank of Israel is committed to a certain action, I believe that it will be carried out.	Will Perform	Trust and Fairness
2	The Bank of Israel is trustworthy compared with other institutions.	Trust—General	Trust and Fairness
3	There is not a necessary correspondence between the Bank of Israel's announcements and its actions in reality.	Will Perform (r)	Trust and Fairness
4	The Bank of Israel operates in a fair and ethical manner.	Fair	Trust and Fairness
5	The Bank of Israel is trustworthy/corrupt (semantic differential).	Trustworthy—Corrupt	Trust and Fairness
6	Most people holding key positions in the Bank of Israel are political appointments.	Political App. (r)	Independence
7	The Bank of Israel actions serve a limited number of stakeholders rather than the whole system or public.	Vested Interest	Independence
8	The Bank of Israel is a political/professional institution (semantic differential).	Political—Prof.	Independence
9	The Bank of Israel is a professional institution independent of the political system.	Professional, Not Political	Prefessionalism

(*continued*)

Table 1. (Continued)

No.	Statement	Encoding	Aspect
10	Employees of the Bank of Israel lack skills and profession.	Professional (r)	Professionalism
11	The Bank of Israel tends to act well in times of economic crises.	Manage Crisis Well	Professionalism
12	Every decision made in the Bank of Israel is known to the public.	Transparency: Decisions	Transparency
13	The Bank of Israel tends to share its policies with the public.	Transparency: Consideration	Transparency
14	Some of the Bank of Israel's decisions are unknown to the public.	Transparency: Decisions (r)	Transparency
15	Information regarding the Bank of Israel's considerations in decision making is accessible to the public.	Transparency: Consideration	Transparency
16	Compared with other institutions, the Bank of Israel is innovative, has initiative, and is original.	Innovation and Initiative	Image
17	Social justice considerations are important to the Bank of Israel along with financial and economic considerations.	Socially Aware	Image

Notes: (r) represents negative (reverse) formulation, used to prevent mindless perseveration and ensure that statements are individually evaluated.

status, 74 respondents perceived themselves as having lower-than-average income, 288 as having average income, and 180 as having above-average income. In terms of occupational status, 327 were salaried employees and 92 were independently employed. Regarding the level of exposure to the economic media, 111 reported "rarely exposed," 247 reported "sometimes," and 122 reported "often." As for the nature of their employment, we dichotomized the responses: 109 were classified as managers (either independently employed or supervising at least four employees), and all other 372 participants were classified as employees. Lastly, the mean answer to the question "to what extent do you feel that the Bank of Israel's actions impact your life" was 6.17 (SD = 1.91) on a scale of 1 to 9 (1 = "Very low", 9 = "Very high impact").

3. Results

Analysis of the questionnaires was conducted in a straightforward manner. First, we examined the level of trust in the Bank's predictions compared with that in other economic institutions. Next, we examined perceptions regarding the Bank's performance. Lastly, we combined these two parts, using a regression and mediation analysis, to examine the correlation between perceptions regarding the Bank of Israel and the level of trust in its predictions.

3.1 Measuring Trust in the Bank's Predictions

Overall, the mean trust given to predictions of all the economic institutions about which we asked was 5.31 (SD = 1.66) on a scale of 1 to 9 (1 = "Definitely not" to 9 = "Definitely"). This average is slightly higher than the center of the scale. An ANOVA analysis with repeated measurements showed that not all forecasts are equally trusted: $F(6, 2880) = 82.89$, $p < 0.0001$, $\eta^2 = .14$. The highest level of trust was in the Bank of Israel's CPI forecast (M = 5.98, SD = 1.50), followed by that of Teva's revenue forecast (M = 5.80, SD = 1.58), the Bank of Israel's economic growth forecast (M = 5.66, SD = 1.59), the Ministry of Finance's government deficit forecast (M = 5.18, SD = 1.60), Bank Hapoalim's interest rate forecast (M = 5.14, SD = 1.63), the Manufacturers' Association's hiring growth rate forecast (M = 5.00, SD = 1.54), and last, the Goldman

Sachs U.S. dollar exchange rate forecast (M = 4.43, SD = 1.65). Planned contrasts indicated that the level of trust in the Bank of Israel's inflation and growth forecasts is higher than trust in other economic institutions' forecasts regarding the indicators with which they are associated. The difference between the Bank of Israel and the other institutions pooled is statistically significant: $F(1480) = 190.11$, $p < .01$, $MS = 345.96$. The average level of trust in the Bank of Israel's forecasts (inflation and growth) was 5.82, 95 percent confidence interval (CI) [5.71, 5.93], while the average level of trust given in other institutions was 5.11, 95 percent CI [5.02, 5.20]. The average difference between the level of trust in the central bank and in other institutions, to which we refer hereafter as the central bank credibility advantage (CBCA), is +0.71, 95 percent CI [0.6, 0.8]. We will use these averages as we proceed in the analysis, since averages of mixed indices are a more reliable way to reach conclusions.

3.2 Aspects of Perceptions Regarding the Bank of Israel

We extracted the main aspects of public perceptions by conducting principal component analysis (PCA)—a method for dimensionality reduction aimed at extracting the fundamental structure of a set of variables. We ran PCA on the scores on the thirteen statements regarding the Bank of Israel (see table 2). Results were tested by a variety of methods, with and without rotation. We present here the findings with the simplest orthogonal rotation—Varimax raw method. This method maximizes the variances of the squared raw factor loadings across variables for each factor, thus isolating distinct factors. We excluded those statements which directly deal with perceiving the Bank as trustworthy (statements 1–3 and 5) for reasons that will become clear presently. This procedure yielded three underlying factors[3] that jointly account for 59.43 percent of the total variance:

(i) *Professionalism:* Professionalism accounts for 24 percent of the variance and regroups four statements, presented in bold in table 2. Underlying these is the perception of the central bank as a professional rather than a political institution, an aspect crucial to the central bank's independence.

[3]We did not include factors with eigenvalue < 1.

Table 2. PCA Results

	Factor 1 Professionalism	**Factor 2 Transparency**	**Factor 3 Social Awareness and Innovation**
Professional (r)	**−0.73**	−0.07	−0.04
Political App. (r)	**−0.70**	−0.14	−0.18
Vested Interest	**−0.76**	−0.17	−0.13
Political—Professional	**0.71**	0.27	0.31
Transparency: Decisions	0.06	**0.70**	0.33
Transparency: Decisions (r)	−0.28	**−0.81**	0.08
Innovation and Initiative	0.35	0.01	**0.70**
Socially Aware	0.09	0.14	**0.72**
Transparency: Considerations	0.05	0.54	0.48
Manage Crisis Well	0.51	−0.01	0.52
Fair	0.57	0.11	0.55
Transparency: Considerations	0.13	0.47	0.58
Professional (Not Political)	0.50	0.28	0.51
Prop. Total Variance	**0.24**	**0.14**	**0.21**

Notes: (r) represents negative (reverse) formulation.

(ii) *Transparency:* Transparency accounts for 14 percent of the variance and regroups two statements. The common underlying notion is the transparency of the Bank of Israel—of its decisions, as opposed to its considerations in making those decisions.

(iii) *Social Awareness and Innovation:* This factor accounts for 21 percent of the variance and also regroups two statements, relating to a positive image of the central bank as innovative and socially aware, without reference to its official role in the economy.

Table 3. Correlation Matrix of the Three Indices

	Social Awareness and Innovation	**Professionalism**	**Transparency**
Social Awareness and Innovation	–		
Professionalism	0.505**	–	
Transparency	0.301**	0.379**	–

Notes: ** represents p-value < 0.05.

3.3 The Relationship between Perceptions and Credibility

In order to estimate the relative influence of these factors on shaping the public perception of the Bank, statements loaded with 0.7 and above were grouped into three new indices (*Professionalism, Transparency,* and *Social Awareness and Innovation*) by averaging the scores of the component questions. These indices do correlate with each other (see table 3). This may be expected from the so-called halo effect, a type of cognitive bias in which one's overall impression of a person or an institution influences in return how one evaluates individual components related to that impression. In addition, we devised another index, *General Trust,* by averaging the scores of three statements in the questionnaire that directly deal with the Bank as trustworthy (statements 1, 2, and 5).

To find out how the relevant indices are related and affect belief in predictions of the central bank, we proceeded in several steps. First, we regressed *General Trust* on the three indices in a multiple regression analysis. All three indices were found to affect the general perception of the Bank as trustworthy: $F(4,476) = 147.38$, R^2 adj. $= 0.55$ (see table 4).

We then examined the impact of these three indices on credibility of the Bank's predictions, by running two additional multiple regressions. In the first regression the dependent variable was simply the degree of trust in the central bank's predictions. We regressed the dependent variable on the three indices, along with an additional variable—*Influence*—which represents the answer to the question: "To what extent do you feel that the Bank of Israel's actions impact your life?" $F(4,476) = 16.894$, R^2 adjusted $= 0.117$. However, using this approach may be misleading. We are interested

Table 4. Effect of the Three Indices on *General Trust*

	Beta	S.E. of Beta	B	S.E. of B	p-level
C			0.94	0.15	0.00
Transparency***	0.18	0.03	0.18	0.03	0.00
Influence*	0.06	0.03	0.02	0.01	0.06
Social Awareness and Innovation***	0.26	0.04	0.26	0.04	0.00
Professionalism***	0.47	0.04	0.47	0.04	0.00

Notes: * represents p-value < 0.1; ** represents p-value < 0.05; *** represents p-value < 0.01; Beta are the standardized coefficients, B the unstandardized ones.

in elucidating specifically to what extent attributing those traits to the central bank impacts trust in its predictions, *over and beyond* trust in economic institutions in general. To achieve that focus, we repeated the analysis, substituting as predicted variable *Central Bank Credibility Advantage* (CBCA, see above): $F(4,476) = 4.585$, R^2 adjusted = 0.029.

The patterns of the two analyses are very similar, and only two of the predictors proved significant: there is a positive relationship between perceiving the Bank as a professional institution (competent and apolitical) and as influential, and the credibility of its predictions (see table 5).[4] Strikingly, *Transparency* and *Social Awareness and Innovation* were found to have no effect on the level of trust in the central bank's predictions.

Finally, we investigated whether *General Trust* mediates between the effect of specific perceptions regarding the Bank and trust in its predictions. A mediation model attempts to identify what underlies an observed relationship between predictor and predicted variable via the inclusion of a third explanatory variable, known as a mediator variable, by positing a causal chain in which the predictor variable affects the mediator that, in turn, affects the predicted variable. To test this, we examined several regression results, as recommended by Baron and Kenny (1986):

[4]The higher unstandardized coefficient in the first regression stems from the high correlation between trust in the Bank of Israel's predictions and those of the other institutions.

Table 5. Predicted Trust in Central Bank's Predictions

	Beta	**S.E. of Beta**	**B**	**S.E. of B**	**p-level**
A. Predicted Absolute Trust					
C			3.17	0.36	0.00
Transparency	0.02	0.05	0.04	0.08	0.64
Influence***	0.22	0.04	0.16	0.03	0.00
Social Awareness and Innovation	0.01	0.05	0.01	0.08	0.89
Professionalism***	0.24	0.05	0.40	0.09	0.00
B. Predicted Unique Trust					
C			−0.34	0.32	0.28
Transparency	−0.05	0.05	−0.07	0.07	0.30
Influence***	0.13	0.05	0.08	0.03	0.00
Social Awareness and Innovation	0.02	0.05	0.02	0.07	0.74
Professionalism**	0.13	0.05	0.19	0.08	0.01

Notes: * represents p-value < 0.1; ** represents p-value < 0.05; *** represents p-value < 0.01; Beta are the standardized coefficients, B the unstandardized ones.

- We regressed (see above) *General Trust* on the three perceptions factors (*Professionalism*, *Transparency*, and *Social Awareness and Innovation*) and showed that all three affect it (see table 4).
- The *General Trust* variable significantly affects credibility (for the level of trust in the Bank's predictions; see table 6): $F(1{,}479) = 65.103$, R^2 adj. $= 0.118$; and $F(1{,}479) = 15.635$, R^2 adj. $= 0.030$.
- We compared the outcomes of two regressions first with *General Trust* as an explanatory variable in addition to *Professionalism* and *Influence* (see table 7), and then without it (see table 5). When *General Trust* is added to the equation $F(5{,}475) = 19165$, R^2 adj. $= 0.159$; $F\ (5475) = 5.23$, R^2 adj. $= 0.042$, *Professionalism* no longer has a significant effect on credibility (see table 7).

Table 6. Effect of Perceived General Trust in Central Bank's Predictions

	Beta	S.E. of Beta	B	S.E. of B	p-level
A. Effect on Absolute Credibility of Central Bank's Predictions					
C			3.33	0.31	0.00
General Trust***	0.35	0.04	0.58	0.07	0.00
B. Effect on Unique Credit Given in Central Bank's Predictions					
C			−0.37	0.28	0.18
General Trust***	0.18	0.04	0.25	0.06	0.00

Notes: *** represents p-value < 0.01; Beta are the standardized coefficients, B the unstandardized ones.

These findings are schematized in figure 1: *General Trust* mediates the effect of *Professionalism* on the credibility of the central bank's predictions, whereas *Influence* is an independent factor. The other two factors, *Transparency* and *Social Awareness and Innovation*, are not involved.

The above method is one that many researchers use, but it has come under criticism.[5] A statistically more satisfactory approach is to calculate the indirect effect and test its significance directly, as introduced by Sobel (1982). According to the Sobel product of coefficients approach, the indirect effect may be calculated by multiplying two regression coefficients. For this, we examined the two predictor variables in turn by conducting a regression analysis with (i) the absolute degree of trust in the central bank's predictions, and (ii) *CBCA* as the dependent variables and *General Trust* as the mediator. The two components found significant in our regression analysis above (*Influence* and *Professionalism*) served separately as independent variables. For *Professionalism*, the expected mediation emerged with a sizable indirect effect of 0.33 and 0.15 (Sobel $Z_a = 4.94$ and $Z_b = 2.57$, $p < .05$). That value of 0.15 represents the difference

[5] One issue is that the Baron and Kenny approach does not specifically test the significance of the indirect pathway. Furthermore, the approach tends to miss some true mediation effects, leading to type 2 errors (MacKinnon, Fairchild, and Fritz 2007).

Table 7. Predicted Trust in Central Bank's Predictions, All Indices

	Beta	S.E. of Beta	B	S.E. of B	p-level
A. Predicted Absolute Trust, All Indices					
C			2.68	0.36	0.00
Trust in General***	0.31	0.06	0.52	0.10	0.00
Influence***	0.20	0.04	0.14	0.03	0.00
Social Awareness and Innovation	−0.07	0.05	−0.12	0.09	0.15
Professionalism	0.09	0.06	0.15	0.10	0.11
Transparency	−0.03	0.05	−0.06	0.08	0.47
B. Predicted Trust, All Indices					
C			−0.58	0.33	0.07
Trust in General***	0.18	0.07	0.26	0.09	0.01
Influence**	0.12	0.05	0.07	0.03	0.01
Social Awareness and Innovation	−0.03	0.06	−0.04	0.08	0.58
Professionalism	0.05	0.06	0.07	0.09	0.45
Transparency*	−0.08	0.05	−0.12	0.07	0.09

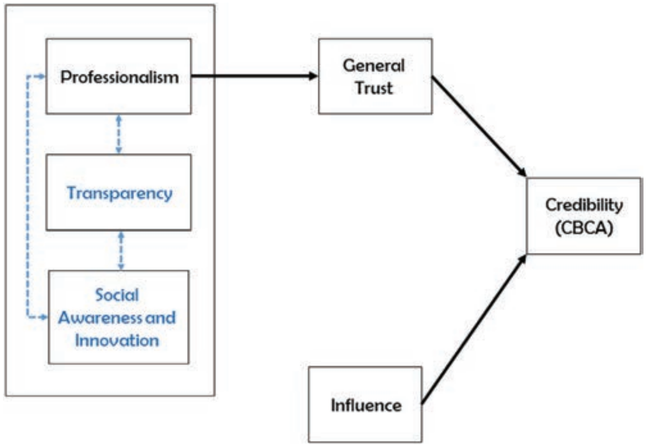
Notes: * represents p-value < 0.1; ** represents p-value < 0.05;*** represents p-value < 0.01; Beta are the standardized coefficients, B the unstandardized ones.

between the effect of *Professionalism* on the level of trust in the Bank's predictions (0.19) and the remaining direct effect (0.04) after introducing the mediator into the equation. In other words, most of the effect of *Professionalism* is mediated. For the *Influence* variable, the mediation contributes a negligible effect of 0.01 (Sobel $Z_a = 2.50$ and $Z_b = 2.27$, $p < .05$). Table 8 summarizes the mediation analysis using Sobel's approach.

In sum, only the effect of *Professionalism* on credibility (*CBCA*) is mediated by *General Trust. Influence* affects credibility (*CBCA*) but is unmediated. The other two perception factors, *Social Awareness and Innovation* and *Transparency*, while they do affect *General Trust*, have no effect on credibility (*CBCA*).

Conceptually, the meaning of these findings may be explicated with reference to the two dimensions of trust presented in the

Figure 1. General Trust as a Mediating Factor



introduction (Castelfranchi and Falcone 2010): reason-based and implicit trust. As mentioned, the halo effect yields correlations between *Professionalism*, *Social Awareness and Innovation*, and *Transparency*; they all contribute to a positive feeling and *General Trust* in the Bank. This is a manifestation of implicit trust, an associative and unanalyzed reaction to the Bank. However, when it comes time to decide whether to trust the central bank's predictions, the respondents evinced reason-based trust and showed that they were able to go beyond that "warm glow" and identify the properties that count. These include *Professionalism* and *Influence* but neither *Social Awareness and Innovation* nor *Transparency*.

3.4 Who Perceived the Bank as Trustworthy?

We now turn to examine how the characteristics of the respondents—such as their social and economic status, background training in economics, and exposure to the economic media—affect lay opinion of the Bank. We used data-mining methods for answering this question. The first step was to classify respondents in accordance with the patterns of their responses on the three perception indices and the *General Trust* variable (see above). The classification was made by K-means clustering (StatSoft, Inc. 2013), an algorithm that divides groups into clusters by maximizing the difference between

Table 8. Indirect Effect, Sobel Product of Coefficients Approach

	A	**S.E.$_A$**	**B**	**S.E.$_B$**	**Sobel Statistic**	**Indirect Effect (A×B)**	**Unstandardized Coefficient without *General Trust* in the Regression**
A. Indirect Effect of Professionalism and Influence on Absolute Trust							
Professionalism	0.67***	0.03	0.50***	0.09	4.94	0.33	0.45***
Influence	0.06***	0.02	0.14***	0.10	2.50	0.01	0.17***
B. Indirect Effect of Professionalism and Influence on Trust							
Professionalism	0.67***	0.03	0.22***	0.09	2.57	0.15	0.19***
Influence	0.06***	0.02	0.23***	0.06	2.27	0.01	0.08***

Notes: * represents p-value < 0.1; ** represents p-value < 0.05; *** represents p-value < 0.01.

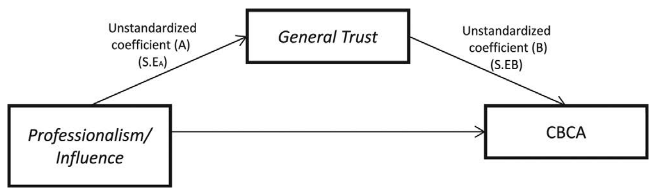
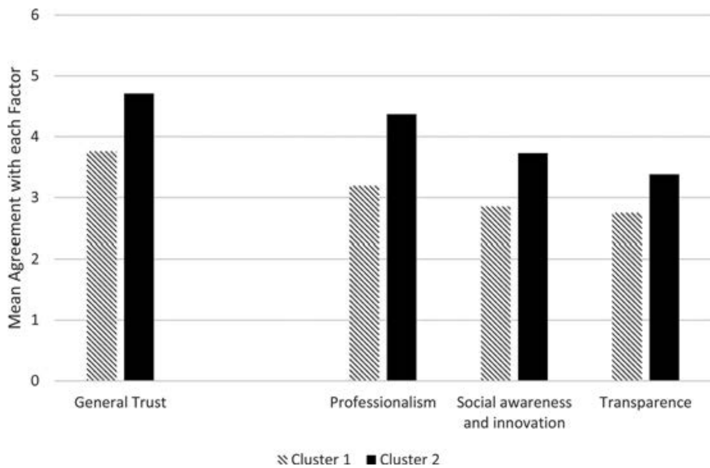


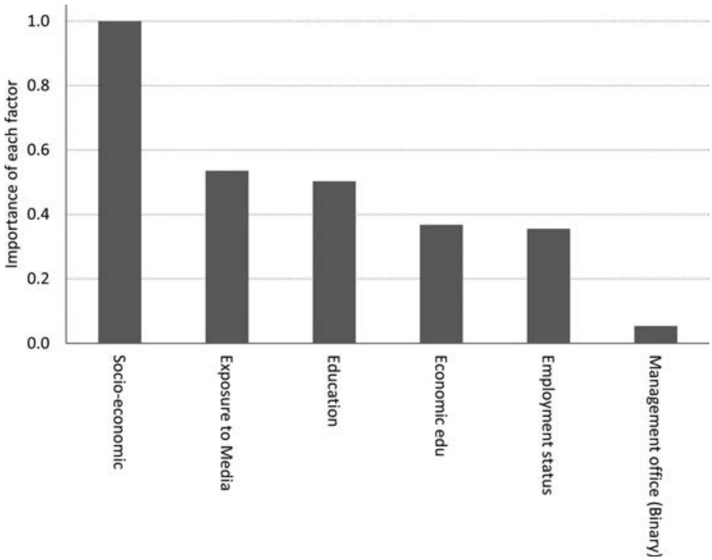
Figure 2. A Comparison of Answering Patterns according to Clusters Means



clusters and minimizing the difference within each cluster. The difference between the clusters, as reflected in the patterns of respondents' answers, appears in figure 2. Respondents who were classified as cluster 1 (shaded) tend to identify the central bank as a political institution rather than a transparent, innovative, socially aware institution, and see it as less trustworthy. Conversely, respondents classified as cluster 2 (black) tend to identify the central bank as a generally trustworthy institution, independent from the political system, transparent, innovative, and socially aware.

Next, we examined how independent variables affect the likelihood of belonging to each cluster. To cope with this classification problem, we used chi-squared automatic interaction detection (CHAID, alpha to split < 0.1)—an algorithm used for constructing non-binary decision trees, which relies on the chi-square test to determine the best split at each step. The CHAID algorithm effectively yields many multi-way frequency tables and therefore is suitable for large data sets (StatSoft, Inc. 2013). Variables that the algorithm could use for the classification were socioeconomic status (self-reported), level of education, nature of employment, exposure to the economic media, and a background including some formal knowledge in economics. Of these, it was *Exposure to Media* and

Figure 3. Importance of Factors Entered in the CHAID Analysis

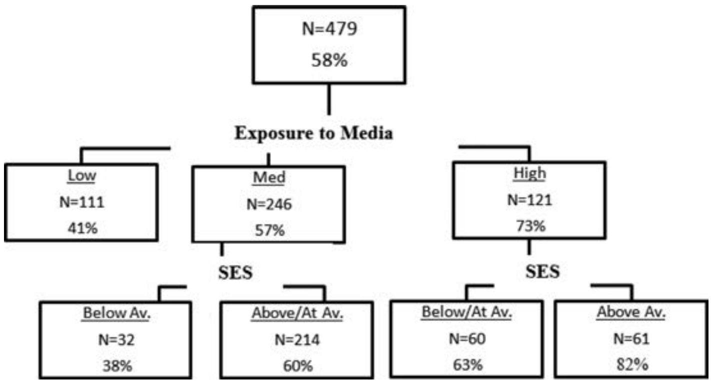


Socio-Economic Status (*SES*) that yielded the best classification (see figure 3). The classification results appear in figure 4. Individuals who reported themselves as unexposed to economic media and those with lower income have a less positive perception of the Bank of Israel. Respondents with high income who reported themselves as consistently exposed to economic media hold the most positive perception of the Bank.

4. Discussion

Trust in the central bank is an essential requirement for fulfilling its basic function. Our study shows that the Israeli public trusts its central bank more than other main economic institutions which were used as reference for the analysis. This is in line with previous findings: according to a longitudinal survey launched in 2001, trust in the Bank of Israel is consistently high as compared with other economic institutions. In 2010, for example, trust in the Bank was valued as 3.12 on a scale of 1 to 5, while trust in the Ministry of

Figure 4. CHAID Tree: Successive Splits of the Overall Sample according to Cluster Membership



Notes: The figure represents the probability of belonging to cluster 1. The main differences between the two clusters are income and the level of exposure to economic media channels: Individuals who are unexposed to economic media have a less positive perception of the bank of Israel—out of those (111), 46 (41 percent) belong to cluster 1. Respondents with higher-than-average income, who are consistently exposed to economic media, perceive the bank as highly trustworthy—out of those (61), 50 (82 percent) belong to cluster 1.

Finance was valued as 2.59 and trust in the tax authority and other Israeli banks was valued as 2.69 (Vigoda and Mizrahi 2010).

We endeavored to identify those people who have a more positive view of the central bank. Respondents cluster in two groups: one cluster tends to view the central bank as a generally trustworthy institution, able to function independently from the political system, transparent, innovative, and socially aware, compared with the second cluster of respondents. Of the demographic factors we collected, two were the most predictive of a positive view: exposure to economic media and socioeconomic status (SES). Belonging to a higher SES and being regularly exposed to economic information in the media were independently associated with a positive view of the central bank. The influence of the media is consistent with Lamla and Lein (2008), who found that the media have power to change inflationary expectations. Media reports on the Bank of Israel tend to be positive, and so it is unsurprising that the media effect in our survey is positive. In 2010, the Bank of Israel used image analysis to measure changes in the Bank's reputation (Bank of Israel, internal unpublished report). Sixty-five percent of the press reports had a positive tone, as did 56 percent of the online reports, whereas only 15 percent of all reports were negative.

Factor analysis of the public perception of the bank yielded three main factors: *Professionalism* (including freedom from political meddling), *Transparency,* and *Social Awareness and Innovation.* All three factors predict general trustworthiness. However, trustworthiness and credibility of inflationary forecasts are not the same. To analyze the latter, we computed a new variable, *CBCA,* representing the extent to which a respondent believes that the predictions of the central bank are credible, beyond the credibility attributed to those of several other institutions. To establish robustness, we also used the absolute value of the trust in the central bank.

The findings are striking and at variance with those of Blinder (2000), who polled central banks' governors. Of the three aspects of perception, *Professionalism* predicts the credibility advantage attributed to the central bank (*CBCA*), while perceived *Transparency* and *Social Awareness and Innovation* do not. The extent to which respondents judge that the central bank impacts their life (*Influence*) also enhances its credibility. Predictions of the central bank are considered credible to the extent that the Bank is perceived as an independent institution and as powerful, influential, and relevant. This interpretation is further strengthened by our mediation analysis: trustworthiness (*General Trust*) mediates only the effect of *Professionalism* on credibility (*CBCA*). *Influence* also affects credibility (*CBCA*), but trustworthiness does not mediate this effect. The other two perception factors, *Social Awareness and Innovation* and *Transparency*, while they affect trustworthiness and have a relatively high correlation with *Professionalism*, do not affect the extra (unique) credit given to the central bank.

High correlations between the perception aspects, and between perception aspects and *General Trust*, suggest that the public perception of the central bank involves a *halo effect.* The halo effect is a cognitive bias in which judgments are influenced by overall impressions without differentiating the details. This is a manifestation of implicit trust (Castelfranchi and Falcone 2010), an associative and unanalyzed reaction to the Bank. In contrast, expectations concerning the credibility of the central bank predictions involve reason-based trust. The pertinent factors are differentiated and identified: *Professionalism* and *Influence*. For the general public, neither the Bank's image regarding *Social Awareness and Innovation*, nor *Transparency* are deemed relevant. *Social Awareness and Innovation* represents notions of the Bank as civic minded and respectful of citizens, notions that do not necessarily relate to the Bank's purposes and relate even less to its ability to carry them out. Openness and success are not necessarily related in the eyes of the public, especially in Israel. Many Israelis take pride in the secret operations of special military units whose legendary discretion serves as a marker of their seriousness and modesty. While central banks increase the level of transparency in decision-making processes (Geraats 2009; Salle 2013), our findings indicate that transparency, much stressed by central bankers, is not perceived by the general public as relevant to the Bank's ultimate success in achieving its goals.

The central bank seeks to manage private expectations in order to achieve a better stabilization of both inflation and economic activity. For the general public, only the core meaning of transparency (informing the public of its goals and predictions; Salle 2013) is relevant. The public takes in that information and uses heuristics to decide whether to credit it. Those heuristics do not include the Bank's reasoning and motivations, as the public is incapable of understanding them. Instead, it judges whether to believe that the goals will be achieved and the predictions will materialize on the basis of its appraisal of the Bank's "willingness and competence" (Castelfranchi and Falcone 2010)—whether it is genuinely willing and able to achieve them.

The situation is of course very different when it comes to economic experts. To them, openness about the basis for the Bank's pronouncements is not a potential heuristic marker of a well-behaved institution: it constitutes a source of information. The opportunity to pore over the considerations underlying the decisions and predictions of the central bank enables experts to evaluate them professionally and to conclude rationally whether to accept them.

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Monetary Policy, Bank Capital, and Credit Supply: A Role for Discouraged and Informally Rejected Firms*

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European Central Bank

This paper conducts the first empirical study of the bank balance sheet channel using data on discouraged and informally rejected firms, in addition to information on the formal loan-granting process, in eight economies that use the euro or are pegged to it over 2004–7. Consistent with previous studies, I find that lax monetary conditions increase bank credit in general and bank credit to ex ante risky firms in particular, especially for banks with lower capital ratios. Importantly, I find that the results are considerably stronger when data on informal credit constraints are incorporated.

JEL Codes: E32, E51, E52, F34, G21.

1. Introduction

The period of low interest rates between 2002 and 2005 was followed first by a monetary contraction and then by a global recession, a widespread banking crisis, and the deepest credit crunch since the Great Depression. Many economists have argued for a causal link between these events. The mechanism suggested is as follows: prolonged periods of expansionary monetary policy induce banks to take on excessive credit risk (see, e.g., Rajan 2006; Brunnermeier 2009; Calomiris 2009; Diamond and Rajan 2009; and Taylor

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2011). When monetary policy contracts and economic conditions worsen, not only does the credit supply decrease (see Bernanke and Gertler 1989, 1995), but also agency problems between investors and lower-capitalized banks are exacerbated (Holmstrom and Tirole 1997; Diamond and Rajan 2011), leading to an even sharper reduction in bank credit. As a result, under tight economic and monetary conditions, a capital crunch begets a credit crunch.

Taking this theoretical mechanism to the data poses a number of econometric challenges. First, monetary policy is often endogenous to the business cycle. For example, short-term interest rates can be determined by output growth expectations through a Taylor (1993)-like rule, or monetary policy can expand in response to increased macroeconomic risk. Consequently, it is difficult to separate the effect of monetary policy on bank credit supply and risk taking from the effect of the business cycle. Second, contractionary monetary policy and adverse economic conditions can increase banks' agency costs and firms' agency costs at the same time; low-net-worth firms may be borrowing from low-net-worth banks (Gertler and Gilchrist 1994); and the composition of credit applicants can be changing as economic conditions deteriorate. This makes it difficult to distinguish a credit supply effect from a credit demand effect and from a simple repricing of risk.

The third challenge deals with unobservable credit constraints. In particular, many customers are discouraged from applying for a loan, anticipating that they would not get one, and many loan applications are informally rejected, which keeps them out of official bank records (see Cavalluzzo and Wolken 2005 for evidence on U.S. business firms, and Cox and Jappelli 1993 and Duca and Rosenthal 1993 for evidence on U.S. households). As a result, firms that do not apply for a loan because they do not need one become observationally equivalent to firms that are informally rejected, and so a potentially significant share of credit-constrained firms becomes unobservable to the econometrician. If firms are more likely to be discouraged when economic conditions worsen, or if informal rejections are higher at banks with lower capital, the sensitivity of the credit supply to monetary policy, to the business cycle, and to bank capital will be systematically under-estimated. While the first two challenges are well understood, the third one is never addressed in empirical work due to the fact that standard data sets of the loan-granting process—such as a credit register—do not include data on discouraged and informally rejected firms.

This paper contributes to the literature by addressing all three identification problems simultaneously. In particular, I use a unique survey data set to analyze firms' credit market experience between 2004 and 2007 in eight central and eastern European countries which are either using the euro or have their currency pegged to the euro. The data come from the 2005 and 2008 waves of the World Bank–EBRD Business Environment and Enterprise Performance Survey (BEEPS) of small and medium enterprises (SMEs) in emerging Europe. They contain detailed information on firms whose loan application was granted or turned down by a bank during the previous year, as well as on firms which had a positive demand for loans but did not apply. While it is not known which bank gave (denied) the loan, the data set contains information on each firm's town of incorporation. I construct the branching network of the banks holding at least 80 percent of each national market, allowing me to match each firm, based on geographic proximity, to the dominant bank(s) in each local market. The final data set consists of 3,418 firms incorporated in 596 local markets served by branches and subsidiaries of fifty-seven banks.

This setup is ideal to address the three identification challenges. Regarding the first challenge, monetary policy in the euro area is clearly exogenous to the business cycle in small economies which use (or are pegged to) the euro, but at the same time, by affecting the banks' borrowing costs, it should affect bank lending and risk taking in these markets. With respect to the second challenge, the detailed firm-specific characteristics contained in the survey allow me to separate the change in credit supply from the change in the level and composition of credit demand. Finally, by relying on survey data rather than on data from a credit register, I can include information from firms that did not formally apply for credit (i.e., they do not appear in any bank records) but are technically credit constrained, as they are either discouraged by tight credit conditions or informally rejected by the loan officer. Considerably more firms in emerging Europe are discouraged and informally rejected than are formally rejected (see Brown et al. 2011), making the identification of such firms crucial for an unbiased analysis.

My key findings are as follows. First, controlling for the level and the composition of credit demand, I find that laxer monetary conditions reduce the share of credit-constrained firms in the economy. Second, credit supply is more sensitive to monetary policy if the bank has a lower core capital ratio. Third, both effects are stronger when the firm that demands credit is ex ante and ex post risky. Fourth, all of the above effects are stronger when discouraged and informally rejected firms are included in the analysis, in addition to formally rejected credit applications. The results are robust to controlling for a wide range of observable firm-specific characteristics. They are also robust to eliminating unobservable heterogeneity at the market and industry level, as well as to controlling for cyclical variations in credit demand and credit supply which are common to all banks and firms at the same stage of the business cycle. Finally, the main results of the paper survive when I analyze the credit experience of a panel of firms over time, which allows me to account for unobservable firm-specific heterogeneity.

This combined evidence suggests that lax monetary policy induces bank risk taking and that the sensitivity of credit supply and risk taking to monetary policy depends on bank balance sheet strength. Even more importantly, the evidence points to the fact that incorporating information on informally constrained firms is key to understanding the true nature of credit supply and the strength of the bank balance sheet channel. My results imply that the bank balance sheet channel is more potent than previously thought.

Jiménez et al. (2014) and Ioannidou, Ongena, and Peydro (2015) study the effect of monetary policy on bank risk taking in Bolivia and in Spain, respectively. My paper is similar to theirs in that it exploits the fact that monetary policy is exogenous to the local markets (set by the U.S. Federal Reserve Board in the case of dollarized Bolivia, and by the European Central Bank (ECB) in the case of Spain). My paper extends these studies by looking at the effect of monetary policy on bank risk taking in multiple markets at varying business-cycle stages, which allows me to separate the effect of monetary policy and of economic conditions not only over time but also in the cross-section. In addition, a voluminous body of empirical work has looked at the transmission of monetary policy through the bank balance sheet channel. Early analysis based on macro data (Bernanke and Blinder 1992), on bank-specific data

(Jayaratne and Morgan 2000; Kashyap and Stein 2000; and Ashcraft 2006, among others), or on firm-specific data (Gertler and Gilchrist 1994; Bernanke, Gertler, and Gilchrist 1996) have found it difficult to fully disentangle supply and demand. More convincingly, Jiménez et al. (2012) use information from a credit register on firms, banks, and loan applications to study how contractionary monetary policy interacts with bank capital to induce an over-and-above decline in the credit supply. Relative to their work, my paper does not use data on multiple credit applications by the same firm within the same time period to identify the bank lending channel. However—and this is its main contribution relative to the extant literature—my paper is the first one to incorporate information on discouraged and informally rejected firms (in addition to formal loan applications) into the analysis of the effect of monetary policy and bank capital on bank credit supply and risk taking.

My results also offer insights into the role of foreign banks in emerging markets. Overall, the effect of foreign banks on business lending in the literature is ambiguous. A large literature has found that foreign bank presence is associated with higher access to loans (Clarke, Cull, and Peria 2006), higher firm-level sales (Giannetti and Ongena 2009), and lower loan rates and higher firm leverage (Ongena and Popov 2011). On the other hand, Berger, Klapper, and Udell (2001), Mian (2006), and Gormley (2010) show that foreign banks tend to finance only larger, established, and more profitable firms, and Peek and Rosengren (1997) and Popov and Udell (2012) show that foreign banks shrink their portfolios abroad in response to domestic shocks. This paper adds to this line of research by providing evidence on how foreign-owned banks' credit supply responds to exogenous monetary policy.

The paper proceeds as follows. Section 2 summarizes the hypotheses and the data. Section 3 describes the empirical methodology and the identification strategy. Section 4 presents and discusses the results. Section 5 concludes and discusses policy implications.

2. Hypotheses and Data

I now summarize briefly the main theories on how loan supply and risk taking by banks responds to monetary policy and economic conditions, and on the role of bank capital in determining the magnitude of this response. I then summarize the data set used in this paper.

2.1 Research Hypotheses

A number of theories have argued that adverse economic conditions and contractionary monetary policy reduce the bank credit supply. For example, in Kiyotaki and Moore (1997) loans are only made against collateral, as financial intermediaries lack the knowledge to continue the investment project if the firm defaults on its debt. Consequently, economic conditions that reduce the value of the collateral decrease the amount of debt firms can acquire, depressing economic activity and pushing the value of the collateral even further. Alternatively, the reduction in credit may be amplified by worsening agency problems. In particular, banks demand that the firm pledge enough of its own wealth into investment projects before they commit funds. Too little own pledgeable wealth reduces the incentives of the firm to behave diligently and forces banks to engage in costly monitoring; however, their own commitment to monitor is an increasing function of their capital.[1] Because borrower net worth is procyclical (Bernanke, Gertler, and Gilchrist 1999), agency costs amplify the effect of monetary policy and adverse economic conditions on credit availability.

Expansionary monetary policy can also spur banks to take on more credit risk by reducing the threat of a bank run (Diamond and Rajan 2006, 2011) and by improving banks' liquidity (Diamond and Rajan 2011; Gennaioli, Shleifer, and Vishny 2013), in addition to improving the banks' net worth (Fostel and Geanakoplos 2008; Adrian and Shin 2009). Combined with acute agency problems when banks have little own capital to pledge,[2] reliance on cheap funding can spur banks to take on more credit risk. Finally, by making risk-free assets less attractive, low interest rates may lead financial intermediaries with short-termist agendas to a search for yield exemplified by riskier investments (Rajan 2006).

[1] See Bernanke and Gertler (1989), Holmstrom and Tirole (1997), Bernanke, Gertler, and Gilchrist (1999), Bernanke (2007), and Gertler and Kiyotaki (2010), among others.

[2] See Dewatripont and Tirole (1994) and Freixas and Rochet (2008) for surveys on the effect of bank capital on the bank's agency problem.

Based on these and similar theories, the following three hypotheses can be formulated:

- Hypothesis 1: Lower interest rates lead to an expansion in the credit supply.
- Hypothesis 2: Lower interest rates lead to more credit risk taking by banks.
- Hypothesis 3: Both effects are stronger for banks with lower capital.

2.2 Data

The ideal data set should contain data on (i) granted loans, loan rejections, and discouraged and informally rejected firms; (ii) the balance sheets of the banks that granted or refused the loans, informally rejected the loan applications, or discouraged firms from applying; and (iii) the balance sheets of firms that applied for a loan or did not apply because they anticipated that they would not be given one. In addition, banks and firms should operate in a setting where monetary policy is exogenous to the business cycle; the same bank should operate in multiple markets, allowing to distinguish the effect of monetary policy and of the business cycle in the cross-section in addition to over time; and the same firm should have credit market experience with multiple financial intermediaries during the same time period in order to identify perfectly the supply of credit.

2.2.1 Firm Data: Credit Demand and Credit Supply

The core firm data come from the 2005 and 2008 waves of the Business Environment and Enterprise Performance Survey (BEEPS), administered jointly by the World Bank and the European Bank for Reconstruction and Development (EBRD). The survey was carried out between March and April 2008 among 11,998 firms from twenty-nine countries in central and eastern Europe and the former Soviet Union, and among 11,399 firms operating in the same countries in March/April 2005. In order to be able to separate the effect of monetary policy from that of the business cycle, I focus on eight countries whose currency is pegged to the euro or is the euro itself.[3] The survey tries to achieve representativeness in terms of the distribution of firms across business activities, as well as in terms of firm size. For example, between three-quarters and nine-tenths of the firms surveyed are "small" (less than twenty workers) and only around 5 percent of the firms surveyed are "large" (more than 100 workers).[4]

To define measures of credit access, I focus on the firms' self-reported credit experience. In both surveys the firms were asked if they have recently obtained a bank loan. If they have not, they are asked what is the main reason, to which the possible answers are "Applied and was rejected" or "Did not apply." Firms that did not apply were further asked for the reason why they did not apply. The possible answers to this question are "No need for a loan," "Interest rates are not favorable," "Collateral requirements are too high," "Size of loan and maturity are insufficient," or "Did not think it would be approved."[5]

This allows me to classify the firms as *credit constrained* using two different criteria. According to the "Credit Register" criterion, *Rejected*, a firm is credit constrained if it applied for a loan and the loan application was rejected. According to the "Survey" criterion, *Rejected or Discouraged*, a firm is constrained if it has a positive demand for a bank loan (i.e., it does not answer "Yes" to "No need for a loan") but has no loan, either because it applied and was rejected or because it was discouraged from applying (i.e., it answers "Yes" to any of "Interest rates are not favorable," "Collateral requirements are too high," "Size of loan and maturity are insufficient," or "Did not think it would be approved"). The first classification is in line with how studies using credit register data define the loan supply (see Jiménez et al. 2012, 2014; and Ioannidou, Ongena, and Peydro 2015), while the latter classification is used in studies that use survey data to define credit constraints

[3]These countries are Bosnia and Herzegovina, Bulgaria, Estonia, Latvia, Lithuania, Montenegro, Slovakia, and Slovenia.

[4]The questionnaire for the BEEPS survey can be obtained by contacting the EBRD via http://ebrd-beeps.com/contact/.

[5]A negligible proportion of the firms in the data set (6 percent) fall into the categories "Application procedures for loans or lines of credit are complex" and "Other."

(see Cox and Jappelli 1993; Duca and Rosenthal 1993; Popov and Udell 2012; and Ongena, Popov, and Udell 2013, among others). The rationale for the latter is that rejected and discouraged borrowers are identical, and discouraged borrowers either anticipate that they will not be given credit or are discouraged from applying by the loan officer without that information entering bank records. In that sense, discouragement is observationally equivalent to informal rejection.[6]

Table 1 gives an idea of the relationship between credit demand, credit application, rejection, and discouragement. While in fiscal year 2007 on average 62 percent of the firms in the eight economies declare positive demand for bank credit (column labeled "Need Loan"), only 45 percent of the firms that do so actually applied for a bank loan. Out of the applicant firms, only 13 percent were rejected. However, out of all firms that declare a positive demand for credit, 35 percent did not have a bank loan, either because they were rejected or because they were discouraged from applying or informally rejected. The difference between rejection and discouragement is similar in 2004, when only 5 percent of applicant firms were rejected but 26 percent of all firms with a positive demand for a loan did not have one. This implies that relative to countries where discouragement is almost non-existent (see Albertazzi and Marchetti 2009 for evidence from Italy; and Jiménez et al. 2012, 2014 for evidence from Spain), in the eight countries in the data set used in this paper discouragement is an important phenomenon. An empirical analysis of the effect of monetary policy and the business cycle on bank credit and risk taking based on loan applications only would lump together, in the category of "non-applicant firms," firms that do not need credit and firms that are discouraged or informally rejected. Such analysis would produce biased results if the share

[6] I formally test this assumption. I construct counterfactual rejection probabilities for firms that did not apply for credit, based on the sample of firms that did apply. I then test for statistical differences in the probability of rejection between firms that applied for credit and firms that were discouraged from applying. The data suggest that discouraged firms are, if anything, even more likely to be rejected than firms which actually apply. In addition to that, a parametric test on the subsample of rejected or discouraged firms reveals that none of the firm-specific characteristics we use in the paper statistically predicts whether a firm will be rejected rather than discouraged. Results are available upon request.

Table 1. Credit Demand and Credit Access

Country	2004				2007			
	Need Loan	Applied	Rejected	Rejected or Discouraged	Need Loan	Applied	Rejected	Rejected or Discouraged
Bosnia and Herzegovina	0.77	0.60	0.01	0.23	0.77	0.55	0.16	0.37
Bulgaria	0.68	0.47	0.08	0.36	0.58	0.32	0.16	0.52
Estonia	0.60	0.50	0.05	0.21	0.54	0.43	0.12	0.27
Latvia	0.69	0.54	0.10	0.29	0.59	0.38	0.19	0.50
Lithuania	0.71	0.51	0.05	0.31	0.60	0.49	0.10	0.00
Montenegro	0.50	0.31	0.00	0.38	0.78	0.44	0.14	0.22
Slovakia	0.61	0.49	0.02	0.22	0.53	0.34	0.10	0.39
Slovenia	0.66	0.61	0.04	0.12	0.64	0.59	0.09	0.14
Total	0.67	0.52	0.05	0.26	0.62	0.45	0.13	0.35

Notes: The table presents statistics on various aspects of credit demand and credit supply. The columns labeled "Need Loan" summarize, by country, the share of firms that declare positive demand for bank credit. The columns labeled "Applied" summarize, by country, the share of firms that applied for a bank loan out of those firms that declare positive demand for bank credit. The columns labeled "Rejected" summarize, by country, the share of firms whose loan application was rejected, out of those firms that applied for a bank loan. The columns labeled "Rejected or Discouraged" summarize, by country, the share of firms that applied for a bank loan, or did not apply because they were discouraged, out of those that declare positive demand for bank credit. The data are for the fiscal years 2004 and 2007. See appendix 3 for exact definitions and data sources.

of credit-constrained non-applicant firms varies systematically with monetary policy and with the business cycle.

2.2.2 Firm Data: Balance Sheets

The main firm-specific variables reported in BEEPS are related to firm size, age, ownership structure, sector of operation, industry structure, export activities, use of external auditing services, and subsidies received from central and local governments, among others. Table 2 provides the summary statistics on the number of firms and their main characteristics, by country.[7] Panel A summarizes the data for all firms, while panel B does the same for the subsample of rejected and discouraged firms. Overall, there are larger differences across countries than across types of firms based on their credit experience. Credit-constrained firms are more likely to be small, non-exporting sole proprietorships, and such firms are more likely to be discouraged than formally rejected.

To tease out the effect of monetary policy and bank capital on bank risk taking, I focus on risky lending. In particular, I look at the firm's informational opacity, which I define as a dummy equal to 1 if the firm does not have its financial accounts verified by an external auditor, and equal to 0 if it does. This variable captures an important dimension of opacity in the sense that having an audit materially affects the informativeness of the financial statements. Audited statements allow banks to underwrite loans primarily based on financial statement ratios and covenants associated with those ratios (Berger and Udell 2006). Information opacity is thus related to ex ante risk because unaudited statements (i.e., financial statements that have not been verified by an external auditor) have a much higher risk of material misstatement.[8]

In addition, for audits performed by an outside audit firm, risk assessment is a crucial stage before accepting an audit engagement. The auditor performs risk-assessment procedures to obtain

[7]While it is also important to control for firm foreign ownership (see Antras, Desai, and Foley 2009), this information is only available for the firms in the 2005 wave, and so it is not used in the empirical exercises.

[8]Given that most of the firms in the data set are SMEs, disclosure is voluntary and firms can only benefit, in terms of transparency of the information they submit to banks, from requesting such services.

Table 2. Summary Statistics: Firm Characteristics

Country	# Firms	Opaque	Small Firm	Big Firm	Public Company	Sole Proprietorship	Privatized	Non-Exporter	Firm Age	Innovative	Subsidized	Competition
A. All Firms												
Bosnia and Herzegovina	530	0.47	0.78	0.03	0.15	0.38	0.22	0.65	21.27	0.53	0.11	0.81
Bulgaria	524	0.56	0.83	0.03	0.06	0.47	0.12	0.74	17.83	0.39	0.06	0.63
Estonia	479	0.19	0.78	0.03	0.13	0.26	0.11	0.65	16.16	0.49	0.15	0.76
Latvia	419	0.27	0.70	0.05	0.01	0.33	0.13	0.68	15.83	0.53	0.11	0.79
Lithuania	463	0.60	0.76	0.03	0.02	0.24	0.15	0.62	15.41	0.61	0.15	0.78
Montenegro	132	0.51	0.86	0.01	0.04	0.70	0.12	0.86	12.75	0.52	0.04	0.69
Slovakia	481	0.45	0.73	0.06	0.06	0.54	0.12	0.67	15.88	0.45	0.13	0.79
Slovenia	390	0.57	0.73	0.04	0.11	0.20	0.19	0.40	23.78	0.55	0.22	0.83
Total	3,418	0.45	0.77	0.04	0.08	0.37	0.15	0.65	17.77	0.51	0.13	0.76
B. Credit-Constrained Firms, by Type												
Rejected	155	0.47	0.79	0.05	0.14	0.35	0.16	0.65	17.84	0.47	0.14	0.79
Discouraged_1	141	0.53	0.86	0.01	0.04	0.52	0.16	0.75	17.64	0.59	0.08	0.77
Discouraged_2	139	0.63	0.88	0.01	0.07	0.54	0.09	0.76	16.69	0.63	0.09	0.63
Discouraged_3	98	0.57	0.90	0.02	0.04	0.41	0.12	0.75	15.03	0.53	0.08	0.73
Discouraged_4	120	0.59	0.88	0.02	0.05	0.45	0.08	0.82	15.74	0.61	0.16	0.79
Rejected or Discouraged	687	0.56	0.85	0.03	0.08	0.44	0.12	0.74	16.43	0.56	0.12	0.75

Notes: The table presents firm statistics, by country. "Opaque" is a dummy equal to 1 if the firm does not employ external auditing services to verify its external accounts. "Small Firm" is a dummy equal to 1 if the firm has from 2 to 49 employees. "Big Firm" is a dummy equal to 1 if the firm has more than 250 employees. "Public Company" is a dummy equal to 1 if the firm is a shareholder company, or if its shares are traded in the stock market. "Sole Proprietorship" is a dummy equal to 1 if the firm is a sole proprietorship. "Privatized" is a dummy equal to 1 if the firm is a former state-owned company. "Non-Exporter" is a dummy equal to 1 if the firm does not have access to foreign markets. "Firm Age" is the firm's age in years. "Innovative" is a dummy equal to 1 if the firm has introduced a new product line in the past three years. "Subsidized" is a dummy equal to 1 if the firm has received subsidies from central or local government in the past three years. "Competition" is a dummy equal to 1 if the firm faces fairly strong, very strong, or extremely strong competition. "Rejected" is a dummy equal to 1 if the firm's loan application was rejected. "Discouraged_1" is a dummy equal to 1 if the firm did not apply for bank credit because interest rates were not favorable. "Discouraged_2" is a dummy equal to 1 if the firm did not apply for bank credit because collateral requirements were too high. "Discouraged_3" is a dummy equal to 1 if the firm did not apply for bank credit because size of loan and maturity were insufficient. "Discouraged_4 is a dummy equal to 1 if the firm did not apply for bank credit because it did not think the loan application would be approved. "Rejected or Discouraged" is a dummy equal to 1 if the firm's loan application was rejected or if it was discouraged from applying. Omitted category in firm size is "Medium Firm." Omitted category in firm ownership is "Private Company." Omitted categories in discouragement are "Application Procedures for Loans or Lines of Credit Are Complex" and "Other." See appendix 3 for exact definitions and data sources.

an understanding of the entity and its environment, including its internal control, and so audited risk includes detection risk, control risk, and inherent risk. Recent evidence suggests that many firms (especially SMEs) choose not to file a financial report when in distress, implying that firms which do not have their accounts verified by an external auditor are more likely to default (Jacobson, Linde, and Roszbach 2013). As a consequence, information opacity also captures an important dimension of ex post risk. Lending based on information opacity is therefore directly related to risk taking by banks. Recent evidence has strongly linked firm opacity to bank risk taking. For example, in an expanded version of the data set used in this paper, Ongena, Popov, and Udell (2013) show that tighter restrictions on bank activities in the bank's primary domestic market leads to more lending to informationally opaque firms by the bank's subsidiaries abroad, suggesting that banks shift risk across national markets in response to regulatory changes.

There is considerable variation across countries in this firm-specific variable of interest. For example, 81 percent of the SMEs in Estonia pay external auditors to verify their accounts, while only 40 percent of the firms in Lithuania do. On average in the sample, 45 percent of the firms are informationally opaque.

2.2.3 Bank Branching Network

The main drawback of BEEPS is that it does not identify the bank that granted or refused to grant the loan. However, BEEPS contains information on the locality in which each firm is incorporated. The firms in the eight sample countries are incorporated in a total of 596 localities, for an average of 5.7 firms per locality. To take advantage of this geographic information, I make use of a unique hand-collected data set on the extent of foreign-owned banks' presence in these local markets.[9] In particular, pursuing a trade-off between representativeness and manageability, I narrow the focus on the banks that comprise at least 80 percent of the banking-sector assets in each country. This gives me a range of between four banks in Estonia and nine banks in Bulgaria.

[9] An expanded version (for sixteen countries) of the same local branching data is used in Popov and Udell (2012) and in Ongena, Popov, and Udell (2013).

Given this criterion, I then extract information from the banks' websites on which localities they are present in and how many branches they have. The localities in the sample turn out to be served by a total of fifty-seven banks. Out of those, fifteen are domestic banks, and forty-two are branches or subsidiaries of eighteen foreign banks. Appendix 1 illustrates the degree of foreign bank penetration in each country in the sample.[10] The final data set consists of 3,418 firms incorporated in 596 local markets.[11]

Figure 1 presents a map of home countries (where the parent banks are domiciled) and of host countries (where the local firms and the branches and subsidiaries of foreign banks operate). In terms of home countries, some markets where large cross-border banks are domiciled, such as Spain, Switzerland, and the United Kingdom, are excluded because the presence of banks such as Santander, UBS, and HSBC in the region of central and eastern Europe is very limited.

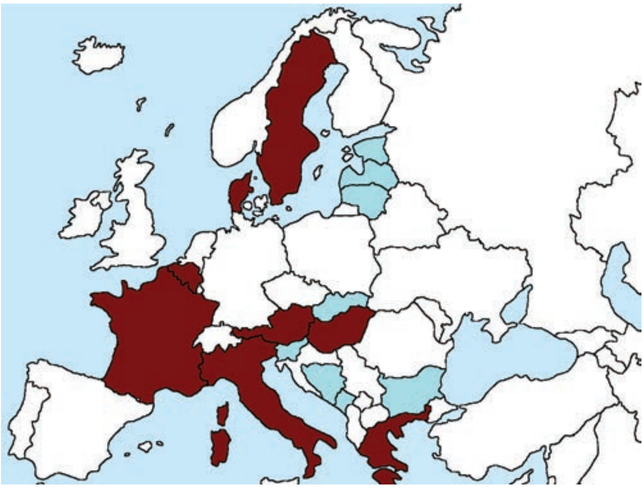
2.2.4 Bank Balance Sheet Data and Macro Data

Finally, I use Bankscope to extract balance sheet information on the banks in the sample. I collect data from 2005 to 2008 in order to evaluate how banks' balance sheet strength relates to credit availability. I focus on core capital (the tier 1 capital ratio), which is the variable most often used in empirical work as a proxy for the bank's net worth (see Jiménez et al. 2012, 2014). While other bank-specific characteristics—such as liquidity and return on assets—are also relevant, I focus on bank capital as the most empirically sound description of the bank's agency problems (see Holmstrom and Tirole 1997). In the case of Crnogorska Komercijalna Banka in Montenegro, for

[10]The eighteen foreign banks in question are Erste Group, Hypo Group, Raiffeisen, and Volksbank (Austria); Dexia and KBC (Belgium); Danske Bank (Denmark); Societe Generale (France); Alpha Bank, EFG Eurobank, National Bank of Greece, and Piraeus Bank (Greece); OTP (Hungary); Intesa Sanpaolo and UniCredit Group (Italy); and Nordea Bank, Swedbank, and Skandinaviska Enskilda Bank (Sweden). There is also substantial regional variation in the degree of penetration: for example, the Greek banks operate mostly in southeastern Europe, the Scandinavian banks in the Baltic countries, and the Austrian banks in central Europe. In addition, there is one domestic "global" bank, the Hungarian OTP, as well as cross-border penetration by, for example, Parex Group—Latvia and Snoras Bank—Lithuania.

[11]Appendix 2 illustrates the representativeness of the bank sample used in this paper.

Figure 1. Origin and Target Countries in the Data



The map shows the cross-border dimension of the underlying data. Countries in darkest shading (Austria, Belgium, Denmark, France, Greece, Hungary, Italy, and Sweden) are those in which the parent banks in the data set are incorporated (home countries). Countries in lighter shading (Bosnia and Herzegovina, Bulgaria, Estonia, Latvia, Lithuania, Montenegro, Slovakia, and Slovenia) are those where the firms in the data set are incorporated (host countries).

which Bankscope does not report data on tier 1 capital, I have used data on the bank's parent instead.

In the absence of a direct match between a firm and a bank, I construct a locality-specific measure of average bank capital by weighting each parent bank's tier 1 capital by the number of branches its subsidiary has in a particular locality. The underlying assumption is that if firms were granted/denied credit, or if they were discouraged or informally rejected, then it was most likely the result of interaction with the dominant banks in the firms' locality of incorporation. Alternatively, I match each firm with the single most prevalent bank in each locality (that is, the bank with the highest number of branches).

This procedure gives me a considerable variation in tier 1 capital within each country, due to the fact that not all banks present in a country are present in each city and, whenever they are, not to the same extent. For example, the 596 localities in the data are characterized by 451 unique values of locality-specific tier 1 capital when data on all banks are branch weighted, although there are only fifty-seven banks involved. Consequently, there is little reason to worry that the country fixed effects in the regressions capture the same variation as locality-specific financial stress.

This matching procedure implicitly assumes that the effect of bank financial distress is localized and realized predominately by firms headquartered in the locality in which the bank has operations. All our empirical specifications presume that firms borrow from banks located near their address of incorporation, which is identical to the approach in, for example, Gormley (2010). In general, this is expected to hold, as banks tend to derive market power ex ante from geographical proximity (e.g., Degryse and Ongena 2005). Lending support to that conjecture, empirical work regarding lending relationships in different countries has demonstrated that the average distance between SMEs and banks is usually very small. For example, Petersen and Rajan (2002) find that the median distance between a firm and its main bank over the 1973–93 period was only four miles; in Degryse and Ongena's (2005) sample, the median distance between a firm and its main bank is 2.25 kilometers (1.6 miles); and in Agarwal and Hauswald's (2010) sample, the median distance between a firm and its main bank is 0.55 miles.

I also determine, for each of the eight countries, the annual rate of GDP growth during the past year. Table 3 summarizes core bank capital and GDP growth by country and year. Finally, given that all countries in the sample either use the euro or have their currency pegged to the euro, central bank policy rates and changes in these do not vary by host country. The ECB policy rate declined from 2.75 in 2002:Q4 to 2.00 in 2003:Q4, and it increased from 2.25 in 2005:Q4 to 3.5 in 2006:Q4, namely, the years immediately preceding the BEEPS sample years. Consequently, changes in the policy rate are calculated on an annual basis for the two periods, and so I assign a value of –0.75 to firms observed in 2004 and a value of 1.25 to firms observed in 2007.[12]

[12]The two BEEPS surveys used in the paper were carried out in 2005:Q1 and in 2008:Q1, asking firms about their experience with access to credit in the past year, and so they reflect the firms' credit experience over the course of 2004 and 2007, respectively. Given this, it seems natural to use changes in monetary policy

Table 3. Bank and Country Characteristics

	Bank Capital		GDP Growth	
Country	**2004**	**2007**	**2004**	**2007**
Bosnia and Herzegovina	7.26	7.85	0.050	0.068
Bulgaria	10.10	8.89	0.062	0.064
Estonia	8.88	8.69	0.081	0.069
Latvia	7.98	6.52	0.088	0.100
Lithuania	8.14	8.19	0.085	0.098
Montenegro	9.89	9.45	0.036	0.107
Slovakia	7.93	8.21	0.055	0.106
Slovenia	8.86	8.82	0.039	0.068
Total	8.45	8.33	0.062	0.085

Notes: The table reports summary statistics on the average locality-specific tier 1 capital ratio of the banks in the respective country, weighted by the number of branches a bank has in a particular locality, and of annual GDP growth in the respective country. The data are for the fiscal years 2004 and 2007. See appendix 3 for exact definitions and data sources.

2.2.5 Discussion of the Data

Early studies of the monetary transmission mechanism and the bank balance sheet channel relied either on firm-specific data but no bank-specific data (Gertler and Gilchrist 1994; Bernanke, Gertler, and Gilchrist 1996), or on bank-specific data but no firm-specific data (Jayaratne and Morgan 2000; Kashyap and Stein 2000; and Ashcraft 2006). Relative to these studies, I use both firm- and bank-specific information which provides a crucial step towards identifying credit supply. In that respect the paper is similar to recent identification efforts using detailed firm- and bank-specific information from the Bolivian (Ioannidou, Ongena, and Peydro 2014) and the Spanish (Jiménez et al. 2012) credit registers. Relative to these studies, however, my data set has two advantages. First and foremost, it uses data on discouraged and informally rejected firms, in addition to formally rejected ones, to construct a measure of credit constraints

right before the periods in question, that is, over the course of 2003 and 2006, respectively. The change in the ECB's main refinancing operations (MRO) rate over the course of 2004, for example, would be an inadequate shifter in banks' propensity to lend to firms which applied for a loan in January 2004.

associated with bank lending. In this way, I manage to capture a potentially significant portion of firms that are relevant for identifying bank credit supply but are not captured by official bank records and hence by credit registers. In addition, I use data on eight countries rather than on one. This allows me not only to investigate the international dimensions of the working of the bank balance sheet channel but also to separate the effect of monetary policy and of the business cycle *in the cross-section* by studying the transmission of the same monetary policy (changes in ECB policy rates) into markets which in the same moment in time are at different stages of the business cycle.

On the cons side, relative to the cited studies, my data are based on a survey of firms; therefore, the data include a sample of firms that formally applied for bank credit rather than the universe of applicant firms.[13] In addition, the survey data contain no information on multiple banking relationships in the same moment in time, which would allow me to eliminate the unobserved component of firm-specific demand, and so I rely on observable firm-specific characteristics to identify the credit supply. Moreover, a credit register contains a direct match between the firm that applied for a loan and the bank that gave or refused it. In comparison, in the data set I have constructed, firms and banks are matched imperfectly, based on geographic proximity, and all firms in a locality are matched either to a locality-average measure of bank balance sheet items (in particular, the capital-to-assets ratio) or to the balance sheet items of the dominant bank in the locality. While this procedure is clearly inferior to having a direct match, it is partially justified by the fact that there are 3.4 times as many discouraged firms in the data set as there are formally rejected firms (532 discouraged/informally rejected vs. 155 formally rejected), and in the case of discouraged/informally rejected firms, there is no exact firm-bank match by default. Nevertheless, in robustness exercises I partially correct this drawback by determining the dominant bank (i.e., the bank with the highest number of branches) in each locality and matching to that bank all firms in that locality.

[13]For example, the Spanish credit register captures all loans above 6,000 euros, and so it contains up to 80 percent of all loans at any point in time. See Jimenez et al. (2012, 2014) for details.

Finally, even though the empirical tests account for the business cycle by controlling for country-specific GDP growth, the regression coefficient on the change in monetary policy is bound to pick up the effects of other events that are sufficiently correlated across countries, such as changes in financial regulation or fiscal policy. As it is very difficult to disentangle these effects from the effect of monetary policy, it is fair to say that my empirical strategy does not perfectly identify the effect of monetary policy.

3. Empirical Methodology and Identification

The goal of this paper is to evaluate how monetary policy and the business cycle interact with bank capital to determine bank lending and risk taking. The immediate approach would be to map short-term rates and GDP growth into loan rejection and the firm risk associated with granted loans, accounting for bank capital. However, this strategy would fail to account for the changing composition across business lenders of firms that demand bank credit, or in other words, for the fact that the sample of firms that apply for credit is not a random subsample of the population of firms.[14]

I address this problem by incorporating information on non-applicant firms in a standard two-step Heckman procedure. The idea is that credit constraints are only observable when a firm demands bank credit (i) when it applies for a loan, according to the "Credit Register" criterion; or (ii) when it says it needs credit, according to the "Survey" criterion). Let the dummy variable Q equal 1 if the firm applies for credit (expresses a need for credit), and 0 otherwise. The value of Q is in turn determined by the latent variable:

$$q = \zeta \cdot Z_{ijklt} + \varepsilon_{ijklt},$$

where Z_{ijklt} contains variables pertinent to firm i in city j in country k in industry l in year t that may effect the firm's fixed costs and convenience associated with using bank credit. The variable $Q = 1$ if $q > 0$, and $Q = 0$ otherwise. The error ε_{ijklt} is normally distributed with mean 0 and variance σ^2. The second-stage regression can now be updated by adding the term $\sigma\frac{\phi(q)}{\Phi(q)}$ to the right-hand side,

[14] See Popov and Udell (2012) for a detailed discussion.

where $\frac{\phi(q)}{\Phi(q)}$ is the inverse of Mills' ratio (Heckman 1979) derived from the first step. Identification rests on the exclusion restriction which requires that q has been estimated on a set of variables that is larger by at least one variable than the set of variables in the second stage.

Thus, in the second-stage regression in which I determine the effect of monetary policy, the business cycle, and bank capital on bank lending and risk taking in foreign markets, I estimate the following model:

$$\begin{aligned}
&Constrained_{ijklt} \\
&\quad = \beta_1 \cdot \Delta IR_t + \beta_2 \cdot \Delta GDP_{kt} + \beta_3 \cdot Capital_{jkt} \\
&\qquad + \beta_4 \cdot \Delta IR_t \cdot Capital_{jkt} + \beta_5 \cdot \Delta GDP_{kt} \cdot Capital_{jkt} \\
&\qquad + \beta_6 \cdot X_{ijklt} + \beta_7 \cdot D_b + \beta_8 \cdot D_k + \beta_9 \cdot D_l + \beta_{10} \cdot D_t \\
&\qquad + \beta_{11} \sigma \frac{\phi(q)}{\Phi(q)} + u_{ijklt}, \qquad (1)
\end{aligned}$$

where $Constrained_{ijklt}$ is a dummy variable equal to 1 if firm i in city j in country k in industry l in year t is constrained (according to one of the two different criteria outlined before); ΔIR_t is the change in monetary policy over the past year, for all countries; ΔGDP_{kt} is the change in GDP over the past year, for each country k; $Capital_{jkt}$ is the average (or the dominant bank's) tier 1 capital ratio in each city j in country k in year t; X_{ijklt} is a matrix of firm characteristics; D_b is a matrix of bank dummies; D_k is a matrix of country dummies; D_l is a matrix of industry dummies; D_t is a matrix of time dummies; $\sigma\frac{\phi(q)}{\Phi(q)}$ is the selection term from the first-stage regression; and ε_{ijklt} is an idiosyncratic error term. The firm-specific covariates control for observable firm-specific heterogeneity. The four sets of dummy variables control for any unobserved bank, market, industry, and business-cycle variation. Essentially, they eliminate the contamination of the estimates by time-invariant bank characteristics (such as appetite for risk), sectoral characteristics (such as growth opportunities), macroeconomic factors (such as host-country bank regulation or taxes), and by time-varying developments common to all sample countries (such as the business cycle or the credit cycle). In additional regressions, I also interact bank dummies with time dummies to eliminate the effect of unobservable time-varying bank heterogeneity.

Hypothesis 1 implies that $\beta_1 > 0$. Hypothesis 2 implies that $\beta_1^r > \beta_1^s$ where I have split the sample in ex ante risky (r) and ex ante safe (s) firms. Hypothesis 3 implies that $\beta_4 < 0$ and that $\beta_4^r < \beta_4^s$.

4. Empirical Results

4.1 First-Stage Regressions

Table 4 presents the results from the first-stage probit regressions. I cluster the standard errors at the level of the locality, which is where the variable $Capital_{jkt}$ varies. In the column labeled "Applied," I study what determines the probability of a firm applying for credit, and in the column labeled "Need Loan," I evaluate the probability of a firm having a strictly positive demand for bank credit. The probability of applying for a loan, or for declaring positive demand for bank credit, is generally lower for firms in localities dominated by higher-capitalized banks, albeit the effect is never significant. Turning to the firm-specific covariates, the demand for bank credit is in both cases higher for informationally transparent firms, possibly indicating a reverse correlation (firms that need credit employ external auditors to make their financial statements transparent to the bank). It may also be the case that audited firms have access to financial statement lending which may be a cheaper lending technology (Berger and Udell 2006). Demand for credit also increases in the size of the firm. One potential explanation is that small firms face higher application costs (Brown et al. 2011), or that small firms are better equipped to finance investment with cash flows than more highly leveraged large firms. Some of the size effects may also be picked by ownership and structural characteristics, as sole proprietorships have a higher demand for loans. Credit demand is higher for exporters and for innovative firms, potentially due to their faster expansion.[15]

[15] The results are broadly consistent with Ongena and Popov (2011), Popov and Udell (2012), and Ongena, Popov, and Udell (2013), who apply versions of this selection model to various subsamples of BEEPS.

Table 4. Determinants of Firm Demand for Bank Credit

	Applied	Need Loan
	(1)	(2)
Bank Capital	−0.005	−0.035
	(0.030)	(0.022)
Opaque	−0.175***	−0.013
	(0.051)	(0.051)
Small Firm	−0.339***	−0.241***
	(0.065)	(0.070)
Big Firm	0.131	0.258*
	(0.133)	(0.135)
Public Company	−0.053	0.074
	(0.089)	(0.092)
Sole Proprietorship	0.044	0.105*
	(0.053)	(0.056)
Privatized	0.052	−0.019
	(0.075)	(0.079)
Non-Exporter	−0.213***	−0.108**
	(0.055)	(0.053)
Firm Age	−0.036	0.058
	(0.157)	(0.158)
Innovative	0.219***	0.114**
	(0.058)	(0.054)
Competition	0.106**	0.126**
	(0.054)	(0.053)
Subsidized	0.200**	0.353***
	(0.081)	(0.073)
Country Fixed Effects	Yes	Yes
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Number of Observations	3,237	3,213
Pseudo R-squared	0.07	0.05

Notes: The dependent variable is a dummy variable equal to 1 if the firm applied for bank credit (column labeled "Applied") and a dummy equal to 1 if the firm needs bank credit (column labeled "Need Loan"). "Bank Capital" is the weighted average of the tier 1 capital ratio of the banks present in a particular locality. The variable is locality specific and is constructed by weighting by number of branches the tier 1 capital ratio for each bank which has at least one branch or subsidiary in that locality. "Opaque" is a dummy equal to 1 if the firm does not have its financial accounts verified by an external auditor. "Small Firm" is a dummy equal to 1 if the firm has from 2 to 49 employees. "Big Firm" is a dummy equal to 1 if the firm has more than 250 employees. "Public Company" is a dummy equal to 1 if the firm is a shareholder company, or if its shares are traded in the stock market. "Sole Proprietorship" is a dummy equal to 1 if the firm is a sole proprietorship. "Privatized" is a dummy equal to 1 if the firm is a former state-owned company. "Non-Exporter" is a dummy equal to 1 if the firm does not export to foreign markets. "Firm Age" is the firm's age in years. "Innovative" is a dummy equal to 1 if the firm has introduced a new product line in the past three years. "Competition" is a dummy equal to 1 if the firm faces fairly, very, or extremely strong competition. "Subsidized" is a dummy equal to 1 if the firm has received subsidies from central or local government in the last three years. Omitted category in firm size is "Medium Firm." Omitted category in firm ownership is "Private Company." All regressions include country, industry, and year fixed effects. White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. See appendix 3 for exact definitions and data sources.

In terms of the exclusion restriction, the variables *Competition* and *Subsidized* are included in this demand model but excluded from the rest of the exercises. The rationale for using these particular variables as instruments for demand is the following. Firms in more competitive environments will likely have a higher demand for external credit (due to lower profit margins and hence lower retained earnings), but it is unlikely that credit decisions will be correlated with product market competition. Analogously, having applied for state subsidies is likely a signal for external financial need. These considerations make both variables good firm demand shifters.[16] Both variables are very positively correlated with the demand for bank credit, and the effect is statistically significant at the 1 percent level. The F-statistic from these first-stage regressions of loan demand on the two variables (unreported) is between 15 and 24, which satisfies the relevance test that the instrument is strongly correlated with the endogenous variable.

Finally, due to information limitations in the data, I use at most 3,237 firms in these regressions rather than the 3,418 reported in table 1, because 150 firms lack various components of firm-specific information.

4.2 Monetary Policy and Bank Lending and Risk Taking: Evidence from Formal Loan Rejections

In this section, I report the estimates from model (1), where a firm is defined as credit constrained if it applied for credit and was rejected by the bank. Consequently, information is not used on firms that did not apply for a bank loan. I do so regardless of whether these firms selected themselves out of the application process because they did not need credit or because they were rejected (informally rejected) for the purpose of consistency with studies based on the analysis

[16] I cannot ensure, however, that the exclusion restriction is not violated. On the one hand, the competition the firm faces and whether it receives subsidies is less readily observed by the bank than other firm characteristics, such as size. On the other hand, firms in more competitive environments could be more efficient, and if a firm is backed by government subsidies, it can be viewed as less risky. While both variables appear to be uncorrelated in a statistical sense with the probability of a firm being constrained, all else equal, I need to acknowledge this caveat.

of credit register data. The empirical analysis is performed on the sample of 1,625 firms that formally applied for bank credit, out of which 155 (about 9.5 percent) were rejected and the rest received a loan.

The regressions control for country, industry, time, and bank fixed effects, in various combinations, and they incorporate information on firms that did not apply for a loan by including the inverse of Mills' ratio from the first-stage regression in column 1 of table 4. All firm-specific covariates from table 4 are included with the exception of "Competition" and "Subsidized," whose omission from the regressions is meant to satisfy the exclusion restriction.

Finally, all regressions control for a variety of observable firm-specific characteristics. In later tests, I also control for firm-specific heterogeneity by including firm fixed effects; however, this reduces the sample substantially, as only 373 firms are observed both in fiscal year 2004 and in fiscal year 2007. All percentage differences that are reported from now on are based on the marginal effects at the sample means.

4.2.1 Bank Lending

In table 5, I report the estimated coefficients for the baseline probit regression model. As in the previous subsection, I cluster the standard errors at the level of the locality year, which is where the interaction terms ($\Delta IR_t \cdot Capital_{jkt}$ and $\Delta GDP_{kt} \cdot Capital_{jkt}$) vary.

I start by analyzing, in column 1, the effect of changes in monetary policy and in business-cycle conditions on bank lending. As changes in both types of macroeconomic conditions are annual, the regressions do not make use of year dummies. I find that a reduction in the policy rate spurs loan granting, while an increase in GDP growth has an insignificant (albeit positive) effect on the supply of credit. A 100-basis-point reduction in the policy rate is associated with a 4.5 percent lower probability that a loan application will be rejected.

In column 2, I interact macroeconomic changes with the locality-specific measure of bank capital. The estimates suggest that the negative effect of a positive change in the policy rate on loan granting does not depend, in a statistical sense, on bank balance sheet strength. This result is broadly inconsistent with Jiménez et al.

Table 5. Home-Country Monetary Policy, Host-Country GDP Growth, Bank Capital, and Credit Application Rejection

	Rejected			
	(1)	(2)	(3)	(4)
Δ CB Rate	0.045***		0.054***	
	(0.012)		(0.011)	
Δ CB Rate × Bank Capital		−0.009		−0.001
		(0.008)		(0.007)
Δ GDP	1.194	−5.004	0.712	0.995
	(0.911)	(5.647)	(0.816)	(1.591)
Δ GDP × Bank Capital		0.127		0.020
		(0.104)		(0.072)
Bank Capital	−0.012	−0.020	−0.005	−0.006
	(0.011)	(0.014)	(0.005)	(0.005)
Opaque	0.033*	0.034*	0.039**	0.038**
	(0.018)	(0.018)	(0.018)	(0.018)
Small Firm	0.059***	0.061***	0.061***	0.061***
	(0.019)	(0.019)	(0.018)	(0.018)
Big Firm	0.031	0.030	0.024	0.025
	(0.039)	(0.039)	(0.039)	(0.039)
Public Company	0.111***	0.111***	0.112***	0.111***
	(0.042)	(0.043)	(0.043)	(0.042)
Sole Proprietorship	0.031*	0.032*	0.042**	0.046**
	(0.019)	(0.019)	(0.019)	(0.020)
Privatized	−0.009	−0.009	−0.004	−0.003
	(0.018)	(0.018)	(0.018)	(0.019)
Non-Exporter	0.017	0.018	0.021	0.021
	(0.020)	(0.020)	(0.021)	(0.021)
Firm Age	0.029	0.033	0.045	0.046
	(0.038)	(0.038)	(0.037)	(0.036)
Innovative	−0.032**	−0.032**	−0.032**	−0.032**
	(0.015)	(0.015)	(0.014)	(0.014)
Inverse Mills Ratio (Table 4, Column 1)	0.027	0.029	0.035	0.035
	(0.027)	(0.027)	(0.026)	(0.026)
Country Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes

(*continued*)

Table 5. (Continued)

	Rejected			
	(1)	**(2)**	**(3)**	**(4)**
Year Fixed Effects	No	Yes	No	Yes
Bank Fixed Effects	No	No	Yes	Yes
Number of Observations	1,549	1,549	1,493	1,493
Pseudo R-squared	0.08	0.08	0.10	0.10

Notes: The dependent variable is a dummy variable equal to 1 if the firm applied for a bank loan and its application was rejected. The tests are performed on the subset of firms that applied for a bank loan. "Δ CB Rate" is the change in the core policy rate over the past year. "Δ GDP" is the change in host-country GDP over the past year. "Bank Capital" is the weighted average of the tier 1 capital ratio of the banks present in a particular locality. The variable is locality specific and is constructed by weighting by number of branches the tier 1 capital ratio for each bank which has at least one branch or subsidiary in that locality. "Opaque" is a dummy equal to 1 if the firm does not have its financial accounts verified by an external auditor. "Small Firm" is a dummy equal to 1 if the firm has from 2 to 49 employees. "Big Firm" is a dummy equal to 1 if the firm has more than 250 employees. "Public Company" is a dummy equal to 1 if the firm is a shareholder company, or if its shares are traded in the stock market. "Sole Proprietorship" is a dummy equal to 1 if the firm is a sole proprietorship. "Privatized" is a dummy equal to 1 if the firm is a former state-owned company. "Non-Exporter" is a dummy equal to 1 if the firm does not export to foreign markets. "Firm Age" is the firm's age in years. "Innovative" is a dummy equal to 1 if the firm has introduced a new product line in the past three years. "Inverse Mills Ratio" (table 4, column 1) is the inverse of Mills' ratio from the probit model in table 4, column 1. Omitted category in firm size is "Medium Firm." Omitted category in firm ownership is "Private Company." Omitted categories from the probit equation in column 1 of table 4 are "Competition" and "Subsidized." All regressions include fixed effects as specified. White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. See appendix 3 for exact definitions and data sources.

(2012), who find that bank credit supply is more sensitive to changes in monetary policy if banks have lower capital.[17]

In columns 3 and 4, I repeat the two regressions by replacing the locality-average measure of bank capital with the tier 1 capital

[17] This regression includes year fixed effects; therefore, I do not include monetary policy on its own, as it is common across countries and hence its effect is subsumed in the year fixed effects. The coefficient on monetary policy is once again positive and significant (at the 5 percent statistical level) in an unreported regression without year fixed effects.

ratio of the dominant bank in a particular locality. This allows me to compare directly the effect of lending by subsidiaries of, for example, UniCredit in Bulgaria and in Slovenia. I can thus separate the effect on lending of the business cycle from the effect on lending of monetary policy in the cross-section too, and that is one of the empirical contributions of the paper. These regressions also include bank fixed effects. The results from columns 1 and 2 are broadly confirmed: a 100-basis-point reduction in the policy rate is associated with a 5.4 percent lower probability that a loan application will be rejected (column 3), but the effect is uniform across banks and does not depend on how well capitalized they are (column 4).

In all regressions, the estimates of the regression coefficients on the non-excluded firm-specific variables imply that small firms, sole proprietorships, and non-innovative firms tend to be more constrained in credit markets. Regarding my main proxy for ex ante risk, namely informational opacity, I find that non-audited firms also tend to be more credit constrained.

4.2.2 Bank Risk Taking

I now turn to investigating the effect of monetary policy and business-cycle fluctuations on bank risk taking. Given my baseline model (1), the empirical test boils down to comparing statistically β_1 and β_4 for two sets of firms, one comprised of ex ante risky ones, and one comprised of ex ante safe firms.[18] Therefore, I split the samples along the lines of informational transparency, with non-audited (informationally opaque) firms considered ex ante risky, and audited (informationally transparent) firms considered ex ante safe.

Table 6 reports that a reduction in the policy rate spurs loan granting for ex ante safe firms only (columns 5 and 7). It makes it clear that the effect of monetary policy on bank credit supply does depend—in a statistical sense—on ex ante risk. In the preferred specification with bank fixed effects, a 100-basis-point reduction in the policy rate is associated with a 2.8 percent lower probability that a loan application by a non-audited firm is rejected (column 3, statistically non-significant effects), and with a 5.4 percent lower

[18] Another approach would be to interact the "non-audited" dummy with monetary policy change and with bank capital, but this would run into the intrinsic problems associated with interpreting coefficients on triple interactions.

Table 6. Home-Country Monetary Policy, Host-Country GDP Growth, Bank Capital, and Credit Application Rejection: Distinguishing between Opaque and Transparent Firms

	Rejected							
	Opaque = 1				Opaque = 0			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ CB Rate	0.021		0.028		0.048***		0.054***	
	(0.024)		(0.026)		(0.011)		(0.011)	
Δ CB Rate × Bank Capital		−0.010		0.006		−0.002		−0.001
		(0.012)		(0.011)		(0.008)		(0.008)
Bank Capital	0.006	−0.014	−0.004	−0.011	−0.024*	−0.032*	−0.005	−0.005
	(0.014)	(0.017)	(0.009)	(0.010)	(0.013)	(0.017)	(0.005)	(0.005)
Firm-Specific Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Bank Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Number of Observations	610	610	577	577	939	939	896	896
Pseudo R-squared	0.08	0.08	0.13	0.13	0.13	0.13	0.14	0.14

Notes: The dependent variable is a dummy variable equal to 1 if the firm applied for a bank loan and its application was rejected. The tests are performed on the subset of firms that applied for a bank loan. The analysis is performed on the subset of informationally opaque firms (columns labeled "Opaque = 1") and on the subset of informationally transparent firms (columns labeled "Opaque = 0"). "Δ CB Rate" is the change in the core policy rate over the past year. "Δ GDP" is the change in host-country GDP over the past year. "Bank Capital" is the weighted average of the tier 1 capital ratio of the banks present in a particular locality. The variable is locality specific and is constructed by weighting by number of branches the tier 1 capital ratio for each bank which has at least one branch or subsidiary in that locality. The regressions include all firm-level variables from table 5, as well as GDP growth and its interaction with bank capital. Omitted category in firm size is "Medium Firm." Omitted category in firm ownership is "Private Company." Omitted categories from the probit equation in column 1 of table 4 are "Competition" and "Subsidized." All regressions include fixed effects as specified. White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. See appendix 3 for exact definitions and data sources.

probability that a loan application by an audited firm is rejected (column 7, effect significant at the 1 percent statistical level).

Turning to the effect of bank balance sheet strength, I find that core bank capital does not affect the sensitivity of bank credit supply to monetary policy. In particular, while the reduction in bank credit is higher for lower-capitalized banks when the applicant firm is informationally opaque (columns 2 and 4), the effect is not significant. Furthermore, there is no statistical difference in credit supply to audited and to non-audited firms.

I conclude that when looking at applicant firms only (an analysis consistent with studies that have relied on credit register-type data), there is strong evidence of a decrease in bank lending in response to contractionary monetary policy. However, the data suggest that lower rates do not lead to more risk taking.

4.3 Monetary Policy and Bank Lending and Risk Taking: Evidence from Formal Rejections and from Informal Constraints

In this section, I report the estimates from model (1) where a firm is defined as credit constrained if it (i) applied for credit and was rejected by the bank, or (ii) did not apply because it was informally rejected or because it was discouraged by unfavorable credit conditions. Consequently, in addition to the 1,625 firms that formally applied for credit, in this section I also use information on 532 firms which declare a positive need for bank credit but were discouraged from applying (informally rejected). Thus, I analyze a sample of 2,151 firms that formally applied for bank credit, out of which 687 (about 31.6 percent) were rejected or discouraged, and the rest have been granted a loan.

All regressions incorporate information on firms that do not demand a bank loan by including the inverse of Mills' ratio from the first-stage regression in column 2 of table 4. As before, *Competition* and *Subsidized* are omitted from the regressions in order to satisfy the exclusion restriction, and all regressions control for various combinations of country, industry, time, and bank fixed effects.

4.3.1 Access to Finance

Table 7, panel A, replicates the analysis from table 5 on the expanded sample of firms where discouraged and informally rejected firms

Table 7. Home-Country Monetary Policy, Host-Country GDP Growth, Bank Capital, and Credit Constraints

A. Rejected or Discouraged Firms

	Rejected or Discouraged			
	(1)	**(2)**	**(3)**	**(4)**
Δ CB Rate	0.066***		0.073***	
	(0.019)		(0.019)	
Δ CB Rate × Bank Capital		−0.039***		−0.028**
		(0.012)		(0.012)
Bank Capital	−0.014	−0.039***	−0.014	−0.018**
	(0.015)	(0.015)	(0.011)	(0.008)
Inverse Mills Ratio (table 4, column 2)	0.030	0.033	0.025	0.032
	(0.025)	(0.025)	(0.026)	(0.026)
Firm-Specific Controls	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	No	Yes
Bank Fixed Effects	No	No	Yes	Yes
Number of Observations	2,044	2,044	1,974	1,974
Pseudo R-squared	0.10	0.11	0.11	0.12

B. Discouraged Firms, by Reasons for Discouragement

	Discouraged_1	Discouraged_2	Discouraged_3	Discouraged_4
	(1)	**(2)**	**(3)**	**(4)**
ΔCB Rate × Bank Capital	−0.012*	−0.011**	−0.009**	−0.002
	(0.007)	(0.006)	(0.004)	(0.005)
Bank Capital	−0.007	−0.013*	−0.004	−0.016*
	(0.010)	(0.007)	(0.005)	(0.008)
Firm-Specific Controls	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	No	No
Number of Observations	1,533	1,553	1,512	1,936
Pseudo R-squared	0.09	0.12	0.11	0.13

Notes: In panel A, the dependent variable is a dummy variable equal to 1 if the firm applied for a bank loan and its application was rejected, or if it was discouraged from applying. In panel B, the dependent variable is a dummy variable equal to 1 if the firm did not apply for bank credit because interest rates were not favorable (column 1), because collateral requirements were too high (column 2), because size of loan and maturity were insufficient (column 3), and because it did not think the loan application would be approved (column 4). The tests are performed on the subset of firms with positive demand for bank credit. "Δ CB Rate" is the change in the core policy rate over the past year. "Δ GDP" is the change in host-country GDP over the past year. "Bank Capital" is the weighted average of the tier 1 capital ratio of the banks present in a particular locality. The variable is locality specific and is constructed by weighting by number of branches the tier 1 capital ratio for each bank which has at least one branch or subsidiary in that locality. "Inverse Mills Ratio" (table 4, column 1) is the inverse of Mills' ratio from the probit model in table 4, column 2. The regressions include all firm-level variables from table 5, as well as GDP growth and its interaction with bank capital. Omitted category in firm size is "Medium Firm." Omitted category in firm ownership is "Private Company." Omitted categories from the probit equation in column 2 of table 4 are "Competition" and "Subsidized." All regressions include fixed effects as specified. White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. See appendix 3 for exact definitions and data sources.

are treated not as invisible to the econometrician but as credit-constrained firms. In column 1, I analyze the effect of changes in monetary policy and in business-cycle conditions on bank lending. Consistent with column 1 in table 5, I find that a reduction in the policy rate spurs loan granting, while an increase in GDP growth again has no statistically significant effect on the supply of credit. A 100-basis-point reduction in the policy rate is associated with a 6.6 percent lower probability that a firm will be credit constrained (formally rejected, informally rejected, or discouraged).

Now I turn to analyzing the role of bank balance sheet strength in the transmission of monetary policy by interacting macroeconomic changes with the locality-specific measure of bank capital. As indicated in column 2, in this subset of firms the results markedly diverged from what I recorded in column 2 of table 5. In particular, the estimates suggest that the negative effect of a monetary tightening on access to finance strongly depends—both economically and statistically—on bank agency costs. In particular, the same increase in the policy rate is associated with a 3.9 percent higher probability of a firm being credit constrained if it is incorporated in a locality at the 25th rather than the 75th percentile of the distribution of locality-average bank capital.[19] Importantly, this specification controls for year fixed effects, so it nets out the effect of unobservable time-varying macroeconomic conditions. This result is fully consistent with theoretical predictions outlined in section 2, as well as with recent empirical investigations (see Jiménez et al. 2012, 2014).

In columns 3 and 4, I repeat the analysis from columns 1 and 2, respectively, but this time use each locality's dominant bank's core capital, instead of a locality-average one, and I include bank fixed effects in the regressions. This allows me to eliminate unobserved bank-specific heterogeneity, as well as to separate the effect of the business cycle and of monetary policy in the cross-section too (given that the same parent bank has subsidiaries in different foreign markets). The results remain qualitatively unchanged: a 100-basis-point reduction in the policy rate is associated with a 7.3 percent lower probability that a loan application will be credit constrained (column 3), and this reduction is 3.3 percent larger if the firm is

[19]The magnitude implied by the coefficient on the interaction term is calculated using the point estimate and the difference between the 25th and the 75th percentile in terms of locality-average bank capital, which is 1.14.

incorporated in a locality whose dominant bank is at the 25th rather than the 75th percentile of the distribution of locality-average bank capital (column 4).

This set of tests makes it obvious that when discouraged and informally rejected firms are included in the analysis—in addition to firms that participate in the formal application process—the bank credit supply becomes more sensitive to monetary policy. In particular, there is strong evidence of a decrease in bank lending in response to contractionary monetary policy, and in addition to that, the transmission of monetary policy to the real sector is much stronger for undercapitalized banks.

In panel B, I study the mechanisms via which informally rejected and discouraged firms are more likely to opt out of the loan application process during monetary tightening in localities dominated by lowly capitalized banks. I repeat the test from column 2 after separating the four possible types of informal constraints: "Interest rates are not favorable"; "Collateral requirements are too high"; "Size of loan and maturity are insufficient"; and "Did not think it would be approved." The tests imply that with the exception of expectations about the loan application being rejected, all other mechanisms of discouragement are operational. This indicates that indeed firms may be given an informal offer by the loan officer which they find unacceptable, and so they drop out halfway through the loan-granting process. Alternatively, they may collect information from friends and/or competitors as to current credit terms and not apply for a loan or line of credit at all.

4.3.2 Bank Risk Taking

In table 8, I replicate the analysis from table 6 on the sample of firms where discouraged and informally rejected firms are treated as formally rejected instead of invisible to the econometrician. I therefore estimate equation (1) on the two subsets of ex ante risky and ex ante safe firms, using information opacity as a proxy for ex ante riskiness, and then compare statistically the estimates from the relevant terms.

In panel A, I run the test on all rejected or informally constrained firms. Focusing on my preferred specification where I control for bank fixed effects, the data suggest that the overall transmission of monetary policy is stronger when firms are of lower ex ante risk.

Table 8. Home-Country Monetary Policy, Host-Country GDP Growth, Bank Capital, and Credit Constraints: Distinguishing between Opaque and Transparent Firms

A. Rejected or Discouraged Firms								
	Rejected or Discouraged							
	Opaque = 1				**Opaque = 0**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Δ CB Rate	0.033		0.032		0.065***		0.085***	
	(0.032)		(0.035)		(0.020)		(0.019)	
Δ CB Rate × Bank Capital		−0.064***		−0.053***		−0.011		−0.001
		(0.020)		(0.018)		(0.015)		(0.015)
Bank Capital	0.007	−0.052**	−0.006	−0.028**	−0.060***	−0.070***	−0.030***	−0.029***
	(0.017)	(0.022)	(0.014)	(0.013)	(0.020)	(0.026)	(0.007)	(0.008)
Firm-Specific Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Bank Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Number of Observations	902	902	874	874	1,142	1,142	1,095	1,095
Pseudo R-squared	0.11	0.12	0.13	0.14	0.09	0.09	0.10	0.10

(*continued*)

Table 8. (Continued)

B. Discouraged Firms, by Reasons for Discouragement

	Discouraged_1	Discouraged_2	Discouraged_3	Discouraged_4	Discouraged_1	Discouraged_2	Discouraged_3	Discouraged_4
	Opaque = 1				**Opaque = 0**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Δ CB Rate × Bank Capital	-0.022^{**}	-0.032^{**}	−0.012	−0.006	−0.006	0.001	−0.002	0.002
	(0.010)	(0.012)	(0.009)	(0.010)	(0.007)	(0.006)	(0.004)	(0.006)
Bank Capital	−0.007	-0.022^{*}	−0.005	-0.044^{**}	−0.014	−0.018	-0.021^{**}	−0.003
	(0.014)	(0.012)	(0.010)	(0.021)	(0.010)	(0.012)	(0.009)	(0.008)
Firm-Specific Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	No	Yes	Yes	No	No	Yes	Yes
Number of Observations	605	625	596	603	934	923	911	829
Pseudo R-squared	0.13	0.19	0.13	0.13	0.08	0.10	0.11	0.14

Notes: In panel A, the dependent variable is a dummy variable equal to 1 if the firm applied for a bank loan and its application was rejected, or if it was discouraged from applying. In panel B, the dependent variable is a dummy variable equal to 1 if the firm did not apply for bank credit because interest rates were not favorable (columns 1 and 5), because collateral requirements were too high (columns 2 and 6), because size of loan and maturity were insufficient (columns 3 and 7), and because it did not think the loan application would be approved (columns 4 and 8). The tests are performed on the subset of firms with positive demand for bank credit. The analysis is performed on the subset of inflormationally opaque firms (columns labeled "Opaque = 1") and on the subset of informationally transparent firms (columns labeled "Opaque = 0"). "Δ CB Rate" is the change in the core policy rate over the past year. "Δ GDP" is the change in host-country GDP over the past year. "Bank Capital" is the weighted average of the tier 1 capital ratio of the banks present in a particular locality. The variable is locality specific and is constructed by weighting by number of branches the tier 1 capital ratio for each bank which has at least one branch or subsidiary in that locality. The regressions include all firm-level variables from table 5, as well as GDP growth and its interaction with bank capital. Omitted category in firm size is "Medium Firm." Omitted category in firm ownership is "Private Company." Omitted categories from the probit equation in column 2 of table 4 are "Competition" and "Subsidized." All regressions include fixed effects as specified. White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. See appendix 3 for exact definitions and data sources.

A 100-basis-point reduction in the policy rate is associated with a 3.2 percent decrease in the probability that a non-audited firm is credit constrained (column 3), and with an 8.5 percent decrease in probability that an audited firm is credit constrained (column 7). In addition, this effect is significant at the 1 percent in the latter case and statistically insignificant in the former case.

Turning to the effect of bank balance sheet strength, this time I find that core bank capital strongly affects the sensitivity of credit supply to monetary policy. In particular, the same expansion in monetary policy is associated with a 4.6 percent larger decline in the probability that an ex ante risky firm is credit constrained if the firm is incorporated in a locality whose dominant bank is at the 25th rather than the 75th percentile of the distribution of locality-average bank capital (column 4), and this effect is significant at the 1 percent statistical level. The same expansion in monetary policy, however, is associated with only a 0.9 percent larger decline in the probability that an ex ante safe firm is credit constrained if the firm is incorporated in a locality whose dominant bank is at the 25th percentile of the distribution of locality-average bank capital than for a firm incorporated in a locality at the 75th percentile of the distribution of locality-average bank capital (column 8), the effect being statistically insignificant. The difference between the two coefficients is also significant at the 5 percent level, and the evidence is robust to employing a locality-specific measure of capital instead of a bank-specific one (columns 2 and 6).

The estimates thus imply that the sensitivity of credit supply to monetary policy and the impact of bank capital to that sensitivity depends crucially on whether discouraged and informally rejected firms are used in the analysis. When they are, the data suggest that credit supply responds more forcefully to changes in monetary policy, and there is much stronger evidence of bank risk taking in response to expansionary monetary policy. When informally constrained firms are also accounted for, the bank balance sheet channel turns out to be even more potent than previously thought.

Finally, in panel B I once again separate the firms across the four types of informal constraints. The regression estimates suggest that the probability of firms saying that "Interest rates are not favorable" or that "Collateral requirements are too high" declines during monetary tightening in localities dominated by lower-capitalized banks, and this is the case only for informally opaque firms. This once again points to higher risk taking by banks which takes place through the mechanism of lower discouragement of ex ante risky firms.

4.4 Controlling for Unobserved Firm-Specific Heterogeneity

A total of 373 of the firms are observed both in 2004 and in 2007. This allows me to include firm fixed effects in the analysis in addition to all firm-specific covariates and fixed effects used so far. While this procedure controls for unobserved firm-specific heterogeneity over time, it is not identical to Khwaja and Mian (2008) and to Jiménez et al. (2012), who use firm fixed effects to eliminate the unobservable component of firm demand *within the same time period*, that is, when a firm simultaneously borrows from multiple banks. Given my empirical strategy, I have constrained each firm to borrow from the same bank (set of banks) in all time periods; therefore, I simply eliminate the unobservable component of firm demand over time.

Table 9 reports the estimates from this regression where the sample has been reduced to the 373 firms observed both in 2004 and in 2007. I estimate model (1) by lumping formal and informal rejections as in tables 7 and 8. In this reduced sample, one of the two main results of the paper survives, namely that the increase in credit supply to ex ante risky firms in response to expansionary monetary policy is stronger for weakly capitalized banks (column 4). This implies that the risk-taking effect I registered before is not driven by a failure to control for unobserved firm-specific heterogeneity. However, the statistical significance of the effect declines relative to previous tests.

5. Conclusion

In this paper, I conduct the first empirical analysis of the balance sheet channel incorporating information on discouraged and informally rejected firms, which standard analysis based on credit register data excludes by definition. Paying attention to such firms is crucial: if credit-unworthy applicants systematically drop out of the application process when bank capital is high, when monetary policy is expansive, or when economic conditions improve, the effect of monetary policy, of the business cycle, and of agency costs on bank lending and risk taking will be systematically over-estimated.

I analyze a detailed survey data set on firms in small central and eastern European markets which either use the euro or have their

Table 9. Home-Country Monetary Policy, Host-Country GDP Growth, Bank Capital, and Credit: Accounting for Unobserved Firm-Level Heterogeneity

	Rejected or Discouraged					
	All Firms		Opaque = 1		Opaque = 0	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ CB Rate	0.146**		−0.109		0.179	
	(0.066)		(0.350)		(0.221)	
Δ CB Rate × Bank Capital		−0.044		−0.092*		0.167
		(0.043)		(0.053)		(0.190)
Bank Capital	−0.039**	−0.026	−0.066	−0.077	−0.039	−0.117
	(0.020)	(0.029)	(0.096)	(0.086)	(0.049)	(0.120)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	Yes	No	Yes	No	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	448	448	206	206	242	242
Pseudo R-squared	0.78	0.76	0.91	0.92	0.90	0.91

Notes: The dependent variable is a dummy variable equal to 1 if the firm applied for a bank loan and its application was rejected, or if it was discouraged from applying. The tests are performed on the subset of firms with positive demand for bank credit. The analysis is performed on all firms in the data set (columns labeled "All Firms"), on the subset of inflormationally opaque firms (columns labeled "Opaque = 1") and on the subset of informationally transparent firms (columns labeled "Opaque = 0"). "Δ CB Rate" is the change in the core policy rate over the past year. "Δ GDP" is the change in host-country GDP over the past year. "Bank Capital" is the weighted average of the tier 1 capital ratio of the banks present in a particular locality. The variable is locality specific and is constructed by weighting by number of branches the tier 1 capital ratio for each bank which has at least one branch or subsidiary in that locality. The regressions include all firm-level variables from table 5, as well as GDP growth and its interaction with bank capital. Omitted category in firm size is "Medium Firm." Omitted category in firm ownership is "Private Company." Omitted categories from the probit equation in column 2 of table 4 are "Competition" and "Subsidized." All regressions include fixed effects as specified. White (1980) robust standard errors are reported in parentheses, where *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level. See appendix 3 for exact definitions and data sources.

currency pegged to the euro. This allows me to separate the effect of monetary policy from that of the business cycle, and to identify the effect of credit supply by observing changes in the level and composition of credit demand. Importantly, while I do not observe the universe of applications, I do observe data on discouraged and informally rejected firms that do not appear in official bank records and credit registers. My main finding is that the balance sheet channel is much more potent when such firms are included in the analysis. In particular, when I analyze loan granting to formal applicants only, I find strong evidence that a monetary policy expansion results in more granted loans, but bank risk taking does not seem to depend on bank balance sheet strength. However, when I include discouraged and informally rejected firms in the analysis, I find evidence of both higher lending and higher credit risk taking by banks in response to monetary loosening, and both effects are amplified when banks are undercapitalized.

While my results imply that in terms of quantifying the effect of agency costs in the transmission of monetary policy there is value added to analyzing survey data in addition to credit register data, the question of how generalized this result is remains. For example, Albertazzi and Marchetti (2009) and Jiménez et al. (2014) argue that firm discouragement and informal rejection is an almost nonexistent phenomenon in Italy and Spain, respectively. At the same time, using data from the 1993 National Survey of Small Business Finance in the United States, Cavalluzzo and Wolken (2005) report that half of all small business owners that needed credit reported that they did not apply for credit in the past three years because they believed that they would not be able to obtain it. Cox and Jappelli (1993) and Duca and Rosenthal (1993) report that discouragement is a non-negligible phenomenon in the case of households as well. Chakravarty and Xiang (2013) show that around 20 percent of all firms are discouraged from applying for a loan in a sample of Latin American, Asian, and African countries.

If loan discouragement is an international phenomenon which varies by country, then identifying the bank balance sheet channel by observing the outcomes of formal loan applications only may under- or over-estimate the potency of that channel, depending on how the share of discouraged and informally rejected firms varies with the business cycle and with bank soundness. While my results suggest that informal rejections increase when monetary policy is tight and when banks are undercapitalized, implying that the bank balance sheet channel is in reality even more potent than analysis based on credit register data would suggest, this need not be the case at all times and in all markets. For example, the firms in my data set come from countries in transition from communism where credit markets are relatively less developed. In such markets, discouragement may be prevalent because it takes a firm longer to develop a reputation, or because it is more difficult to tap into household sources of credit, such as home equity, and so firms have more to lose from a rejection. By incorporating survey data from other markets, future research can greatly contribute to our understanding of the transmission of monetary policy and the effect of bank capital on the credit supply and on bank risk taking.

Appendix 1

Table 10. Domestic and Parent Banks in the Sample

Country	Bank	Parent Bank and Country of Incorporation
Bulgaria	Alpha Bank	Alpha Bank—Greece
	Unicredit Bulbank	UniCredit Group—Italy
	DSK	OTP—Hungary
	First Investment Bank	Domestic
	PostBank	EFG Eurobank—Greece
	Expressbank	Societe Generale—France
	United Bulgarian Bank	National Bank of Greece—Greece
	Reiffeisen	Raiffeisen—Austria
	Piraeus	Piraeus Bank—Greece
Bosnia and Herzegovina	Raiffeisen Bank Bosna i Hercegovina	Raiffeisen—Austria
	UniCredit Bank	UniCredit Group—Italy
	Hypo Alpe-Adria-Bank-Mostar	Hypo Group—Austria
	Intesa Sanpaolo Banka Bosna i Hercegovina	Intesa Sanpaolo—Italy
	NLB Tuzlanska Banka	KBC—Belgium
	Volksbank Sarajevo	Volksbank—Austria

(*continued*)

Table 10. (Continued)

Country	Bank	Parent Bank and Country of Incorporation
Estonia	Swedbank Estonia	Swedbank—Sweden
	SEB	Skandinavska Enskilda Banken—Sweden
	Sampo Bank	Danske Bank—Denmark
	Nordea	Nordea Bank—Sweden
Latvia	Parex	Domestic
	Hansabank	Swedbank—Sweden
	Latvijas Krajbanka	Snoras Bank—Lithuania
	SMP Bank	Domestic
	Rietumu Banka	Domestic
	Trasta Komercbanka	Domestic
Lithuania	SEB	Skandinavska Enskilda Banken— Sweden
	Sampo Bank	Danske Bank—Denmark
	Nordea	Nordea Bank—Sweden
	Snoras Bank	Domestic
	Ukio Bankas	Domestic
	Hansabankas	Swedbank—Sweden
	Parex Bankas	Parex Group—Latvia
Montenegro	AtlasMont Bank	Domestic
	Crnogorska Komercijalna Banka	OTP—Hungary
	Hypo-Alpe-Adria Bank	Hypo Group—Austria
	Komercijalna Banka ad Budva	Domestic
	NLB Montenegro Banka	KBC—Belgium
	Prva Banka Crne Gore	Domestic
	Invest Banka Montegnegro	Domestic
	Podgoricka Banka SG	Societe Generale—France
	Opportunity Bank	Domestic
Slovakia	Vseobecna Uverova Banka	Intesa Sanpaolo—Italy
	Slovenska Sporitelna	Erste Group—Austria
	Tatra Banka	Raiffeisen—Austria

(*continued*)

Table 10. (Continued)

Country	Bank	Parent Bank and Country of Incorporation
Slovakia	OTP Banka Slovensko	OTP—Hungary
	Dexia Banka Slovensko	Dexia—Belgium
	UniCredit Bank Slovakia	UniCredit Group—Italy
	Volksbank Slovensko	Volksbank—Austria
	CSOB Slovakia	KBC—Belgium
Slovenia	Nova Ljubljanska Banka	KBC—Belgium
	Nova Kreditna Banka Maribor	Domestic
	Abanka	Domestic
	SKB	Societe Generale—France
	UniCredit	UniCredit Group—Italy
	Banka Koper	Intesa Sanpaolo—Italy
	Banka Celje	Domestic
	Reiffeisen Krekova Banka	Raiffeisen—Austria

Appendix 2

Table 11. Bank Data Coverage

Country	Ratio of Assets of the Banks in the Data Set to Total Assets of the Country's Banking Sector
Bosnia and Herzegovina	0.842
Bulgaria	0.857
Estonia	0.956
Latvia	0.851
Lithuania	0.896
Montenegro	0.862
Slovakia	0.925
Slovenia	0.862

Source: Bankscope.

Appendix 3

Table 12. Variables—Definitions and Sources

Variable Name	Definition	Source
	Firm Characteristics	
Opaque	Dummy = 1 if the firm does not subject its financial accounts to external audit.	BEEPS 2005 & 2008
Small Firm	Dummy = 1 if the firm has less than 20 employees.	BEEPS 2005 & 2008
Medium Firm	Dummy = 1 if the firm has between 20 and 100 employees.	BEEPS 2005 & 2008
Big Firm	Dummy = 1 if the firm has more than 100 employees.	BEEPS 2005 & 2008
Public Company	Dummy = 1 if the firm is a shareholder company/has shares traded in the stock market.	BEEPS 2005 & 2008
Private Company	Dummy = 1 if the firm is a shareholder company/has shares traded privately, if at all.	BEEPS 2005 & 2008
Sole Proprietorship	Dummy = 1 if the firm is a sole proprietorship.	BEEPS 2005 & 2008
Privatized	Dummy = 1 if the firm went from state to private ownership in the past year.	BEEPS 2005 & 2008
Subsidized	Dummy = 1 if the firm has received state subsidies in the past year.	BEEPS 2005 & 2008
Non-Exporter	Dummy = 1 if no part of the firm's production is exported to foreign markets.	BEEPS 2005 & 2008
Competition	Dummy = 1 if pressure from competitors is "fairly" or "very" severe.	BEEPS 2005 & 2008
Firm Age	The number of years since the firm was officially incorporated.	BEEPS 2005 & 2008
Innovative	Dummy = 1 if the firm has introduced at least one new credit line in the past three years.	BEEPS 2005 & 2008

(*continued*)

Table 12. (Continued)

Variable Name	Definition	Source
	Credit Demand and Credit Access	
Need Loan	Dummy = 1 if the firm needs a loan because it cannot cover operating expenses with retained earnings.	BEEPS 2005 & 2008
Applied	Dummy = 1 if the firm applied for bank credit.	BEEPS 2005 & 2008
Rejected	Dummy = 1 if the firm's application for a bank loan was rejected.	BEEPS 2005 & 2008
Discouraged_1	Dummy = 1 if the firm did not apply for bank credit because interest rates were not favorable.	BEEPS 2005 & 2008
Discouraged_2	Dummy = 1 if the firm did not apply for bank credit because collateral requirements were too high.	BEEPS 2005 & 2008
Discouraged_3	Dummy = 1 if the firm did not apply for bank credit because size of loan and maturity were insufficient.	BEEPS 2005 & 2008
Discouraged_4	Dummy = 1 if the firm did not apply for bank credit because it did not think the loan application would be approved.	BEEPS 2005 & 2008
Rejected or Discouraged	Dummy = 1 if (a) the firm's application for a bank loan was rejected, or (b) the firm does not have a loan because it was discouraged from applying for one of the following reasons: "Interest rates are not favorable," "Collateral requirements are too high," "Size of loan and maturity are insufficient," or "Did not think it would be approved."	BEEPS 2005 & 2008
	Bank-Level Variables	
Tier 1	The bank's risk-adjusted capital ratio.	Bankscope
	Country Variables	
Δ CB Rate	The change, in terms of basis points, in the ECB's policy rate over the previous year.	ECB
Δ GDP	The percentage change in GDP over the previous year.	Penn Tables

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Money-Market Rates and Retail Interest Regulation in China: The Disconnect between Interbank and Retail Credit Conditions*

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Interest rates in China are composed of a mix of both market-determined interest rates (interbank rates and bond yields) and regulated interest rates (retail lending and deposit rates), reflecting China's gradual process of interest rate liberalization. This paper investigates the main drivers of China's interbank rates by developing a stylized theoretical model of China's interbank market and estimating an EGARCH model for seven-day interbank repo rates. Our empirical findings suggest that movements in administered interest rates (part of the People's Bank of China's monetary policy toolkit) are important determinants of market-determined interbank rates, in both levels and volatility. The announcement effects of reserve requirement changes also influence interbank rates, as well as liquidity injections from open-market operations in recent years. Our results indicate that the regulation of key retail interest rates influences the behavior of market-determined

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interbank rates, which may have limited their independence as price signals. Further deposit rate liberalization should allow short-term interbank rates to play a more effective role as the primary indirect monetary policy tool.

JEL Codes: E43, E52, E58, and C22.

1. Introduction

Short-term interbank interest rates play an important role in the economy. They indicate the state of macroeconomic and liquidity conditions, and provide an important anchor for the pricing of financial assets. In many economies, but not yet in China, they are also central to the implementation of monetary policy. Consequently, large benefits are likely to follow—through the allocation of capital and risk in the economy—from ensuring that short-term funding rates provide independent market-based price signals. Recognizing this, China has been gradually liberalizing interest rates for more than a decade. However, while interbank interest rates and bond yields are now market determined, other key interest rates continue to remain regulated. In particular, there is an administrative cap on retail deposit rates and a floor on retail lending rates.

In this paper, we ask whether short-term interbank rates can effectively reflect liquidity conditions and provide a basis for asset pricing in China. Our answer is that further reform is needed before they can fully play these roles. Although interbank rates are market determined, these rates are not independent of the regulation of other key interest rates. Regulating the deposit rate influences the supply of funds into the financial system and, consequently, affects liquidity and the interbank rate. Similarly, regulating the lending rate affects the volume of loans demanded and so should also alter the interbank rate.

We build on the microeconomic model of the banking sector in Freixas and Rochet (2008) and develop a stylized theoretical model of China's banking sector that pins down the analytical relationship between regulated and market-determined interest rates. The model, although stylized, captures the key features of the interbank market and monetary policy in China, including the role of "informal" bank-level credit restrictions and administered interest rates in monetary policy, the regulated nature of retail interest rates, institutional demand in the interbank market, and a desire to hold excess reserves. To our knowledge, our paper presents one of the first theoretical models of the interbank market in China, where market-determined and regulated interest rates coexist. Our theoretical model predicts that regulated rates influence interbank rates, and asset valuations made using interbank rates largely reflect the position of the administered rates, which are adjusted by the People's Bank of China (PBC) on an irregular basis as monetary policy tools. Similarly, interbank rates would less effectively indicate fluctuations in retail credit market conditions.

Our empirical strategy is related to several recent studies on the behavior of interbank interest rates and the impact of monetary policy on the interbank market; see, for example, Hamilton (1996), Bartolini, Bertola, and Prati (2001), Prati, Bartolini, and Bertola (2003), and Bartolini and Prati (2006). Until now, the literature on interbank markets has largely focused on the interbank rates in G7 and euro-area economies, while little has been studied on emerging-market economies such as China. This paper aims to address this gap and provides, to our knowledge, the first comprehensive analysis on the determinants of interbank interest rates in China, taking into account the extent of interest rate liberalization and the institutional arrangements of key interest rate markets. This is particularly relevant for China and other developing countries that have experienced partial liberalization of their financial systems. Deregulating particular portions of the financial system (in this case interbank rates) does not ensure that those key interest rates can act as independent price signals.

As in the empirical studies of mature interbank markets mentioned above, an EGARCH model (Nelson 1991) of China's seven-day repo rate is estimated using daily data from April 2003 to April 2012, which cover three distinct phases of macroeconomic environments: (i) China's pre-crisis expansion and period of growing surplus liquidity (reflecting rapid reserve accumulation); (ii) the massive post-Lehman credit expansion (2008–10); and (iii) the subsequent monetary tightening beginning in 2010. The results of the estimated empirical model (presented in section 4) confirm the predictions from the theoretical model that China's interbank rates are not truly independent of administered interest rates. In particular, parameter estimates suggest that the interbank rate increases with administered lending rates and falls with administered deposit rates, even after controlling for systematic variations in liquidity throughout the week, during the month, or due to the timing of the Chinese New Year. Liquidity injections from reserve requirements do not have any significant influence on the level of the interbank rate, while the announcement effect does have a significant impact. Open-market operations are found to be significant in driving interbank interest rates in the full sample (but not in a shorter subsample), in both levels and volatility. Finally, changes to administered interest rates also affect interbank rate volatility, as do announced changes to reserve requirements and initial public offering (IPO) activities.

Our results indicate that the regulation of key retail interest rates influences the behavior of market-determined interbank interest rates and therefore limits their independence as price signals. In more advanced and liberalized money markets, past interest rate movements and pure liquidity effects related to the reserve maintenance period and holidays explain a far larger share of money-market rate behavior than in China. Further interest rate liberalization should work to strengthen the information conveyed by movements in interbank rates and help to further advance the development of China's financial market. Simultaneously removing the regulatory distortions in the interbank rate and allowing retail deposit and loan markets to clear would help to reconnect wholesale and retail credit conditions. While interest rate volatility may increase after liberalization, as has happened elsewhere (Demirguc-Kunt and Detragiache 2001), this volatility would be associated with the incorporation of macroeconomic and financial news into the pricing of risk and capital. Ultimately, this should be associated with a better allocation of scarce capital, and contribute to China's rebalancing toward greater reliance on domestic consumption and less reliance on exports and investment (see, for example, Aziz 2007).

Our paper is structured as follows. Section 2 describes the institutional arrangements of monetary policy and key interest rate markets. Section 3 presents a stylized model of China's interbank market, reflecting the institutional features highlighted in section 2, including the regulated nature of retail interest rates, the role of window guidance/quantitative credit controls, and the desire to hold excess reserves. Section 4 estimates an EGARCH model of China's seven-day repo rate, controlling for key variables implied by the stylized model, and studies the behavior and drivers of interbank interest rates in China. Section 5 offers some concluding remarks.

2. Monetary Policy and Interest Rates

2.1 Monetary Policy

The PBC's monetary policy relies on a variety of both direct and indirect instruments.[1] While the use of indirect instruments such as open-market operations has grown rapidly over time, the PBC also frequently uses reserve requirements to influence the volume of funds banks have available to lend. Moreover, "the government continues to rely on (bank-specific) quantitative limits to slow credit growth" and uses official "window guidance" to influence the direction of bank lending (International Monetary Fund 2010).[2] The design of reserve requirements in China is likely to increase the volatility of money markets, since they must be strictly met on a daily basis rather than over a *reserve-maintenance* period (reserve averaging), as is common in many other countries.[3] While banks may hold insufficient reserves before closing, they are penalized for not holding sufficient reserves at closing. If reserve requirements were met only over some reserve-maintenance period rather than on a daily basis, then the volatility of short-term interbank rates would likely be lower. This is seen in countries with reserve averaging, where interest rate volatility rises systematically through the reserve-maintenance period, increasing as settlement day approaches (see, for example,

[1]Direct instruments set prices or quantities through regulation and are aimed at the balance sheets of commercial banks, while indirect instruments operate by influencing underlying demand and supply conditions and are aimed at the balance sheet of the central bank (Alexander, Enoch, and Balio 1995).

[2]"Window guidance" is one form of the quantity-based direct monetary policy instruments used in China, which uses benevolent compulsion to persuade the banking sector and other financial intermediaries to follow official guidelines. The PBC has a major influence on the lending decisions for the four large state-owned commercial banks through the use of "window guidance" (Geiger 2006).

[3]The reserve-maintenance period refers to a time frame when banks are required to hold a certain amount of reserves on their balance sheets. The length of these periods varies from country to country: the U.S. averaging is done over a two-week period, while Japan and the euro area average over a month (see, for example, Prati, Bartolini, and Bertola 2003).

Hamilton 1996 and Prati, Bartolini, and Bertola 2003). The one-year administered (benchmark) lending and deposit rates are adjusted by the PBC on an irregular basis, typically in conjunction with movements in other monetary policy indicators (i.e., administered rates of other maturities), although the slope typically changes only at the short end of the yield curve.[4] The PBC also regulates retail interest rates by setting a ceiling on the deposit rates and a floor on lending rates. Despite this array of instruments, Chinese monetary policy has relied heavily on quantity-based instruments and administrative measures (reserve requirements and window guidance/credit ceilings). Indeed Mehrotra, Koivu, and Nuutilainen (2008) argue that observed Chinese monetary growth is consistent with a McCallum monetary growth rule (see McCallum 1988, 2003).[5]

2.2 Regulated and Market-Determined Interest Rates

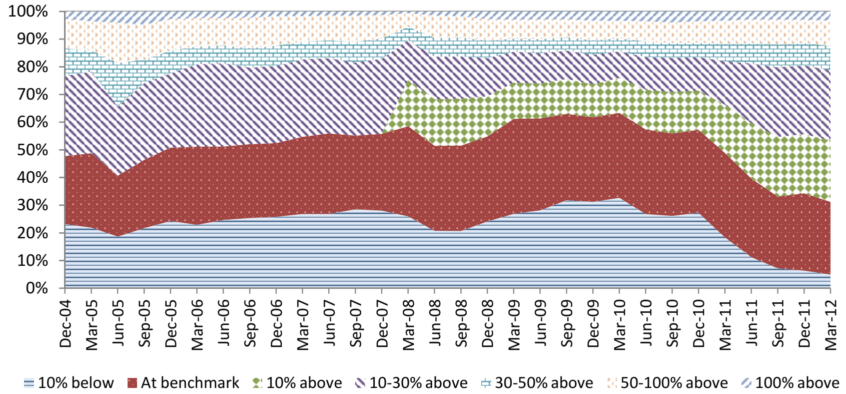
Interest rates in China reflect a mix of regulated and market-determined outcomes. Wholesale interest rates, including interbank rates and bond yields, are largely market determined, while there remains a floor on retail lending rates and a ceiling on retail deposit rates, which in effect protect the profit margins of commercial banks, which average around 3 percent.[6] Retail lending rates can typically be no lower than 70 percent of the administered lending rate, and retail deposit rates could rise to 110 percent of the administered deposit rate. As can be seen in figure 1, more than 80 percent of loans occur at or above the administered lending rate, suggesting that this rate is not effective. The ceiling on deposit rates is generally considered binding, with deposit rates typically clustered at

[4]The proportion of adjustment in the administered deposit and lending rates is typically greater at the front end of the yield curve than at the back end. For example, the administered deposit rates were adjusted in February 2011 from 2.25 to 2.60 (three month), 2.50 to 2.80 (six month), 2.75 to 3.00 (one year), 3.55 to 3.90 (two year), 4.15 to 4.50 (three year), and 4.55 to 5.00 (five year).

[5]Under the McCallum monetary growth rule, money growth is equal to target (nominal) GDP growth less the velocity growth of money, and plus half the previous deviation of nominal GDP from its target; see Mehrotra, Koivu, and Nuutilainen (2008) for details.

[6]See a longer working paper version of this study, "What Drives China's Interbank Market?" (Porter and Xu 2009), for a detailed history of China's interest rate liberalization.

Figure 1. Retail Lending Rates Relative to Administered Lending Rates



Source: People's Bank of China and Haver Analytics (CEIC).

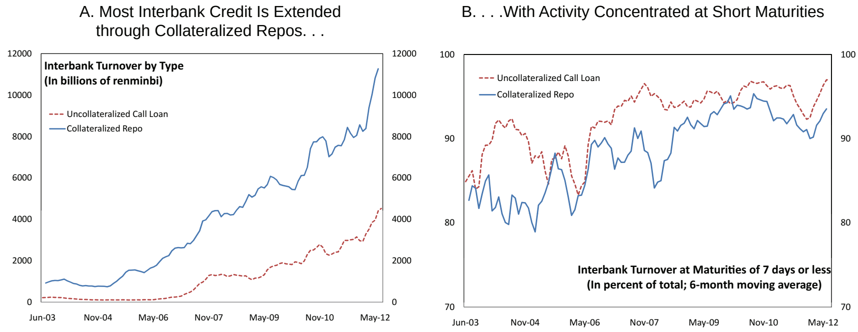
their benchmarks (administered deposit rates). This conclusion was reinforced by the fact that deposit rates jumped to their new ceiling following the June 2012 reform.[7] While generally positive, real deposit rates have, at times, been close to zero or negative for long periods.[8]

While interbank interest rates and bond yields have been liberalized since the late 1990s, funding costs continue to be subject to a number of other restrictions. For example, there have been various restrictions on the issuance of securities in the interbank and exchange markets (Cassola and Porter 2011). Among the two types of interbank lending—uncollateralized lines of credit and collateralized repos—the latter is by far the most important; see figure 2. Repo lending is typically short term (overnight to seven days, with

[7]Given the binding nature of the deposit rate ceiling, six major banks in Beijing raised their retail deposit rates (10 percent above the administered rate for demand deposits and 7.69 percent above the administered rate for one-year time deposits) immediately after the announcement of a higher deposit rate ceiling in June 2012.

[8]For example, the ex post real one-year deposit rates in our sample period (April 2003 to April 2012) were negative for three episodes: November 2003 to December 2004; February 2007 to October 2008; and February 2010 to January 2012.

Figure 2. The Importance of the Interbank Repo Market



Source: CEIC, People's Bank of China, and IMF staff estimates.

more than 60 percent of the transactions at seven days), although transactions with a maturity of up to one year are possible. Activity in these markets would seem somewhat segmented, with the largest banks in China principally borrowing in the (unsecured) call loan market while being net lenders in the (secured) repo market. Other, smaller, commercial banks exhibit the opposite behavior (see Porter and Xu 2009).

3. A Stylized Model of China's Interbank Market

While interbank interest rates have been largely market determined, we consider whether these rates can act as independent price signals, free from the impact of other retail interest rates in China that have been regulated. We discuss this question with the aid of a stylized model of China's banking sector, which we set out below. Subsequently, we examine some empirical evidence that bears on this issue.

The model, although highly stylized, captures the key features of the market highlighted in the previous section on the institutional setup of the interbank market in China, including the regulated nature of retail interest rates, the role of window guidance/quantitative credit control, and, despite the absence of reserve averaging, a desire to hold excess reserves.[9] Following Freixas and Rochet (2008), we consider a competitive model of risk-neutral commercial banks, where there are N independent price-taking banks, and they optimize over the number of deposits to take and loans to make in each period. The banks take as given the lending rate (r_L), the deposit rate (r_D), the bond yield (r_B), the reserve remuneration rate (r_R) for required reserves, the reserve remuneration rate (r_x) for excess reserves, and the interbank lending rate (r). The retail lending and deposit rates are regulated off the administered interest rates, which are set by the PBC. Banks are also assumed to face administratively set individual lending constraints on the volume of loans (represented by $\bar{L}_n$).[10] Taking into account the need to maintain some operational excess reserves, management costs, and the need to withstand deposit fluctuations, we assume that the typical bank has some liquidity preference β ($\beta > 0$) and faces real costs when their own reserve target, $\bar{T}_n$, is not met (see, for example, Bartolini, Bertola, and Prati 2001). Finally, banks face credit risk on both their retail and wholesale lending portfolios. We assume that these banks have well-diversified loan portfolios, meaning that expected loan losses are the same as actual realized losses.

The profit-maximization problem of bank n is given below:

$$\begin{aligned}\Pi_n = \max_{R_n^e, D_n, L_n, B_n, M_n} \Big[& \hat{r}_L L_n + \hat{r} M_n + r_R \alpha D_n + r_x R_n^e + r_B B_n \\ & - r_D D_n - c(D_n, L_n) - \frac{\beta}{2}(R_n^e - \bar{T}_n)^2 \Big], \\ \text{s.t. } & R_n^e \geq 0, L_n \leq \bar{L}_n, \\ \text{where } & \hat{r}_L \equiv r_L(1-\kappa) + \kappa\delta_L; \ \hat{r} \equiv r(1-\gamma) + \gamma\delta_M. \qquad (1)\end{aligned}$$

[9] The stylized model focuses on the *level* of interbank rates, to study the analytical relationship between interbank rates and other interest rates. For the purposes of exposition, we model banks and the interbank market in a deterministic framework to illustrate the potential spillover from regulated interest rates to unregulated market-determined ones.

[10] We abstract from modeling the impact of window guidance on the direction of lending (for example, directed lending to industries with environmentally friendly technology or directed lending away from the real estate sector). Instead, we focus on the impact of window guidance and the quantitative credit ceiling on the total loan target (the volume of loans), to keep the model tractable.

For simplicity, we define $\hat{r}_{L}$ and $\hat{r}$ as the default-adjusted loan rate and the interbank interest rate, respectively. The probability κ is the default rate of bank loans, and γ is the probability of default in the interbank market. δ_L and δ_M are the recovery rates of loans (one minus the loss-given-default rate) for bank and interbank loans, respectively. We assume that $\kappa > \gamma$ and $\kappa\delta_L < \gamma\delta_M$.[11] M_n is the net position of the bank on the interbank market, D_n is the level of deposits, and B_n is the security holdings of the bank (which are assumed to be supplied inelastically by the government). αD_n is the level of required reserves, and R_n^e is the level of excess reserves each bank voluntarily decides to hold. The cost of managing deposits and loans is given by $c(D_n, L_n)$, which we assume to be strictly convex, twice continuously differentiable, and separable in its arguments.

Since each bank's balance sheet requires $M_n = D_n - B_n - L_n - \alpha D_n - R_n^e$, the profit-maximization condition in (1) can be expressed as

$$\Pi_n = \max_{R_n^e, D_n, L_n, B_n} \Big[(\hat{r}_{L} - \hat{r})L_n + (r_{B} - \hat{r})B_n + (r_{R} - \hat{r})\alpha D_n + (r_x - \hat{r})R_n^e + (\hat{r} - r_{D})D_n - c(D_n, L_n) - \frac{\beta}{2}(R_n^e - \bar{T}_n)^2\Big],$$
$$\text{s.t. } R_n^e \geq 0, L_n \leq \bar{L}_n. \tag{2}$$

First-order conditions with regard to R_n^e, L_n, D_n, and B_n are

$$\frac{\partial \Pi_n}{\partial R_n^e} = (r_x - \hat{r}) - \beta(R_n^e - \bar{T}_n) + \lambda = 0,$$
$$\frac{\partial \Pi_n}{\partial L_n} = (\hat{r}_{L} - \hat{r}) - c_{L}(D_n, L_n) - \xi = 0,$$
$$\frac{\partial \Pi_n}{\partial D_n} = \alpha(r_{R} - \hat{r}) + (\hat{r} - r_{D}) - c_{D}(D_n, L_n) = 0,$$
$$\frac{\partial \Pi_n}{\partial B_n} = r_{B} - \hat{r} \leq 0; B_n > 0, (r_B - \hat{r})B_n = 0.$$

The first-order conditions have intuitive interpretations. The first condition determines the overall amount of excess reserves that a

[11] This condition is not necessary for an equilibrium, but it simplifies the existence condition.

bank wishes to hold, suggesting that the amount is determined by equating the opportunity cost of holding excess reserves, $(r_x - \hat{r}) + \lambda$, with the marginal cost incurred by deviating from the reserve target, $\beta(R_n^e - \bar{T}_n)$. Notice that if target reserves exceed zero, reserves will typically fall short of the bank's own target, given the cost of holding them (as typically $r_x < \hat{r}$). The second condition implies that lending continues until the lending rate (accounting for the anticipated default in the loans market) equals the cost of marginal funds (the interbank rate accounting for the possibility of default in the interbank market) and the marginal administrative costs of lending and the shadow cost of a binding credit ceiling. If the lending constraint is binding (and $\xi > 0$), then $\hat{r}_L - \hat{r} > c_L(D_n, L_n)$. Given that $c_L(D_n, L_n)$ is upward sloping in loans L_n, this condition suggests that a binding credit ceiling holds the level of loans below its equilibrium level. The third condition determines deposit holdings by equating the marginal profits from additional deposits (in terms of interbank lending), $\hat{r} - r_D$, with the marginal costs from managing deposits, $c_D(D_n, L_n)$, and the marginal cost of meeting the reserve requirement $\alpha(\hat{r} - r_R)$. Finally, in this simple framework, a no-arbitrage condition requires that all liquid funds (for bonds or in the interbank market) attract the same yield, given that these rates are market determined. The first-order conditions characterize a unique solution to each bank's profit-maximization problem. The solution to the first-order conditions implies the optimal demand for deposits, the supply of loans, demand for (excess) reserves, and the optimal demand for bonds that depend on the key interest rates and the reserve requirement (as well as parameters governing the bank's costs and liquidity preferences).[12]

We now turn to the competitive equilibrium in the interbank market. Indexing the banks by $n = 1, 2, \ldots, N$, they each have a *loan supply* function $L_n(r_L, r)$ and a *deposit demand* function $D_n(r_D, r)$. Under binding lending restrictions, the loan supply function $L_n(r_L, r) = \bar{L}_n$ would be inelastic. Let $L^d(r_L)$ be the demand function for loans and $S(r_D)$ the supply function for deposits (savings). Typically, the loan and deposit markets would be cleared (and relevant interest rates determined) by equating the demand and supply in these markets. However, given the extent of retail interest

[12] The second derivatives of the system ensure that the solution leads to a global maximum.

rate regulation in China and the clustering of the deposit rate at its ceiling, it is likely that the regulated deposit rate is below its equilibrium level (savings market does not clear at r_D).[13] The lending rate, reflecting its regulated floor, is probably no longer binding on many (especially marginal) borrowers, given that more than 80 percent of loans occur at and above the administered lending rates (figure 1), implying that the floor on the administered lending rate is not binding. However, under the assumption of a binding credit ceiling, the level of bank loans would be lower than equilibrium, implying that the loan market does not clear at r_L. If either the borrowing or lending market does not clear, then the quantity would be determined by the short side at the regulated interest rate.

The competitive equilibrium is then characterized by three conditions, assuming N is sufficiently large:

$$L^d(r_L) \geq \sum_{n=1}^{N} L_n(r_L, r) \text{ (loans market)}, \tag{3}$$

$$S(r_D) \leq \sum_{n=1}^{N} D_n(r_D, r) \text{ (savings market)}, \tag{4}$$

$$D^I(r) + \sum_{n=1}^{N} L_n(r_L, r) = (1-\alpha)S(r_D) - B - \sum_{n=1}^{N} R_n^e(r_x, r, \bar{T}_n, \beta) \text{ (interbank market)}, \tag{5}$$

where $R_n^e(r_x, r, \bar{T}_n, \beta)$ is the level of excess reserves for bank n, B is the aggregate level of the security holdings of bank n, and $B = \sum_{n=1}^{N} B_n(r_B)$. $D^I(r)$ is the net demand for interbank funds from institutional investors, where $D^I(r)$ is decreasing in r, the interbank interest rate. Institutional investors are net borrowers in the interbank market, while domestic commercial banks are net lenders.[14]

[13] Provided the following condition holds: $\bar{T}_n > (\hat{r} - r_x)/\beta$.

[14] Foreign banks also borrow in renminbi terms in the interbank market for their subsidiary activities in China. Given the binding capital controls in China, these subsidiaries in effect operate in a closed capital market. We model them in

RESULT 1. *There exists an equilibrium market-determined interbank rate, r^*, that solves equation (5), which is a unique function of the administratively set benchmark interest rates r_L and r_D, as well as reserve requirements and government bond issues. The same holds for the market-determined bond yields. The equilibrium interbank rate, r^*, lies between the interest rate on excess reserves, r_x, and the administered lending rate, r_L, provided certain conditions hold.*

Proof. For a given r_L, r_D, r_R, α, B, and the reserve target function parameters, there exists a unique interbank rate that solves equation (5). Note that the right-hand side of equation (5) is an increasing function in the interbank rate ($\frac{\partial R_n^e(r_x,r,\bar{T}_n,\beta)}{\partial r} < 0$). For the left-hand side, we consider two different cases: in the first case, the credit cap does not bind ($\xi = 0$), and the left-hand side is downward sloping in the interbank rate ($\frac{\partial L_n(r_L,r)}{\partial r} < 0$, $\frac{\partial D^I(r)}{\partial r} < 0$). In the second case, the credit cap binds ($\xi > 0$) and $L_n(r_L, r) = \bar{L}_n$, the left-hand side of equation (5) is also downward sloping in the interbank rate ($\frac{\partial \bar{L}_n}{\partial r} = 0$, $\frac{\partial D^I(r)}{\partial r} < 0$). In both cases, the necessary condition is satisfied.

On the sufficient condition of the existence of equilibrium, note that both the left- and right-hand sides of equation (5) are monotone in r, given the reserve target function assumed.

If $r \to r_L$, then by first-order conditions and the assumptions of γ, δ_L, δ_M, and κ, we must have $L_n = 0$, since $c_L(D_n, L_n) \neq (\gamma - \kappa) + (\kappa\delta_L - \gamma\delta_M)$ and $c_L(D_n, L_n) > 0$. Consequently, the right-hand side of (5) is greater than the left-hand side, provided that $B \leq (1-\alpha)S(r_D) - \sum_{n=1}^{N} R_n^e(r_x, r, \bar{T}_n, \beta)$ (condition A), where $R_n^e(r_x, r, \bar{T}_n, \beta) = \max[0, (\hat{r} - r_x)/\beta + \bar{T}_n]$ and $D^I(r_L) = 0$. If $r \to r_x$, then $R_n^e(r_x, r, \bar{T}_n, \beta) = (\hat{r} - r_x)/\beta + \bar{T}_n > \bar{T}_n$, so a sufficient condition for the left-hand side of (5) to be greater than or equal to the right-hand side is $B \geq (1-\alpha)S(r_D) - D^I(r_x) - c_L^{-1}(S(r_D), \hat{r}_L - \hat{r}_x) - \sum_{n=1}^{N} \bar{T}_n$ (condition B). The equilibrium interbank rate, r*, lies between the interest rate on excess reserves, r_x, and the administered lending rate, r_L, provided conditions A and B are met. ■

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a similar approach as institutional investors, since the majority of foreign banks operate in China under the QFII (qualified foreign institutional investors) scheme.

The direct implication of result 1 is that the market-determined interbank and bond rates cannot be independent of the administratively determined interest rates.[15] Some key properties of the resulting equilibrium interbank interest rate are summarized in results 2 and 3.

RESULT 2. *Provided the lending rate does not exceed its equilibrium, the equilibrium interbank rate, r^*, that solves (5) is increasing or flat in the lending rate, decreasing in the deposit rate, and increasing in central bank bond issuance and the loan target under credit control. An increase in the required reserve ratio has an ambiguous impact on the interbank rate. If the lending rate exceeds its equilibrium, then the interbank rate is decreasing in the lending rate.*

Proof. We consider two different cases here:

(i) Case 1: The lending rate does not exceed equilibrium: $r_L \leq r_L^*$, where r_L^* is the equilibrium lending rate.
- Subcase 1.1: Credit control does not bind for any banks ($\xi = 0$): $L_n^* < \bar{L}_n$, $\forall n$, where L_n^* is the equilibrium level of loans determined by market forces. The following comparative statics follow from equation (5), where

$$\Delta \equiv \frac{\partial D^I(r)}{\partial r} + \sum_n \left[\frac{\partial L_n(r_L, r)}{\partial r} + \frac{\partial R_n^e(r_x, r, \bar{T}_n, \beta)}{\partial r}\right] < 0, \tag{6}$$

$$\frac{dr}{dr_L} = -\frac{\sum_n \frac{\partial L_n(r_L, r)}{\partial r_L}}{\Delta} = -\frac{(+)}{(-)} > 0,$$

$$\frac{dr}{dr_D} = \frac{(1-\alpha)\frac{\partial S(r_D)}{\partial r_D}}{\Delta} = \frac{(+)}{(-)} < 0,$$

$$\frac{dr}{d\alpha} = -\frac{S(r_D)}{\Delta} = -\frac{(+)}{(-)} > 0,$$

[15] Note that we abstract from frictions in the interbank market and assume that, at the unique interbank rate, the interbank market clears without any cost. For models that consider financial frictions faced by the banking sector, see, for example, Christiano, Motto, and Rostagno (2010) and Gertler and Kiyotaki (2010).

$$\frac{dr}{dB} = -\frac{1}{\Delta} > 0.$$

- Subcase 1.2: Credit control binds for all banks ($\xi > 0$): $\bar{L}_n < L_n^*$, $\forall n$ and $L_n(r_L, r) = \bar{L}_n$. In this case,

$$\Delta \equiv \frac{\partial D^I(r)}{\partial r} + \sum_n \left[0 + \frac{\partial R_n^e(r_x, r, \bar{T}_n, \beta)}{\partial r} \right] < 0. \quad (7)$$

The comparative statics for $\frac{dr}{dr_D}$, $\frac{dr}{d\alpha}$, and $\frac{dr}{dB}$ hold as in subcase 1.1. We have the following new conditions:

$$\frac{dr}{dr_L} = -\frac{\sum_n \frac{\partial \bar{L}_n}{\partial r_L}}{\Delta} = -\frac{0}{(-)} = 0,$$

$$\frac{dr}{d\bar{L}_n} = -\frac{\sum_n \frac{\partial \bar{L}_n}{\partial \bar{L}_n}}{\Delta} = -\frac{1}{(-)} > 0.$$

Since the above conditions hold for the two extreme cases, they also hold for the intermediate case where credit control is binding for some banks but not all banks.

(ii) Case 2: The lending rate exceeds its equilibrium: $r_L > r_L^*$.

In this case, $L^d(r_L) \leq \sum_{n=1}^{N} L_n(r_L, r)$, and Δ is same as in subcase 1.2. Hence, we have

$$\frac{dr}{dr_L} = -\frac{\frac{\partial L^d(r_L)}{\partial r_L}}{\Delta} = -\frac{(-)}{(-)} < 0. \qquad \blacksquare$$

The result that a rise in the deposit rate reduces the interbank rate follows from the fact that interest rate regulation holds the deposit rates below their equilibrium level. With rates below their equilibrium level, a rise in the deposit rate increases deposits in the system, resulting in additional liquidity in the banking system and lower overall interest rates. If, however, such regulation was not binding, then an exogenous rise in the deposit rate (due to developments in that market) would result in higher costs for the bank, thereby limiting their demand for deposits and resulting in higher interbank rates because of a reduction in the liquidity in the system. This is result 3.

Result 3. *If the deposit (savings) market were allowed to clear*

$$S(r_D) = \sum_{n=1}^{N} D_n(r_D, r),$$

then an increase in the deposit rate would increase the interbank rate. All other comparative static results from result 2 would continue to hold.

Proof. We present the case where credit control is not binding. In this case, equation (5) would become

$$D^I(r) + \sum_{n=1}^{N} L_n(r_L, r) = (1-\alpha)\sum_{n=1}^{N} D_n(r_D, r) - B - \sum_{n=1}^{N} R_n^e(r_x, r, \bar{T}_n, \beta),$$

and

$$\Delta \equiv \frac{\partial D^I(r)}{\partial r} + \sum_n \left[\frac{\partial L_n(r_L, r)}{\partial r} + \frac{\partial R_n^e(r_x, r, \bar{T}_n, \beta)}{\partial r} - (1-\alpha)\frac{\partial D_n(r_D, r)}{\partial r}\right] < 0,$$

where $\frac{\partial D_n(r_D, r)}{\partial r} > 0$, as the demand for deposits is upward sloping in the interbank rate. Then

$$\frac{dr}{dr_D} = \frac{(1-\alpha)\sum_n \frac{\partial D_n(r_D, r)}{\partial r_D}}{\Delta} = \frac{(-)}{(-)} > 0.$$

All other comparative static expressions remain as in the proof of result 2. The case where the credit cap is binding can be obtained by putting $\frac{\partial L_n(r_L, r)}{\partial r} = 0$. ■

The results from the stylized theoretical model have several implications: first, market-determined interbank interest rates cannot be independent of administratively determined interest rates, such as regulated deposit and lending rates. Second, the model implies that interbank interest rates are influenced by changes in the reserve requirement ratio, an important monetary policy tool employed by the PBC. The model also yields some predictions on the direction of the responses in the interbank rate. In particular, the interbank rate is increasing in the lending rate (providing the lending rate has not already exceeded its equilibrium) and decreasing in the deposit rate (as interest rate regulation holds the deposit rate below the equilibrium level).

4. Empirical Analysis

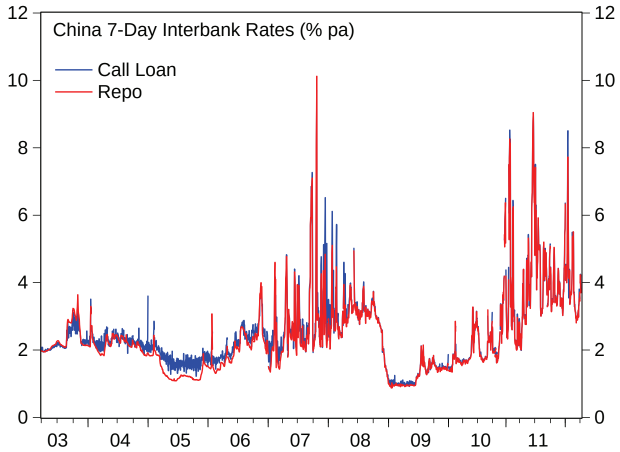
In this section, we estimate an empirical model of the interbank interest rate in China and examine the extent to which administered interest rates influence interbank rates, as predicted by the stylized theoretical model. We note that short-term exogenous factors that affect liquidity, such as open-market operations (OMOs) and IPO activities, should influence interbank rates in the same way as the exogenous changes in bond holdings (as seen in the stylized model), increasing the interbank rate when liquidity falls and reducing the interbank rate when liquidity rises. As a result, we include administered interest rates, net liquidity injections from OMOs and reserve requirements, and IPO funds as exogenous (independent) factors in the empirical model of the interbank rate.[16] We also control for the predictable (seasonal) factors that tend to affect liquidity in money markets in advanced economies, such as within-week, within-month, and end-of-year effects. Finally, we undertake some robustness checks, which show that, despite changes in the extent of liquidity and policy stance over the sample, the conclusion regarding the impact of administered interest rates (and hence retail interest rate regulation) on market-determined rates holds.

4.1 Properties of Interbank Interest Rates in China

As can be seen from figure 3, the two main market-determined rates for short-term interbank funds (the call loan and the repo rates) have

[16]Other exogenous variables, such as exchange rate intervention, or capital inflows could also influence the interbank interest rates. However, the analysis of their impact is beyond the scope of the current version of the paper.

Figure 3. Seven-Day Interbank Rates in China (Observation Dates: April 2003 to April 2012)



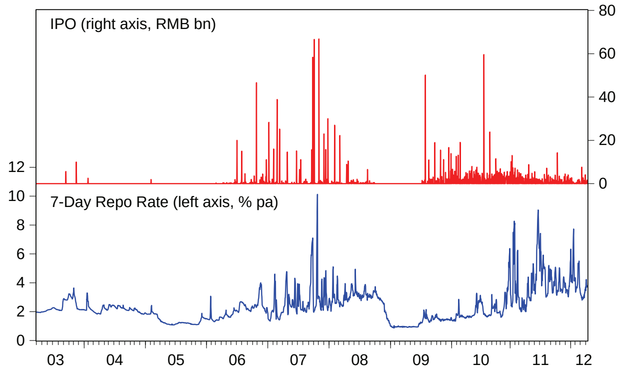
Source: People's Bank of China and Haver Analytics (CEIC).

followed each other very closely over the past few years, with volatility having increased substantially since late 2005.[17] The rise in volatility reflects the growing depth of these markets (see, for example, Xu 2006) and is also coincident with the development of other parts of the financial market, especially the foreign exchange market and the equity market (as seen by IPO activity, figure 4).

While the extent of the volatility is likely driven by several other institutional and policy factors, it is also probably affected by the institutional arrangements governing reserve requirements (for example, the period of reserve averaging). Given the greater liquidity in the repo market (with the turnover in the repo market far exceeding that in the uncollateralized call loan market), and the

[17]In addition to the call loan (CHIBOR: China Interbank Offered Rate) and repo rates, SHIBOR (Shanghai Interbank Offered Rate) is the other key reference interest rate in the interbank market. SHIBOR is not determined in a funding market, but is set in a similar way to LIBOR, with the rate calculated as an arithmetic average of renminbi offered rates by participating banks (currently sixteen).

Figure 4. Seven-Day Repo Rate and IPO Activities (Observation Dates: April 2003 to April 2012)



Source: People's Bank of China, Haver Analytics (CEIC), and Stockstar.

close relationship between the call loan and repo (see figure 3), we focus on the seven-day repo rate as the measure of interbank interest rates in the empirical analysis that follows.[18]

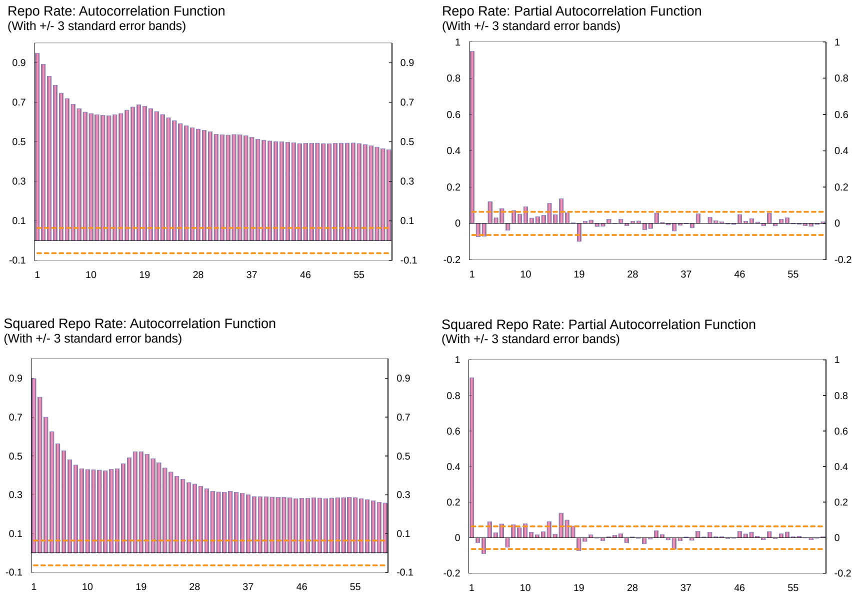
Before moving on to discuss the empirical model, we consider the key empirical properties of the repo rate. As can be seen from figure 5, the repo rate is clearly persistent, with its mean seemingly well characterized by autoregressive processes (slow decay in the autocorrelation function (ACF) and decay after more than five to fifteen lags of the partial ACF (PACF)). Despite the persistence, the unit-root test is clearly rejected.[19] There are also clear signs of volatility clustering, with similar indications of significant persistence in the squared repo rate.[20]

[18]The correlation between seven-day repo and call loan rates is very high, at around 0.99.

[19]The augmented Dickey-Fuller test is rejected with a p-value of 0.012, and the Phillips-Perron test is rejected with a p-value of 0.000.

[20]Volatility clustering refers to the phenomenon that large changes in the price of an asset (here we refer to interbank interest rates) tend to be followed by further large changes and, similarly, small changes in asset prices (interbank rate) tend to be followed by further small changes (see Mandelbrot 1963).

Figure 5. Interbank Rate Persistence



4.2 The Empirical Model

China's interbank rates, like those in advanced economies, exhibit high volatility as well as volatility clustering (figure 5). Consequently, we model the interbank rate using an exponential GARCH (EGARCH) model (Nelson 1991), which allows for rich specifications for both the time-varying mean and the time-varying volatility of the observed interest rate.[21] Given the apparent "fat tails" exhibited by the Chinese interbank data, we assume that these innovations follow Student's t-distribution, with degrees of freedom estimated to match the "fat tails" found in the data. Such a model has been applied to many advanced-country interbank markets (see, for example, Prati, Bartolini, and Bertola 2003; Moschitz 2004; and Quiros and Mendizabal 2006). The focus of these studies differs from ours in that they examine the interbank markets in developed (G7) economies, where

[21] For a discussion of the properties of the EGARCH model and a comparison with standard GARCH, see, for example, Terasvirta (2009).

the central bank targets a short-term interbank rate for monetary policy purposes. Their primary concern is to identify the liquidity effects within the market, driven by the differences between reserve settlement and non-settlement days, as well as the impact of the parameters of the interest-rate-targeting regime on the interbank rate. We, however, are principally concerned with the impact of administered interest rates and other monetary policy instruments, such as open-market operations and reserve requirements, on interbank rates in a less-developed market with partial financial liberalization.

Our basic empirical model of the interbank interest rate r_t is given by

$$r_t = \mu_t + \sqrt{h_t}\nu_t, \tag{8}$$

where ν_t is a unit variance, serially uncorrelated, zero-mean, i.i.d error term, and μ_t and h_t are the time-varying mean and variance, respectively, of the interbank interest rate. The mean μ_t is assumed to show persistence in the interbank interest rates, as well as in exogenous factors that affect the interbank interest rate, $\mathbf{X}_t^m$,

$$\mu_t = c + \sum_{i=1}^{s} \phi_i r_{t-i} + \beta_m' \mathbf{X}_t^m, \tag{9}$$

where the autoregressive coefficient, ϕ_i, is aimed to capture the possible persistence of the interbank interest rate, and $\beta_m' \mathbf{X}_t^m$ reflects the impact of exogenous factors on the average interbank rate. Consistent with the volatility clustering observed in the interbank data, the variance of the interbank rate is specified as follows:

$$\begin{aligned} ln(h_t) = \omega + \sum_{i=1}^{q} \gamma_i ln(h_{t-i}) + \sum_{j=1}^{p} \alpha_j \frac{|\nu_{t-j}|}{\sqrt{h_{t-j}}} \\ + \sum_{k=1}^{l} \lambda_k \frac{\nu_{t-k}}{\sqrt{h_{t-k}}} + \beta_\nu' \mathbf{X}_t^\nu, \end{aligned} \tag{10}$$

where $ln(h_t)$ is the logarithm of the conditional variance h_t, the α_j terms are the "ARCH" effects (based on innovations in the absolute standardized residual), the γ_i terms are the "GARCH" terms, and the λ_k terms capture the asymmetric impact of positive or negative innovations to the standardized residuals.[22] If $\lambda_k = 0$, then both positive and negative innovations have symmetric impacts on interest rate volatility. $\beta_\nu' \mathbf{X}_t^\nu$ measures the impact of exogenous factors that drive volatility. The EGARCH specification implies that the forecasts of conditional variance are always non-negative.

4.3 Model Specification

Based on our stylized model of China's banking sector, the interbank rate should reflect the administered deposit and lending rates, and the extent of liquidity in the interbank system. We use the one-year administered deposit and lending rates to capture the impact of interest rate regulation on the mean of the interbank rates. To capture the impact of monetary policy changes on liquidity in the banking system, we use measures of open-market operations and reserve requirements. Specifically, the open-market operations variable is defined as the level of net liquidity injection from the expiration of repos and PBC central bank bills (expiration less issuance), and the issuance of reverse repos. For reserve requirements, the measure reflects the liquidity injected from a fall in required reserves. The change in the liquidity condition is constructed as the change in the reserve requirement ratio times the deposit base. Given that changes in reserve requirements are usually announced one or two weeks before the effective date, we also construct a dummy variable to capture the announcement effect of reserve requirement changes, where the dummy is equal to the change in the reserve requirement ratio on the date of the announcement. IPOs are also posited as an important contributor to short-term fluctuations in the interest rate, as they lock up significant funds in the banking system for around one or two weeks ahead of the IPO, and so these are included as exogenous explanatory variables. Data on IPOs cover the total amount of funds raised (in billions of renminbi) on a particular day.[23] Finally, we allow for interbank liquidity to vary systematically through the year, as it does in other interbank markets (Prati,

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[22] In the empirical analysis in the model, the lag orders p, l, and q are set at 1, 1, and 1, respectively, to capture the volatility clustering as observed in the seven-day repo rate.

[23] The data sources for all series were the People's Bank of China, Haver Analytics (CEIC), and Stockstar. See the data appendix for more details.

Table 1. Variables Included in the GARCH Model

Variables	Level Equation	Variance (Volatility) Equation
Endogenous	Seven-day repo rate	Seven-day repo rate
Exogenous	One-year administered deposit rate	Changes in one-year administered deposit rate
	One-year administered lending rate	Changes in one-year administered lending rate
	Net liquidity injection from OMO	Net liquidity injection from OMO
	Net liquidity injection from RR	Net liquidity injection from RR
	Announcement effect of changes in RR ratio	Announcement effect of changes in RR ratio
	IPO volume	IPO volume (incl. leads)
	System liquidity dummies	System liquidity dummies

Bartolini, and Bertola 2003 and Moschitz 2004). In particular, we allow for liquidity effects resulting from the day of the week, the proximity to the end of the month, and the timing of the Chinese New Year to possibly influence the average interbank rate, as well as its volatility (see table 1).

A similar set of variables is hypothesized to influence the variance of the interbank rate, particularly policies such as changes in the administered lending rates and changes in liquidity. In the former case, a sudden increase in the incentive to lend is likely to cause a short-term rush for interbank funds (until, say, the level of deposits can increase) and temporarily increases volatility. In the latter case, policy-induced changes in liquidity (through open-market operations and reserve requirement changes) are likely to drive changes in volatility in the short run, as are exogenous changes in liquidity that may occur through the week, around the end of a month, or at the Chinese New Year. The main difference in the variance equation is that we control the absolute change in administered interest rates, rather than their levels (see table 1). This difference reflects the fact that *changes* in administered rates are likely the drivers of (short-term) volatility, and any impact is more likely to be symmetric to both increases and reductions. With IPOs resulting in a significant amount of funds being locked up in the banking system (for about a week or so), we included leads of five and ten days to capture the impact of this "lock-up" ahead of the IPO in the variance equation.[24]

Given the persistence in the seven-day repo rate, we consider a lag order of five (approximately one week) in the mean equation. All (exogenous) explanatory variables are restricted to have the same lag order, except for the IPO in the variance equation, where leads were included to capture the lock-up effect of funds. The final equation specification is obtained using the general-to-specific approach and captures the key relationships in the interbank market in a parsimonious manner.

4.4 Empirical Results

We now turn to the empirical results on the drivers of China's interbank rate, both in levels and variance. The estimation sample spans from April 2003 to April 2012 at a daily frequency. We start from April 2003, since daily data on open-market operations in China only became available at that time. The sample period covers three distinct phases of macroeconomic environments: the pre-crisis liquidity surplus, the post-crisis credit expansion, and the subsequent monetary tightening. The detailed estimation results and relevant tests are presented in tables 2–5.

4.4.1 Mean Interest Rates

Persistence. China's interbank rate, like those in G7 and euro-area countries, is extremely persistent. There is a more-than-proportionate response to a change in the repo rate on the previous day, which is then unwound in the following days (table 2).

Administered Interest Rates. Changes to administered (benchmark) lending and deposit rates clearly have a significant

[24]The "locked-up" funds are subsequently released from the banking sector on the date of the IPO.

Table 2. Estimated GARCH Parameters (Full Sample: April 2003 to April 2012)

	Coefficient	**Std. Error**	**z-Statistic**	**p-Value**
Mean Equation				
C	−0.038*	0.014	−2.768	0.006
Repo (−1)	1.169*	0.009	130.181	0.000
Repo (−2)	−0.076*	0.019	−3.934	0.000
Repo (−3)	−0.121*	0.024	−5.019	0.000
Repo (−4)	0.053*	0.022	2.406	0.016
Repo (−5)	−0.028*	0.014	−2.014	0.044
Administered Lending Rate	0.016*	0.004	3.929	0.000
Administered Deposit Rate	−0.021*	4.4E-03	−4.671	0.000
OMO	3.5E-05*	1.7E-05	2.037	0.042
RR	1.7E-05	0.000	0.453	0.651
RR Announcement	0.069*	2.4E-02	2.929	0.003
IPO	6.4E-04	4.0E-04	1.604	0.109
Liquidity Effects (See Table 3)				
Variance Equation				
C	−0.100	0.095	−1.051	0.293
ARCH Effect (−1)	1.735†	0.932	1.862	0.063
Asymmetric Effect (−1)	0.439†	0.250	1.758	0.079
GARCH Effect (−1)	0.969*	0.004	242.210	0.000
Δ in Administered Lending Rate	9.025*	2.854	3.162	0.002
Δ in Administered Deposit Rate	−9.794*	2.853	−3.433	0.001
OMO	0.002*	6.9E-04	2.918	0.004

(*continued*)

Table 2. (Continued)

	Coefficient	Std. Error	z-Statistic	p-Value
Variance Equation				
RR	−0.001†	6.7E-04	−1.896	0.058
RR Announcement	2.036†	0.378	5.381	0.000
IPO	−0.008	0.008	−1.012	0.311
IPO (+5)	2.6E-04	0.007	0.036	0.971
IPO (+10)	0.030*	0.007	4.504	0.000
Liquidity Effects (See Table 3)				
T-DIST. DOF	2.03*	0.0294	68.884	0.000
R-Squared	0.897	Adjusted R-Squared		0.895
S.E. of Regression	0.372	Sum Squared Residual		298.359
Log-Likelihood	2609.018			
Akaike Info Criterion	−2.112	Schwarz Criterion		−2.112
Hannan-Quinn Criterion	−2.236	Durbin-Watson Statistics		2.208

Notes: Dependent variable: Repo (seven-day repo rate); sample period: April 1, 2003 to April 12, 2012. Included observations: 2,197 after adjustments. Method: ML-ARCH (Marquardt) – Student's *t*-distribution. * indicates significance at the 5 percent level, and † indicates significance at the 10 percent level.

impact on the interbank rate.[25] Increases in the administered lending rate lead to higher average interbank rates, since the higher lending rates translate into pressure for interbank funds. The impact of a 100-basis-point rise in the one-year lending rate is to increase the interbank rate by 1.6 basis points. A rise in the one-year deposit rate has the opposite effect, reducing the interbank rate, possibly reflecting a likely supply response on the part of depositors, given

[25] At a daily frequency, the null hypotheses that the administered deposit and lending rates do not Granger-cause the seven-day repo rate can be rejected, with p-values of 6E-07 and 5E-06, respectively.

Table 3. Estimated Liquidity Effects (Full Sample: April 2003 to April 2012)

	Mean Equation		Variance Equation	
Lag	**Coefficient**	**p-Value**	**Coefficient**	**p-Value**
Day of Week:				
Monday	−4.5E-04	0.561	−0.693*	0.000
Wednesday	−2.4E-05	0.974	−0.435*	0.018
Friday	3.7E-04	0.684	0.072	0.660
End of Month:				
5	6.8E-04	0.581	0.004	0.986
4	−7.9E-04	0.512	−0.427†	0.070
3	0.001	0.470	−0.511*	0.031
2	−2.2E-05	0.991	0.162	0.485
1	0.001	0.434	−0.563*	0.011
0	−0.003	0.192	−0.252	0.305
–1	0.005*	0.013	−0.196	0.473
–2	0.002	0.439	0.556*	0.036
–3	0.004*	0.017	−0.204	0.432
–4	0.002	0.97	−0.099	0.704
–5	0.003*	0.019	−0.059	0.782
Chinese New Year:				
5	−0.016*	0.026	−1.147†	0.094
4	−2.6E-05	0.998	0.977	0.394
3	0.003	0.792	−0.014	0.991
2	0.037*	0.004	−2.155*	0.036
1	0.062†	0.070	0.258	0.792
0	−0.477*	0.000	−0.194	0.815
–1	0.005	0.952	0.074	0.928
–2	0.341*	0.000	0.465	0.520
–3	0.089	0.240	2.689*	0.000
–4	0.060*	0.000	−0.953	0.184
–5	0.004	0.423	0.003	0.996

Notes: Dependent variable: Repo (seven-day repo rate); sample period: April 1, 2003 to April 12, 2012. Included observations: 2,197 after adjustments. Method: ML-ARCH (Marquardt) – Student's t-distribution. * indicates significance at the 5 percent level, and † indicates significance at the 10 percent level.

Table 4. Joint Significance Tests (Full Sample)

	Total Impact	LR Statistic	p-Value
Mean Equation			
Before and at End of Month	0.013	33.70	7.7E-06
After End of Month	0.002	12.49	3.4E-12
Before Chinese New Year	0.499	45.46	1.2E-08
At and After Chinese New Year	−0.392	65.14	4.0E-12
Weekdays (Monday, Wednesday, Friday)	−1.0E-04	135.73	3.1E-29
Variance Equation			
Before and at End of Month	−0.255	35.462	3.5E-06
After End of Month	−1.336	45.814	9.9E-09
Before Chinese New Year	2.277	47.22	5.1E-09
At and After Chinese New Year	−2.275	61.258	2.5E-11
Weekdays (Monday, Wednesday, Friday)	−1.056	35.486	9.6E-08

Notes: Dependent variable: Repo (seven-day repo rate); sample period: April 1, 2003 to April 12, 2012. Included observations: 2,197 after adjustments. Method: ML-ARCH (Marquardt) – Student's t-distribution. Null hypothesis: the coefficients of the selected subsets of variables are jointly zero.

the low level of the regulated deposit rate as suggested by our stylized model. The impact of a 100-basis-point rise in the deposit rate is a 2.1-basis-point fall in the mean interbank rate (table 2). This empirical finding is consistent with the prediction from the stylized theoretical model that the interbank rate is increasing in the lending rate and decreasing in the deposit rate.

Open-Market Operations and Reserve Requirements. Conditional on the level of administered interest rates, liquidity changes from reserve requirements do not have any significant impact on the mean interbank rate. The announcement effect of reserve requirements, however, does have a positive impact on the

Table 5. Standardized Residuals: ARCH Tests (Full Sample)

Lag	F-Test (p-value)	LM-Test (p-value)
1	0.752	0.752
5	0.962	0.961
10	0.992	0.992
15	0.995	0.995
20	0.999	0.999
25	0.987	0.986
30	0.998	0.998
35	1.000	0.999
40	1.000	1.000
45	1.000	1.000
50	1.000	1.000

Notes: Null hypothesis: There is no ARCH effect up to order q in the residuals. The F-statistic is an omitted variable test for the joint significance of all lagged squared residuals. The LM test statistics are computed as the number of observations times the R-squared from the test regression.

mean interbank rate. The impact of a 50-basis-point rise in the reserve requirement ratio (a typical move) is a 3.5-basis-point rise in the mean interbank rate (table 2). Liquidity changes from open-market operations have a significant impact on the level of interbank interest rates.

IPOs. IPOs have apparently no significant impact on the mean interest rate. While this is surprising, given the volume of funds tied up during the IPO, the result could reflect offsetting policy actions (for example, a reduction in sterilization operations during IPOs) or the guiding role played by administered (benchmark) interest rates in driving the interbank interest rates (table 2).

Liquidity Effects. Of the three variables measuring liquidity effects, the timing of the Chinese New Year has the largest impact on average interest rates, owing to the strong tendency of households to withdraw deposits ahead of the New Year. Average interbank rates are higher during the week before the New Year, and then fall significantly below average on the day of the New Year, with the New Year effect gradually declining over the subsequent week.

There are also liquidity effects associated with the end of the month, with the average interest rate notably higher before the end of the month. Finally, the within-week liquidity effects do not seem to be significant for the mean interbank rates; however, jointly, they are significantly negative (tables 3 and 4).

4.4.2 Interest Rate Volatility

Volatility clustering in the seven-day repo rate is confirmed with the significant GARCH effects found in our estimation (table 2). The variance is relatively persistent and is driven by similar factors as the average interest rates. The first-order ARCH effect is marginally significant, as is the asymmetric term. Consequently, "negative innovations" (a reduction in interbank rates) have a smaller impact on interest rate volatility than news that increases the interest rate. Policy variables, IPOs, and liquidity effects affect interbank volatility as follows.

Administered Interest Rates. Changes in administered interest rates have a significant impact on the variance of the interbank rate (table 2). Changes in the lending rate tend to increase volatility, as the incentive to raise funds for lending changes with the lending rate. Changes in the deposit rate tend to reduce volatility, which is somewhat surprising, but may be an artifact of the structural liquidity surplus during the sample period.

Open-Market Operations and Reserve Requirements. Policy changes, at least those through reserve requirements, seem to have a more significant impact on interest rate volatility than on the mean of the interbank rate. However, the impact of changing reserve requirements tends to anticipate the actual change in policy, commencing with a jump in volatility when the change is announced (table 2).[26] The strength of this anticipatory effect probably reflects the daily nature of reserve requirements and the importance of reserve requirements as a monetary policy tool in China (see discussions in section 2.1). An increase in net liquidity injections through

[26]Changes in reserve requirements are usually announced one to two weeks ahead of the execution dates. For example, the PBC announced on March 18, 2011 its decision to raise the renminbi (RMB) reserve requirement ratio for depository financial institutions by 0.5 percentage points, effective from March 25, 2011; see the PBC website for details.

open-market operations has a small significant impact on volatility, as would be expected if open-market operations act as a sterilization tool to adjust liquidity in the system and to stabilize interest rates in the interbank market.

IPOs. While IPO activities did not change the behavior of average interbank rates, they seem to increase the volatility of interbank rates marginally when they occur (table 2), which is consistent with the observation in figure 4. In particular, volatility increases significantly ahead of the IPO (when funds are locked up), but there is little sign of above-average volatility after that (including when surplus funds are released).

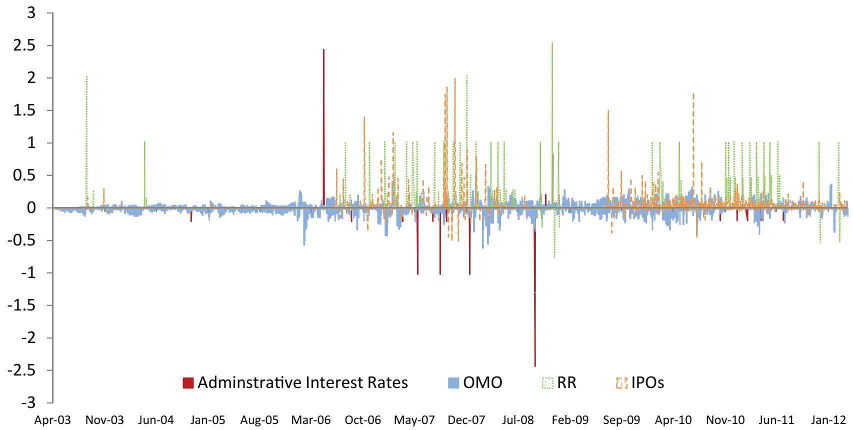
Liquidity Effects. As with the level, the liquidity effect of the Chinese New Year is the largest (tables 3 and 4). Volatility is typically above average one week before the New Year, as households withdraw deposits ahead of the New Year, and then it declines gradually in the trading week after the holiday. Volatility is significantly lower at the beginning of the week (Monday and Wednesday) and increases gradually toward the end of the week. There are also significant liquidity effects on interbank volatility through each month, with volatility typically higher than average as the end of the month approaches and then declining during the first week of the month.

As can be seen in figure 6, IPO activities, reserve requirements (including the announcement effect), and administered interest rates contribute most to the volatility of interbank interest rates, if we extract from liquidity, GARCH, and ARCH effects. Monetary policy variables such as open-market operations also contribute to interbank volatility, although their impact is smaller in comparison.

The resulting estimates also confirm the extent of extreme movements in China's interbank rate. The estimated degrees of freedom for the error term are only marginally above the lower limit of two (table 2), and far smaller than those estimated in models of other interbank markets. For example, Prati, Bartolini, and Bertola (2003) present degrees-of-freedom estimates between 2.23 and 3.95 for short-term G7 and euro-area interbank rates. With such a low estimate for the degrees of freedom of the error terms, estimated innovation (news events) is far more fat tailed than implied by a normal distribution.

The model equation has well-behaved residuals, with no signs of volatility clustering in the standardized residuals. There are also no

Figure 6. Contributions to Interbank Volatility



Notes: Contribution to the log of variance, which excludes constant, liquidity, ARCH, asymmetric, and GARCH effects. RR includes both the liquidity and announcement effects.

signs of persistence in either the standardized residuals or squared standardized residuals, suggesting that there are no residual autocorrelation or ARCH effects (see table 5 and figure 7).

4.5 News and Information

The empirical analysis on the determinants of interbank interest rates confirms our expectation that administered rates are important drivers of the interbank market. We are interested in how these interventions (regulations) in lending and deposit rates may have influenced the informativeness of interbank rates for news and market conditions. In particular, we try to address three additional questions. First, how informative are money-market rates in China compared with other economies without interventions in the interest rate market? Second, how informative are interbank rates on market conditions like liquidity or other types of macro news? Third, what do event studies say about the impact of interventions on the informativeness of rates for news?

To address the first question, we consider regressions for U.S. and UK interbank markets for the same sample period, following

Figure 7. Standardized Residuals (Full Sample)

the specification in Prati, Bartolini, and Bertola (2003). Specifically, for both countries, we control for lagged interbank rate and dummies for weekdays, the end of month, the end of quarter, and the end of year. Given that the United States adopts reserve averaging, we also include dummies for the reserve maintenance period (ten days) to account for the liquidity effects toward the end of the maintenance period to capture exogenous (but systematic) changes in liquidity demand. We consider the share of variation explained by these regressions (or R^2) as a measure of the extent of information in the specification, which explains the money-market rate solely through autoregressive terms and market liquidity effects. The adjusted R^2 is found to be 0.998 for the United States and 0.999 for the United Kingdom (table 6), both higher compared with adjusted R^2 seen in the model for China's interbank rate (0.895). The results suggest that interventions in the interest rate market in China may have led to reduced R^2 (and therefore informativeness) of money-market rates, in comparison with those typically seen in markets without such interventions.

On the second question with regard to liquidity and macroeconomic news, recall that the baseline regression suggests that liquidity injections from reserve requirements do not have any significant influence on the level of the interbank rate, while the announcement effect does have a significant impact. Liquidity injections from open-market operations are found to be significant drivers of interbank interest rates in both levels and volatility, while IPO activities are significant in determining interbank volatility (table 2). In addition, as in other markets, there are substantial systematic liquidity effects due to particular dates on the calendar (table 4). To assess the impact of macroeconomic news, we consider additional regressions by controlling for the following macroeconomic variables in turn: GDP growth rate, inflation rate, industrial production (IP) growth rate, and PMI (headline as well as the new orders component). All five variables are found to be significant in driving the level of the seven-day repo rate, while inflation rate and IP growth rate are also significant in driving the volatility of interbank rate.[27] In addition, we control for the China policy uncertainty index constructed by Baker, Bloom, and Davis (2013).[28] This news-based index of economic policy uncertainty is found to be significant in driving the level and volatility of interbank rates. Given that macro variables tend to be of lower frequency (monthly for all except GDP), we construct a daily dummy variable to capture the date when quarterly GDP is announced in China. Using consensus forecast data, we also construct a GDP surprise dummy, which captures the difference between the actual GDP release and the latest consensus forecast.

[27]The results are robust to different specifications, including when macro variables enter in lagged terms.

[28]The variable is constructed based on counts of policy-related terms in Chinese newspaper and hence represents the occurrence or intensity of economic news at the time. The detailed description of this variable is available at http://www.policyuncertainty.com/china_monthly.html.

Table 6. Estimated GARCH Parameters for Interbank Markets in the United States and the United Kingdom

	United States	United Kingdom
Mean Equation		
C	−0.001	−1.2E-04†
Interbank Rate (–1)	1.001*	1.000*
End of Month (+1)	0.0008	−1.6E-05
End of Month	0.008*	6.5E-05
End of Month (–1)	0.0004	6.2E-07
End of Quarter (+1)	0.019*	4.5E-05
End of Quarter	−0.020*	0.001*
End of Quarter (–1)	−0.0005	2.0E-05
End of Year (+1)	−0.006	−0.0003
End of Year	−0.021	0.0002
End of Year (–1)	0.0005	1.5E-04
Monday	0.001	6.7E-06
Wednesday	6.4E-05	5.3E-06
Friday	0.0004	7.7E-06
End of Maintenance Period	−7.3E-05	
End of Maintenance Period (–1)	−0.001	
End of Maintenance Period (–2)	−0.0002	
End of Maintenance Period (–3)	−0.0002	
End of Maintenance Period (–4)	0.001	
End of Maintenance Period (–9)	0.001	
Variance Equation		
C	−0.304	−0.219*
ARCH Effect (–1)	0.757*	1.075*
Asymmetric Effect (–1)	0.137*	−0.343
GARCH Effect (–1)	0.966*	0.997*
End of Month (+1)	0.038	0.659*
End of Month	0.406	1.337*
End of Month (–1)	0.231	0.297†
End of Quarter (+1)	−1.446*	−1.250*
End of Quarter	3.157*	1.253*
End of Quarter (–1)	0.258	1.546*
End of Year (+1)	0.917	0.622

(continued)

Table 6. (Continued)

	United States	United Kingdom
Variance Equation		
End of Year	−0.658	−1.657†
End of Year (–1)	0.479	−0.272
Monday	−0.301	−0.492*
Wednesday	−0.727*	0.030
Friday	−0.914*	0.081
End of Maintenance Period	0.479*	
End of Maintenance Period (–1)	0.112	
End of Maintenance Period (–2)	−0.102	
End of Maintenance Period (–3)	0.777*	
End of Maintenance Period (–4)	−0.575*	
End of Maintenance Period (–9)	−0.499*	
Adjusted R-Squared	0.998	0.999

Notes: U.S. Model: Dependent variable: Federal funds rate; sample period: April 2, 2003 to April 30, 2012. Included observations: 2,369 after adjustments. UK Model: Dependent variable: one-week LIBOR; sample period: April 2, 2003 to April 30, 2012. Included observations: 2,303 after adjustments. Method: ML-ARCH (Marquardt) – Student's t-distribution. * indicates significance at the 5 percent level, and † indicates significance at the 10 percent level.

While the announcement dummy is not significant, the GDP surprise dummy is significant in driving both the levels and the volatility of interbank interest rate in China, despite the relatively short sample period. These results suggest that interbank rates in China are informative on liquidity conditions including open-market operations, and the rates reflect important macroeconomic news, such as GDP release, and movements in other key macro variables (table 7).

Finally, we use event-study analysis to assess how interventions impact the informativeness of rates for news or market conditions. Following Thornton (2014), we consider the following regression:

$$r_t = \alpha_e + \beta_e \times Dummy_t + \gamma_e \times News_t + \sigma_e Dummy_t \times News_t + \epsilon_t, \tag{11}$$

Table 7. Estimated GARCH Parameters: Macroeconomics News

	GDP Growth	IP Growth	Inflation Rate	PMI	Uncertainty	GDP Surprise
Mean Equation						
C	−0.076*	0.011	−0.012	−0.097*	−0.091*	0.026*
Repo (–1)	1.155*	1.160*	1.151*	1.119*	1.165*	1.138*
Repo (–2)	−0.065*	−0.084*	−0.066*	−0.062*	−0.098*	−0.042†
Repo (–3)	−0.130*	−0.097*	−0.106*	−0.130*	−0.111*	−0.113*
Repo (–4)	0.071*	0.051*	0.028	0.093*	0.060*	0.044*
Repo (–5)	−0.035*	−0.033*	−0.009	−0.029	−0.021	−0.028*
Administered Lending Rate	0.027*	0.002	0.009*	−0.025*	0.029*	−0.004
Administered Deposit Rate	−0.0245*	−0.007	−0.015*	0.044*	−0.030*	−0.002
OMO	1.2E-05	2.82E-05†	2.6E-05†	6.4E-05*	3.2E-05†	3.0E-05†
RR	5.6E-05	3.5E-05	−9.5E-06	6.3E-05*	8.6E-05†	3.2E-05†
RR Announcement	0.073*	0.072*	0.067*	0.014*	0.067*	0.067*
IPO	6.0E-04†	4.1E-04	5.8E-04	0.0005	0.0006	0.0006
GDP Growth	−0.002*					
IP Growth		−0.0004*				
Inflation Rate			−0.001*			
PMI				0.003*		
Uncertainty					4.7E-05*	
GDP Surprise						0.898*
Liquidity Effects (Available upon Request)						

(*continued*)

Table 7. (Continued)

	GDP Growth	IP Growth	Inflation Rate	PMI	Uncertainty	GDP Surprise
Variance Equation						
C	0.065	0.0235	−0.452*	−0.102	−0.324*	−0.114
ARCH Effect (–1)	1.346*	1.413†	1.622†	1.648	1.367†	1.671
Asymmetric Effect (–1)	0.553*	0.439†	0.289†	0.662	0.285†	0.508†
GARCH Effect (–1)	0.977*	0.969*	0.944*	0.958*	0.956*	0.967*
Δ in Administered Lending Rate	5.369*	6.637*	9.709*	0.406	7.353*	7.068*
Δ in Administered Deposit Rate	−6.134*	−6.675*	−10.513*	−1.602	−7.546*	−7.614*
OMO	0.001*	0.001†	0.003*	0.002*	0.002*	0.002*
RR	−0.001*	−0.002*	−0.001	−0.001	−0.003*	−0.001
RR Announcement	1.964*	2.067*	2.115*	1.599*	2.149*	2.112*
IPO	−0.010	−0.005	−0.006	−0.014†	−0.004	−0.007
IPO (+5)	−0.002	5.3E-04	0.006	9.9E-05	0.003	0.0005
IPO (+10)	0.029*	0.032*	0.036*	0.025*	0.038*	0.029*
GDP Growth	−0.005*					
IP Growth		−0.009*				
Inflation Rate			0.028*			
PMI				−4.7E-05		
Uncertainty					0.001*	
GDP Surprise						11.742*
Liquidity Effects (Available upon Request)						

Notes: Dependent variable: Repo (seven-day repo rate); sample period: April 8, 2003 to March 27, 2012. Included observations: 2,197 after adjustments. Method: ML-ARCH (Marquardt) – Student's *t*-distribution. * indicates significance at the 5 percent level, and † indicates significance at the 10 percent level.

Table 8. Changes in Administered Lending and Deposit Rates

Date	Changes in Repo Rate	Changes in Administered Rate	Lending or Deposit Rate
Oct. 29, 2004	0.1549	Increase (27 bps)	Both
Apr. 28, 2006	0.1645	Increase (27 bps)	Lending
Aug. 21, 2006	0.0911	Increase (27 bps)	Both
Mar. 20, 2007	0.0401	Increase (27 bps)	Both
May 21, 2007	−0.0254	Increase (27 bps–dep, 18 bps–lend)	Both
Jul. 23, 2007	0.0396	Increase (27 bps)	Both
Aug. 22, 2007	0.236	Increase (27 bps–dep, 18 bps–lend)	Both
Sep. 17, 2007	0.2057	Increase (27 bps)	Both
Dec. 21, 2007	−0.1773	Increase (27 bps–dep, 18 bps–lend)	Both
Sep. 16, 2008	−0.0386	Decrease (27 bps)	Lending
Oct. 9, 2008	−0.0524	Decrease (27 bps)	Both
Oct. 30, 2008	−0.0547	Decrease (27 bps)	Both
Nov. 27, 2008	−0.5424	Decrease (108 bps)	Both
Dec. 23, 2008	−0.0016	Decrease (27 bps)	Both
Oct. 20, 2010	0.0405	Increase (25 bps)	Both
Dec. 28, 2010	0.7569	Increase (25 bps)	Both
Feb. 9, 2011	0.867	Increase (25 bps)	Both
Apr. 6, 2011	0.132	Increase (25 bps)	Both
Jul. 7, 2011	−1.816	Increase (25 bps)	Both

where r_t is the interbank rate, $Dummy_t$ captures the dates when administered deposits and/or lending rates are changed (table 8), $News_t$ captures the uncertainty variable constructed by Baker, Bloom, and Davis (2013), and $Dummy_t \times News_t$ is the interaction term. The coefficients β_e and σ_e for the dummy variable and the interaction term are found to be significant, but not γ_e, the coefficient of the news term. This result confirms our expectation that the announced policy change does have an impact on how news is viewed and therefore the informativeness of rates for news (table 9).

Table 9. Event Study on Interbank Rates in China

	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001	0.016 * 0.074	0.941	
Changes in Administered Rates	0.361*	0.178	2.036	0.042
News/Uncertainty	−1.4E-05	0.0001	−0.114	0.909
Interaction Term	−0.002†	0.001	−1.849	0.065
R-Squared	0.002	Adjusted R-Squared		0.0005
S.E. of Regression	0.369	Sum Squared Residual		300.180
Log-Likelihood	−929.791			
Akaike Info. Criterion	0.845	Schwarz Criterion		0.855
Hannan-Quinn Criterion	0.849	Durbin-Watson Statistics		1.902

Notes: Dependent variable: Changes in repo (seven-day repo rate); sample period: April 6, 2003 to April 12, 2012. Included observations: 2,211 after adjustments. Method: Least squares. * indicates significance at the 5 percent level, and † indicates significance at the 10 percent level.

4.6 Robustness Check

We undertake three types of robustness checks and reestimate our empirical model separately: (i) over the first half of the sample (effectively, most of the period of structural surplus liquidity, but before China's large post-crisis monetary expansion); (ii) with different measures of liquidity injections; and (iii) using different specifications of administered interest rates. Our main results continue to hold, particularly regarding the importance of administered interest rates as drivers of interbank rates.

4.6.1 Subsample: April 2003 to October 2007

To study the evolution of the main drivers of interbank interest rates in China, we examine a shorter subsample to October 2007 (first half of the sample). We find that, with the shorter sample, administered lending and deposit rates remain important drivers of China's interbank interest rates, in both levels and variances, although the importance of these interest rates has declined over time (as seen from the regression coefficients). While liquidity injection from open-market operations is found to be significant in the full sample to April 2012, it is not significant in the subsample to October 2007, neither in levels nor in variances (tables 10 and 11). This finding suggests that the importance of open-market operations in influencing interbank interest rates has increased over time, and interbank rates are starting to reflect changes in liquidity conditions, owing to open-market operations in recent years.

4.6.2 Liquidity Injection

In order to check the robustness of our results to different GARCH specifications, we carry out several further experiments. First, we consider a specification where changes in liquidity from open-market operations, reserve requirements, and IPOs are introduced in real terms, by accounting for inflation in the economy. The results are found to be robust, particularly in both the impact coefficients and the significance of key variables of interest—namely, administered lending and deposit rates, liquidity injections from open-market operations, reserve requirements, and IPOs (tables 12 and 13).

In a second experiment, we sum up open-market operations and reserve requirements (real terms) into one quantitative monetary policy variable. We postulate that the earlier baseline result that open-market operations and changes in reserve requirements have a limited impact on the interbank rate in levels may be a result of the shift in monetary policy instruments in China (Qin et al. 2005). Reserve requirements played a prominent role between 2006 and 2008, and then between 2010 and 2011 as part of monetary policy tools. As expected, the combined monetary policy variable is significant in influencing the level of the interbank interest rates. The impact of a 100-basis-point rise in liquidity conditions (injection due to open-market operations and reserve requirements) is a 0.4-basis-point rise in the mean interbank rate. However, the variable does not seem to be significant in explaining the volatility of interbank interest rates, which was driven mainly by changes in

Table 10. Estimated GARCH Parameters (Subsample: April 2003 to October 2007)

	Coefficient	**Std. Error**	**z-Statistic**	**p-Value**
Mean Equation				
C	−0.130*	0.026	−5.014	0.000
Repo (–1)	1.344*	0.022	62.484	0.000
Repo (–2)	−0.160*	0.038	−4.288	0.000
Repo (–3)	−0.315*	0.038	−8.304	0.000
Repo (–4)	0.165*	0.033	5.057	0.000
Repo (–5)	−0.040*	0.018	−2.143	0.032
Administered Lending Rate	0.050*	0.010	5.202	0.000
Administered Deposit Rate	−0.063*	0.013	−5.023	0.000
OMO	2.5E-05	1.8E-05	1.402	0.161
RR	2.0E-04*	9.5E-05	2.068	0.039
RR Announcement	0.056	0.039	1.428	0.153
IPO	2.1E-04	5.5E-04	0.388	0.698
Liquidity Effects (See Table 11)				
Variance Equation				
C	−0.621*	0.166	−3.734	0.000
ARCH Effect (–1)	1.578†	0.882	1.789	0.074
Asymmetric Effect (–1)	0.223	0.164	1.357	0.175
GARCH Effect (–1)	0.922*	0.010	92.007	0.000
Δ in Administered Lending Rate	18.876*	4.707	4.010	0.000
Δ in Administered Deposit Rate	−17.889*	4.479	−3.994	0.000
OMO	0.002	0.002	1.401	0.161

(*continued*)

Table 10. (Continued)

	Coefficient	Std. Error	z-Statistic	p-Value
Variance Equation				
RR	−0.009*	0.003	−3.215	0.001
RR Announcement	3.423*	0.773	4.428	0.000
IPO	0.002	0.015	0.156	0.876
IPO (+5)	0.009	0.014	0.677	0.498
IPO (+10)	0.038*	0.012	3.110	0.002
Liquidity Effects (See Table 11)				
T-DIST. DOF	2.06*	0.072	28.728	0.000
R-Squared	0.930	Adjusted R-Squared		0.928
S.E. of Regression	0.193	Sum Squared Residual		40.000
Log-Likelihood	2222.893			
Akaike Info Criterion	−3.856	Schwarz Criterion		−3.518
Hannan-Quinn Criterion	−3.729	Durbin-Watson Statistics		2.128

Notes: Dependent variable: Repo (seven-day repo rate); sample period: April 1, 2003 to October 12, 2007. Included observations: 1,114 after adjustments. Method: ML-ARCH (Marquardt) – Student's t-distribution. * indicates significance at the 5 percent level, and † indicates significance at the 10 percent level.

administered interest rates, the announcement effect from changes in reserve requirements, and IPOs (tables 12 and 13).

4.6.3 Interest Rate Variables

In the baseline specification, both administered lending rates and deposit rates are introduced to capture the impact of policy changes in administered interest rates. The one-year administered lending rates typically move at the same time as the one-year deposit

Table 11. Estimated Liquidity Effects (Subsample: April 2003 to October 2007)

Lag	Mean Equation		Variance Equation	
	Coefficient	p-Value	Coefficient	p-Value
Day of Week:				
Monday	−1.1E-05	0.990	−0.896*	0.000
Wednesday	1.0E-04	0.905	−0.132	0.621
Friday	2.4E-04	0.835	0.616*	0.010
End of Month:				
5	8.8E-04	0.504	−0.045	0.879
4	8.2E-05	0.948	−0.401	0.236
3	8.0E-04	0.581	−0.448	0.185
2	0.001	0.556	0.062	0.866
1	0.003	0.023	−0.316	0.366
0	−0.003	0.149	−0.702*	0.031
–1	0.004†	0.051	0.084	0.820
–2	0.003	0.130	0.341	0.359
–3	0.004*	0.041	0.132	0.729
–4	0.001	0.423	−0.123	0.748
–5	0.005*	0.000	−0.408	0.221
Chinese New Year:				
5	−0.013	0.136	−2.571*	0.029
4	0.002	0.936	0.611	0.724
3	−0.003	0.916	0.458	0.786
2	0.083*	0.028	−0.813	0.685
1	0.153*	0.000	1.750	0.473
0	−0.511*	0.000	−1.906	0.378
–1	−0.061	0.882	1.367	0.497
–2	0.320	0.207	−0.132	0.930
–3	0.081	0.465	4.130*	0.012
–4	0.062*	0.000	2.143	0.110
–5	0.003*	0.001	−3.914*	0.008

Notes: Dependent variable: Repo (seven-day repo rate); sample period: April 1, 2003 to October 12, 2007. Included observations: 1,114 after adjustments. Method: ML-ARCH (Marquardt) – Student's *t*-distribution. * indicates significance at the 5 percent level, and † indicates significance at the 10 percent level.

Table 12. Estimated GARCH Parameters: Robustness–Liquidity Injection

	Real Liquidity Injection	**Combined Monetary Policy Variable**
Mean Equation		
C	−0.040*	−0.033*
Repo (–1)	1.151*	1.141*
Repo (–2)	−0.065*	−0.060
Repo (–3)	−0.143*	−0.142*
Repo (–4)	0.081*	0.072*
Repo (–5)	−0.027†	−0.015
Administered Lending Rate	0.015*	0.012*
Administered Deposit Rate	−0.019*	−0.014*
Real OMO	0.004*	
Real RR	0.002	
Real OMO + RR		0.004*
RR Announcement	0.065*	0.061*
Real IPO	0.047	0.037
Liquidity Effects (See Table 13)		
Variance Equation		
C	−0.093	−0.177†
ARCH Effect (–1)	1.569†	1.296*
Asymmetric Effect (–1)	0.386†	0.347†
GARCH Effect (–1)	0.969*	0.969*
Δ in Administered Lending Rate	7.910*	6.962*
Δ in Administered Deposit Rate	−8.597*	−7.481*
Real OMO	0.208*	
Real RR	−0.121†	
Real OMO + RR		0.049
RR Announcement	2.110*	2.066*
IPO	−0.773	−0.725
IPO (+5)	−0.082	0.114
IPO (+10)	3.256*	3.406*
Liquidity Effects (See Table 13)		

Notes: Dependent variable: Repo (seven-day repo rate); sample period: April 1, 2003 to April 12, 2012. Included observations: 2,197 after adjustments. Method: ML-ARCH (Marquardt) – Student's t-distribution. * indicates significance at the 5 percent level, and † indicates significance at the 10 percent level.

Table 13. Estimated Liquidity Effects: Robustness–Liquidity Injection

Lag	Mean Equation: Real Liquidity Injection	Mean Equation: Combined Monetary Policy Variable	Variance Equation: Real Liquidity Injection	Variance Equation: Combined Monetary Policy Variable
Day of Week:				
Monday	−7.4E-04	−8.3E-04	−0.734*	−0.667*
Wednesday	−2.8E-04	−2.9E-04	−0.484*	−0.396
Friday	1.7E-04	1.6E-04	0.073	0.221
End of Month:				
5	3.2E-04	1.1E-05	0.002	0.039
4	−6.4E-04	−0.001	−0.418†	−0.362
3	9.0E-04	7.1E-04	−0.545*	−0.595*
2	−2.0E-04	−5.5E-04	0.161	0.147
1	0.001	0.001	−0.545*	−0.547*
0	−0.003	−0.003	−0.255	−0.283
–1	0.005*	0.005*	−0.188	−0.170
–2	0.002	0.002	0.564*	0.568*
–3	0.004*	0.004*	−0.251	−0.251
–4	0.001	0.002	−0.107	−0.024
–5	0.003*	0.003*	−0.074	−0.120
Chinese New Year:				
5	−0.015	−0.016	−1.097	−1.053
4	−0.005	−0.011	1.197	1.321
3	0.005	0.006	−0.141	−0.275
2	0.036*	0.038*	−2.029*	−2.113*
1	0.065*	0.064	−0.113	−0.143
0	−0.470*	−0.463*	0.022	0.067
–1	0.015	0.019	−0.002	0.033
–2	0.343*	0.345*	0.920	0.955
–3	0.090*	0.091*	2.566*	2.741*
–4	0.061*	0.061*	−1.273†	−1.116†
–5	0.004	0.003	−0.110	−0.112

Notes: Dependent variable: Repo (seven-day repo rate); sample period: April 1, 2003 to April 12, 2012. Included observations: 2,197 after adjustments. Method: ML-ARCH (Marquardt) – Student's t-distribution. * indicates significance at the 5 percent level, and † indicates significance at the 10 percent level.

rates, although there are several episodes of exception in our sample period.[29] To check the robustness of our results to different specifications of administered interest rates, we carry out two further experiments. First, only one administered interest rate is introduced to the regression at a time. The results are robust in that the seven-day repo rate is persistent, and open-market operations and the announcement effect of reserve requirements have a significant impact on the level of interbank interest rates. The administered deposit rate also has a negative and significant impact on the interbank interest rate; however, the impact from the administered lending rate does not appear to be significant. This result is consistent with our view that the deposit rate ceiling is binding and the administered deposit rate is expected to be important in influencing the level of interbank interest rates. While changes in administered interest rates jointly influence the volatility of interbank interest rates, individually, their impact does not appear to be as significant as open-market operations, the announcement effect of reserve requirements, and the lock-up effect from IPOs (tables 14 and 15).

Finally, we consider a specification in which the spread between administered lending and deposit rates is introduced in the regression. The spread is found to be significant in explaining both the level and volatility of interbank interest rates. The impact of a 100-basis-point rise in the spread between one-year administered lending and deposit rates is a 0.7-basis-point rise in the mean interbank rate, while a change in the interest rate spread (100-basis-point rise) could increase interbank volatility by 6.8 basis points. The magnitude and significance of the responses in other key variables such as open-market operations, reserve requirements, and IPOs are very similar to those in the baseline specification (tables 14 and 15).

[29] In September 2008, the one-year administered lending rate was reduced by 27 basis points, while the one-year administered deposit rate remained unchanged. The magnitude of changes in the administered lending rate was sometimes smaller than that in the administered deposit rate. For example, the one-year administered lending rate was increased by 18 basis points in May and December 2007, while the one-year administered deposit rate was raised by 27 basis points.

Table 14. Estimated GARCH Parameters: Robustness–Interest Rates

	Lending Rate	Deposit Rate	Spread
Mean Equation			
C	−0.004	0.010*	−0.022†
Repo (–1)	1.149*	1.168*	1.162*
Repo (–2)	−0.065*	−0.078*	−0.075*
Repo (–3)	−0.096*	−0.126*	−0.115*
Repo (–4)	0.046*	0.069*	0.056*
Repo (–5)	−0.036*	−0.034*	−0.030*
Administered Lending Rate	0.001		
Administered Deposit Rate		−0.004†	
Interest Rate Spread			0.007†
OMO	3.5E-05*	3.2E-05†	3.7E-05*
RR	4.1E-05	3.2E-05	3.6E-05
RR Announcement	0.065*	0.067*	0.066*
IPO	5.0E-04	5.3E-04	4.9E-04
Liquidity Effects (See Table 15)			
Variance Equation			
C	−0.077*	−0.103	−0.062*
ARCH Effect (–1)	1.602†	1.389†	1.632†
Asymmetric Effect (–1)	0.444†	0.388†	0.427†
GARCH Effect (–1)	0.972*	0.970*	0.971*
Δ in Administered Lending Rate	−0.860		
Δ in Administered Deposit Rate		−0.888	
Interest Rate Spread			6.786*
OMO	0.002*	0.002*	0.002*
RR	−0.001*	−0.001	−0.001
RR Announcement	1.953*	1.969*	2.141*
IPO	−0.009	−0.008	−0.010
IPO (+5)	−3.4E-04	−3.6E-04	−1.0E-04
IPO (+10)	0.029*	0.030*	0.029*
Liquidity Effects (See Table 15)			

Notes: Dependent variable: Repo (seven-day repo rate); sample period: April 1, 2003 to April 12, 2012. Included observations: 2,197 after adjustments. Method: ML-ARCH (Marquardt) – Student's t-distribution. * indicates significance at the 5 percent level, and † indicates significance at the 10 percent level.

Table 15. Estimated Liquidity Effects: Robustness–Interest Rates

	Mean Equation			Variance Equation		
Lag	Lending Rate	Deposit Rate	Spread	Lending Rate	Deposit Rate	Spread
Day of Week:						
Monday	−5.7E-04	−3.9E-04	−6.9E-04	−0.687*	−0.680*	−0.745*
Wednesday	−1.7E-04	−1.4E-04	−2.1E-04	−0.409*	−0.423*	−0.481*
Friday	1.5E-06	2.6E-04	1.3E-04	0.050	0.058	0.037
End of Month:						
5	3.8E-04	4.5E-04	2.6E-04	0.005	−0.008	0.017
4	−8.6E-04	−8.9E-04	−9.8E-04	−0.382	−0.370	−0.408†
3	6.3E-04	7.0E-04	8.3E-04	−0.499*	−0.503*	−0.511*
2	−5.4E-04	−2.7E-04	−4.7E-04	0.111	0.103	0.105
1	6.3E-04	0.001	7.6E-04	−0.510*	−0.501*	−0.501*
0	−0.003	−0.003	−0.003	−0.220	−0.244	−0.260
–1	0.004*	0.004*	0.004*	−0.227	−0.189	−0.222
–2	0.001	0.002	0.002	0.542*	0.559*	0.556*
–3	0.004*	0.004*	0.003*	−0.200	−0.220	−0.218
–4	0.002	0.002	0.001	−0.129	−0.130	−0.104
–5	0.003*	0.003*	0.003	−0.005	−0.012	−0.051
Chinese New Year:						
5	−0.018*	−0.016*	−0.017*	−1.390*	−1.250†	−1.218†
4	0.003	0.002	−7.9E-05	1.218	1.062	1.081
3	−9.1E-04	−2.5E-04	0.003	−0.328	−0.073	0.051
2	0.026	0.033*	0.032*	−1.993†	−2.031*	−2.295*
1	0.046	0.063†	0.058	0.251	0.035	0.121
0	−0.476*	−0.475*	−0.476*	−0.187	−0.033	−0.072
–1	0.011	0.007	0.008	0.173	0.223	0.179
–2	0.343*	0.342*	0.342*	0.060	0.238	0.383
–3	0.089	0.089	0.089†	2.669*	2.724*	2.735*
–4	0.060*	0.060*	0.060*	−0.584	−0.899	−0.983
–5	0.004	0.004	0.004	0.214	0.053	0.098

Notes: Dependent variable: Repo (seven-day repo rate); sample period: April 1, 2003 to April 12, 2012. Included observations: 2,197 after adjustments. Method: ML-ARCH (Marquardt) – Student's *t*-distribution. * indicates significance at the 5 percent level, and † indicates significance at the 10 percent level.

5. Conclusion

This paper investigates the main drivers of China's interbank rates by developing a stylized theoretical model of China's interbank market, and estimating an EGARCH model for the seven-day interbank repo rate from April 2003 to April 2012, controlling for administered interest rates, monetary policy variables, IPO volumes, and liquidity effects. The stylized theoretical model pins down the analytical relationship between regulated and market-determined interest rates and predicts that administratively determined deposit rates and lending rates are likely to influence the movements of interbank rates. In particular, the interbank rate is increasing in the lending rate (provided the lending rate has not already exceeded its equilibrium) and decreasing in the deposit rate (as interest rate regulation holds the deposit rate below the equilibrium level).

Our empirical results confirm the predictions from the theoretical model that China's interbank rates are not truly independent. Administered interest rates are found to be important determinants of the interbank rates, in both levels and volatility. Interbank rates are also influenced by the announcement effects of changes in reserve requirements, together with liquidity injections from open-market operations in recent years, and would generally seem less informative than in more developed markets. IPO activities affect interbank volatility, as well as systemic variations in liquidity throughout the week, during the month, and due to the timing of the Chinese New Year. Our results suggest that the regulation of key retail interest rates influences the behavior of market-determined interbank rates, which may have limited their ability to act as independent price signals. While reflecting news, changes in administered interest rates affect the way news impacts rates.

These conclusions raise a number of interesting issues on the liberalization of financial prices in emerging markets. First, the theoretical and empirical results suggest that partial liberalizations may have limited effectiveness. That is, market-determined rates, even longer-term bond yields, can reflect interest rate regulation in other parts of the market. The "policy spillover" thus affects private decisions that are directly determined by unregulated prices. This would include firms that seek to fund projects through bonds, and banks participating in the interbank market, as well as those seeking to protect themselves through derivatives transactions (since derivatives prices depend on interbank rates). Moreover, if the interest rate regulation is binding, the allocation of credit across potential projects is left to the banking sector, rather than independent financial markets. Although it may be imprudent to read these considerations as suggesting a "big-bang" approach to liberalization, or considering financial market liberalization as a general precondition for assistance, they nevertheless suggest moving through the liberalization of domestic yields and asset prices somewhat quickly.[30]

Regarding the conduct of monetary policy in the process of financial and economic development, our results highlight the risks from excessive regulation on monetary policy implementation. The link between market and regulated interest rates suggests limits to the effectiveness of indirect monetary policy instruments. This can be seen in China's experience. Despite a desire to move toward indirect monetary policy instruments, the interest rate channel is still weak in China (see, for example, Maino and Laurens 2007 and Cassola and Porter 2011), although this would apply equally to other emerging and developing markets with partial financial liberalization. For short-term interest rates to become an effective operational target (influencing inflation and economic activity), the PBC has to be able to influence this rate effectively through open-market operations. In addition, the impact of uneven financial developments and interest rate regulation is likely to erode the effectiveness of direct monetary policy tools. In particular, the incentive for disintermediation resulting from regulation (out of the banking sector and into trust companies as part of "shadow banking") is likely to affect movements in the velocity of money and the money multiplier. Maino and Laurens (2007) find that while the PBC is able to meet its base money target, it is less effective at achieving its broad money targets and influencing economic growth.

Further interest rate liberalization should allow the interbank rate (and other interest rates) to provide better essential price signals, to better allocate capital, and to strengthen the tools for

[30] The general precondition for assistance should be "macro-critical," and liberalization may not meet the "macro-critical" criterion in all countries.

macroeconomic management. In particular, further deposit rate liberalization would allow banks to charge higher retail deposit rates to attract additional deposits, and potentially lead to a rise in retail loan rates for banks to maintain their profit margins and to meet capital requirements. This should then increase the cost of capital and thereby help to discourage marginal investment and improve the allocation of capital and the effectiveness of intermediation (Feyzioglu, Porter, and Takats 2009). The liberalization of the deposit rate would also remove an important distortion in the interbank rate, which would allow short-term interbank rates to play a more effective role as the primary indirect monetary policy tool.

China and other emerging-market economies may face two important challenges in the process of further interest rate liberalization and financial development. First, the volatility of interest rates may increase, depending on the post-liberalization conduct of monetary policy.[31] Even if volatility does increase, as has been the experience in other money markets (Demirguc-Kunt and Detragiache 2001), this higher volatility will result from market-determined rates being more responsive to fundamental changes in liquidity in emerging-market economies and risk characteristics rather than changes in regulated interest rates. This is part of strengthening the price signals conveyed by interest rates. In any case, the volatility of Chinese money-market rates could be reduced through a change in the structure of reserve requirements from daily reserve requirements to reserve averaging, irrespective of the extent of liberalization. Second, by creating new channels for banks to attract deposits and compete, liberalization could also lead to excessive lending (if banks choose to increase the quantity of loans instead of retail loan rates in response to liberalization) and place pressure on credit quality and the profitability of banks. If, however, liberalization is accompanied by heightened supervision and strengthened monetary policy, further liberalization could improve the effectiveness of intermediation and monetary transmission with enhanced financial stability.

[31] If the short-term interbank rate becomes a target for monetary policy, then volatility may decline.

Data Appendix: Data Sources

- **China Interbank Interest Rates:** The seven-day call loan and repo (interbank repurchase bond) series are drawn from Haver Analytics and the CEIC Premium China Database. The ticker identifiers for these three interbank interest rates are CDOBC, CDODM, and CDODA, respectively. The three series are nominal and are measured in percent per annum.
- **One-Year Administered (Benchmark) Deposit and Lending Rates:** The one-year administered deposit (CDDAD) and lending rates (CDLBA) are taken from Haver Analytics and the CEIC Premium China Database. The administered interest rates are nominal and are measured in percent per annum.
- **Measure of Open-Market Operations:** The measure of open-market operations captures the level of net liquidity injection from the expiration of repos and PBC central bank bills (expiration less issuance), and the issuance of reverse repos. The data series on open-market operations and reserve requirements are taken from Haver Analytics and the CEIC Premium China Database. Repos are issued at 7-day (CDOHBE), 14-day (CDOHBF), 21-day (CDOHBG), 28-day (CDOHBH), 84-day (CDOHBI), 91-day (CDOHBJ), and 182-day (CDOHBK) maturities. Reverse repos are issued at 14-day (CDOHBT) and 21-day (CDOHBU) maturities. The issuance of PBC central bank bills is typically at three-month (CDOHAA), six-month (CDOHAB), one-year (CDOHAC), and three-year (CDOHAD) maturities. The data series are measured in millions of RMB.
- **Measure of Reserve Requirements:** The variable reserve requirement measures the liquidity injected from a fall in required reserves. We construct the variable using data on the required reserve ratio (CMAAAA) and deposits in financial institutions (local and foreign currency) (CKAHNC). The required reserve ratio is measured in percent per annum and the deposit data are measured in billions of RMB. The change in the liquidity condition is then constructed as the change in the reserve requirement ratio times the deposit base. Given that changes in reserve requirements are usually announced

one or two weeks before the effective date, we also construct a dummy to capture the announcement effect of reserve requirement changes, where the dummy is equal to the change in the reserve requirement ratio on the date of the announcement.

- **IPOs:** The data source on IPO volumes in China is the Stockstar website (http://resource.stockstar.com/DataCenter/StockData/IPODataList.aspx, in Chinese, last accessed May 8, 2012). We construct two IPO series: for the first series (funds raised), we aggregate the total amount of funds raised from IPO activities on a particular listing day to construct a daily time series for IPO volume; for the second series (funds frozen), we aggregate the total amount of funds frozen on the application date, ahead of the IPO date. Note that the application date for an IPO is typically one or two weeks ahead of the actual IPO date. Large amounts of funds are frozen one day after the application date, and the portion of funds that are unsuccessful in bidding are released four days after the application date. (See http://www1.cfi.cn/bcA0A1A8A194A1792.html for details on IPO issuance in China, in Chinese).

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Monetary Policy, Loan Maturity, and Credit Availability*

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The recent financial crisis and economic recovery have renewed interest in how monetary policy affects bank lending. Using loan-level data, we analyze the effect of monetary policy on loan originations. Our results show that tightening monetary policy significantly reduces the supply of commercial loans by shortening loan maturity. A 1-percentage-point increase in the federal funds rate reduces the average maturity of loan supply by 3.3 percent, contributing to an 8.2 percent decline in the steady-state loan supply at a typical bank. This channel of monetary policy affects loan supply similarly at small and large banks. Our results have interesting implications for the effects of monetary policy on bank maturity transformation and credit availability.

JEL Codes: E44, E51, G21.

1. Introduction

Fears of a credit crunch in the recent financial crisis led many observers to call for central banks to ease monetary policy.[1] Such

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[1]There is evidence that a credit crunch, which has been defined as a "significant leftward shift in the supply curve of loans" (Bernanke and Lown 1991), occurred in the recent crisis (Ivashina and Scharfstein 2010; Puri, Rocholl, and Steffen 2011).

views are partly based on the idea that relaxing monetary policy leads to greater credit availability. Similarly, as the Federal Reserve considers raising rates during a relatively weak recovery, there is concern about a premature restriction of credit supply. This paper explores this premise by examining the impact of monetary policy on the characteristics of banks' loan supply. The key findings show that the influence of monetary policy on the amount of loan supply is observed not in aggregate loan levels, but through changes in loan maturity. A tightening (loosening) of monetary policy reduces (increases) the maturity of bank loan supply, which implies a corresponding change in the maturity transformation being provided by the banking sector. Our results show that monetary policy, through its effect on loan maturity, has an effect on credit availability over time. A 1-percentage-point increase in the federal funds rate—our primary measure of monetary policy tightening—reduces the average maturity of loan supply by 3.3 percent, contributing to an 8.2 percent decrease in the steady-state loan supply at a typical bank.

Previous studies have examined the channels through which monetary policy may affect bank loan supply. If tight monetary policy increases banks' external finance premium, banks may respond by reducing the total amount of credit they are willing to supply (Stein 1998). This bank lending channel suggests a relationship between monetary policy and aggregate loan supply. In addition, monetary contractions can reduce the net worth of banks' borrowers. This increase in the agency costs in lending, referred to as the balance sheet channel, can shift available credit toward higher-net-worth firms (Bernanke, Gertler, and Gilchrist 1996).

More recently, the credit channel literature has focused on the impact of monetary policy on credit allocation (as described in Borio and Zhu 2012). For instance, Jimenez et al. (2012) study loan applications in the credit registry of Spain to identify the effect of bank capital and liquidity on loan acceptance rates. In addition, much of the recent work has brought attention to the "risk-taking channel" of monetary policy by analyzing the allocation effects of risk pricing (e.g., Borio and Zhu 2012; Kishan and Opiela 2012). We build on this literature by examining the impact on credit allocation through loan maturity and loan size. Our paper most directly relates to the model of Diamond and Rajan (2006), a liquidity version of the lending channel that emphasizes the risk of funding long-term projects with short-term funds.

We use data on commercial loan originations in the United States from the Federal Reserve's Survey of Terms of Business Lending (STBL) to analyze these potential changes in banks' loan supply. Using the STBL, we can examine how banks adjust their commercial lending in response to monetary policy, including how they alter the maturity of loan supply and the size of loan originations. These redistributions in bank lending can have important real effects as they change the availability of credit for different projects and firms. For instance, the availability of longer-term credit for capital investments may be particularly important during an economic recovery.

A key challenge in this literature is the differentiation of changes in loan supply from changes in loan demand. An increase in lending can be supply or demand driven. We identify changes in supply by differentiating between new "spot loan" originations and loans made under a pre-existing commitment. Loan commitments are a form of credit line, giving firms the ability to decide when to borrow.[2] Therefore, changes in commitment lending (in the short run) are primarily due to changes in loan demand. The level of commitment lending should reflect changes in firms' demand for credit, which could change through the traditional interest rate channel by which monetary policy affects firms' cost of borrowing. We identify changes in loan supply by examining spot lending *relative* to commitment lending. Controlling for changes in commitment lending allows us to net out demand effects and focus on changes in banks' willingness to extend new credit.

Our first step is to estimate how the dollar amount of lending is affected by monetary policy. Early empirical studies of the credit channel examine how the stock of loans outstanding responds to monetary policy (e.g., Bernanke and Blinder 1992; Kashyap, Stein and Wilcox 1993). Some results even indicate that loans outstanding—used as a measure of loan supply—increases slightly, contrary to the intuition behind the bank lending channel. However,

[2]Banks have an advantage in hedging liquidity risk (Kashyap, Rajan, and Stein 2002; Gatev and Strahan 2006) and many firms choose to draw down their existing lines of credit when other sources of liquidity become more strained (Ivashina and Scharfstein 2010).

similar to the more recent credit channel literature, we are better able to differentiate supply from demand by examining the flow of lending rather than the stock (e.g., Jimenez et al. 2014). Although we find an increase in lending with monetary tightening, we explore the issue further by analyzing the effect on credit allocation. By examining both the flow and stock of lending, we find evidence that tightening monetary policy decreases banks' loan supply over time.

Our main results hinge on how monetary policy affects loan maturity. The STBL measures the *flow* of lending by a bank, while the bank lending channel makes predictions about the *stock* of loans. In the aggregate data, this difference is not important, since the best proxy for changes in the stock of loans is the flow of loans. However, if a bank reduces the duration of the loans it makes, its stock of loans can decrease fairly quickly even if the flow of loans remains constant or increases. Research focusing on the dollar amount of bank lending can miss this point. We find that during periods of tight (loose) credit, banks reduce (increase) the maturity of their loan supply, consistent with the operation of a bank lending channel.[3]

We then examine the response of overall lending to monetary policy using our data. Our preferred measure of bank lending according to this approach is the *product* of total lending and loan maturity. With this combined measure, we examine how monetary policy affects the "dollar years" of bank loan supply. The results suggest that an increase (reduction) in the real federal funds rate leads to an overall reduction (increase) in loan supply, consistent with an operative bank lending channel.

We also analyze whether the responsiveness of banks' lending to monetary policy is a function of bank size. We find that the distribution of loan supply at both small and large banks is sensitive to monetary policy. This builds on previous empirical findings (e.g., Kashyap and Stein 2000).

Our combined results point to redistributive effects of monetary policy on bank loan supply and the availability of credit. It appears that banks may alter loan supply during periods of tight (loose) monetary policy by shortening (lengthening) loan maturities and

[3]This also indicates a reduction in banks' maturity transformation during periods of tight credit, which ultimately leads to a decline in liquidity creation (Berger and Bouwman 2009).

thereby increasing the liquidity of their loan portfolio. These results support the premise that monetary policy influences the availability and allocation of credit, with changes in loan maturity being the mechanism that implements these changes.

The remainder of the paper is organized as follows. Section 2 reviews the literature and section 3 describes the data used in our analysis. Section 4 explains our empirical methodology and section 5 lays out the results as well as robustness tests. Section 6 compares small banks with large banks. Section 7 concludes.

2. Literature Review

Monetary policy can affect the real economy both through the demand side (Bernanke and Blinder 1992) and through the supply side. One of the channels of the supply-side effect is known as the credit channel. Financial frictions stemming from information asymmetries may affect the costs for banks to both borrow and lend funds. The relationships between these frictions and short-term interest rates are channels through which monetary policy influences credit availability (Bernanke and Gertler 1995). Our paper contributes to this literature by focusing on changes in loan maturity and loan size.

The credit channel of monetary policy can occur through what is known as the bank lending channel, which operates through banks' liability side. Tight monetary policy drains reserves from the banking system, leaving banks with fewer loanable funds, thereby reducing lending (Bernanke and Blinder 1988). Although this drain in reserves can be partially offset by non-reservable wholesale funds, such as uninsured deposits (Romer and Romer 1990), agency costs between banks and their providers of funds can cause banks to face a greater external finance premium on wholesale funds during periods of tight monetary policy (Stein 1998). This higher cost leads banks to reduce lending. We examine whether the bank lending channel operates through changes in loan maturity.

The credit channel also includes the balance sheet channel, which operates through banks' asset side. In this channel, monetary policy affects agency costs in bank lending, which leads to changes in firms' ability to qualify for credit. Monetary contractions reduce the net worth of borrowers, which increases agency costs, primarily for low-net-worth firms (Bernanke, Gertler, and Gilchrist 1996). When these agency costs increase, only relatively safer borrowers continue to qualify for credit (Bernanke and Gertler 1989).[4] This implies that changes in monetary policy lead to a reallocation of credit availability across investment projects (Matsuyama 2007). As borrowers become riskier, this could reduce borrowers' ability to qualify for longer-maturity loans.

In addition, recent theoretical literature shows how changes in monetary conditions may alter bank risk. Monetary contractions increase the real value that banks must pay to retain deposits, which increases the real liquidity demands on banks. This causes banks to fund fewer long-term projects (Diamond and Rajan 2006, 2011). The Diamond and Rajan model of banks' maturity transformation predicts that the maturity of loan originations will decline following monetary contractions. Our analysis provides a test of this liquidity version of the lending channel. Related to this, agency problems in banks—especially when capital is low or short-term funding is high—may amplify the reduction in banks' risk taking following monetary contractions (Borio and Zhu 2012).

Early empirical work on identifying the credit channel focuses on the response of aggregate lending to a monetary contraction. Kashyap and Stein (1995, 2000), for instance, find that the loan supply of smaller, less liquid banks is more sensitive to changes in monetary policy, because raising wholesale liabilities is more costly for these banks. Other studies find similarly that the effects of monetary tightening are increasing in the expected costs of raising non-reservable liabilities.[5]

Our paper more directly builds on recent empirical literature that examines the transmission of monetary conditions to credit allocation. Much of this literature focuses on the relationship between monetary policy and bank risk. Den Haan, Summer, and Yamashiro (2007) find that, following a monetary tightening, commercial and industrial (C&I) loans increase while real estate and consumer loans decrease, which the authors interpret as a reallocation into

[4]This channel has also been referred to as the "flight to quality."

[5]Kishan and Opiela (2000) examine the effects of bank capitalization, Jayaratne and Morgan (2000) look at dependence on core deposits, Ashcraft (2006) analyzes banks by holding company status, and Black, Hancock, and Passmore (2007) focus on banks' loan-to-core-deposit ratios.

shorter-term, less risky assets. Similarly, low short-term interest rates soften bank lending standards and increase bank risk taking.[6] Buch, Eickmeier, and Prieto (2014) find evidence for this channel among small banks using aggregate STBL time-series data. Although banks with low risk (low expected default) are less sensitive to monetary policy (Altunbas, Gambacorta, and Marques-Ibanez 2010), there appears to be a risk-taking channel of monetary policy.

Our research examines the effect of monetary policy on loan maturity and loan size as key components of credit allocation. It is possible for monetary policy to affect these loan characteristics through each of the channels described above. For instance, monetary contractions can reduce the maturity of bank loan supply through an increase in banks' external finance premium, a reduction in borrowers' net worth, or a reduction in banks' willingness to take on liquidity risk. If loan size proxies for firm size, then a monetary contraction should cause an increase in loan size, which would be a flight to quality for many of the same reasons.

The results for loan maturity have interesting implications for the literature on corporate loan maturity. Berger et al. (2005) use the STBL data to analyze the effects of risk and asymmetric information on debt maturity. Consistent with the models of Flannery (1986) and Diamond (1991), the authors find among low-risk firms that loan maturity increases with borrower quality and decreases with information asymmetries. Ortiz-Molina and Penas (2008) find similar evidence using the Federal Reserve Survey of Small Business Finance. Through the balance sheet channel, monetary contractions increase borrower risk and agency costs. These findings are consistent with monetary contractions reducing loan maturity.

The empirical methodology focuses on the identification of changes in credit allocation in response to monetary policy. The STBL data does not include borrower characteristics, which is a limiting factor relative to data such as the credit registry in Spain (used by Jimenez et al. 2012).[7] However, we are able to use differences

[6]See Delis and Kouretas (2011); Maddaloni and Peydro (2011, 2012); Altunbas, Gambacorta, and Marques-Ibanez (2014); and Jimenez et al. (2014).

[7]Jimenez et al. (2014) include loan maturity in their analysis but do not directly study the effect of monetary policy on loan maturity.

between commitment and spot lending to measure of changes in loan supply. This approach follows other papers with similar methodologies (Sofianos, Wachtel, and Melnik 1990; Berger and Udell 1992; Morgan 1998). We also focus on loan maturity and loan size, which capture important aspects of credit allocation and credit availability. These are particularly important for understanding the rise and fall in the availability of bank credit with the interest rate cycle in the United States.

3. Data and Summary Statistics

The loan data are from the Survey of Terms of Business Lending (STBL), which is a survey conducted by the Board of Governors of the Federal Reserve System. The STBL solicits information from a sample of banks on C&I loans issued during the first full business week of the second month of every quarter.[8] Our sample includes observations from the third quarter of 1982 through the fourth quarter of 2009, a time frame that covers several interest rate cycles. Each quarter, the STBL includes a sample of roughly 340 banks, including both small banks and large banks. While banks move in and out of the STBL panel, the median length of time a domestic bank is surveyed during our sample period is twenty-three quarters.

To reduce noise in the STBL data's time-series dimension, we apply filters to remove banks that have a limited relevance to our analysis or limited presence in the STBL survey. First, we remove banks that issue almost all their loans under commitment or almost all their loans as spot loans, since these banks are unlikely to respond

[8] Although the survey includes several loan types, we focus strictly on C&I loans in the survey (about 95 percent of the STBL loans are C&I loans). We also eliminate several groups of loans which are not appropriate to our analysis. We exclude all add-on loans, loans booked at a foreign office, loans with maturity greater than ten years, and loans for which the interest rate spread over the Treasury of comparable maturity is less than −1 percent or greater than 10 percent. Some banks report for less than a full week and for less than all branches. For these banks, when we aggregate data by bank, we adjust the data as if they reported for all branches for the full week. Finally, the survey can include Veteran's Day. For a bank that makes loans on a Veteran's Day that total less than 75 percent of its average daily loan volume during the other days of that week, we replace data for Veteran's Day with the average lending on other days that week at that bank.

to changes in monetary policy by changing the mix of spot and commitment loans. Formally, we drop all banks where the average share of commitment loans in total loans is above 99 percent or below 1 percent. Second, we remove foreign banks, since they entered the sample in the middle of our sample period. Third, we remove banks that are in the survey fewer than twenty-five times. These banks have a limited time span in the survey, which reduces the possibility for changes over time. Finally, we remove banks that average less than twenty-five loans per week. With these filters, the final sample includes 230 banks and 3,170,846 loans, with banks in the sample for a median fifty-four quarters.

We include data on macroeconomic conditions from publicly available sources and on bank characteristics from the Consolidated Report of Condition and Income (the "Call Report") associated with the bank making the loan.

Table 1 lists summary statistics for the variables used in our tests. All dollar-amount variables are reported in 2007 U.S. dollars.[9] We discuss the variables used in the regressions in the empirical methodology section below.

The primary loan characteristic we use in our identification strategy is whether a loan is made under commitment. A commitment is either a formal commitment or an informal credit line that provides a borrower with the right to borrow up to a certain amount of credit over a fixed period of time. The important aspect of a commitment is that a bank is committed to making a loan to the firm upon request. Although there is evidence that some firms faced credit line reductions during the crisis (Huang 2010; Ivashina and Scharfstein 2010), only the violation of a material adverse change type covenant typically releases the bank from its commitment.[10] We refer to loans made when there is no prior commitment as spot loans. The average share of commitment loans at a bank in our sample is 76 percent.

Firms use loans for different reasons. Some loans are used more to cover day-to-day operations (working capital) while others are used more to finance discrete, often one-off, projects. It is possible that

[9]We use the CPI net of food and energy prices in 2007:Q4 as the deflator.

[10]Loans generally have material adverse change (MAC) clauses which allow banks to renege on their commitment to lend if the credit quality of the firm deteriorates significantly, but these clauses are rarely exercised in normal times.

Table 1. Descriptive Statistics

Variable	Description	Mean	Standard Deviation
Loan Characteristics			
Commitment	Share of loans made under commitment (vs. spot)	0.76	0.30
Fixed Rate	Share of loans with fixed interest rate (vs. floating)	0.64	0.33
Commitment and Fixed Rate	Share of commitment loans with fixed interest rate	0.67	0.34
Spot and Fixed Rate	Share of spot loans with fixed interest rate	0.60	0.36
Dependent Variables			
Total Lending	Log of total loan amount (in thousands of $)	3.99	2.09
Loan Maturity	Log of weighted-average loan maturity (in years)	0.46	0.40
Loan Size	Log of average loan amount (in thousands of $)	0.48	0.60
Total Lending * Loan Maturity	Log of total loan amount multiplied by weighted-average loan maturity	2.99	1.95
Macroeconomic Conditions			
Real Funds Rate	Federal funds rate net of current inflation	2.12	1.98
Baa–Aaa Spread	Baa bond yield – Aaa bond yield	1.05	0.47
Yield-Curve Slope	Ten-year Treasury yield – three-month Treasury yield	1.79	1.19
GDP Growth	Quarterly growth rate in real gross domestic product	0.74	0.66
Unemployment	Percent unemployed	6.04	1.52
SLOOS Net Tightening	Net percentage of banks tightening in SLOOS	6.97	21.31
Pre-SLOOS	Dummy variable: all quarters prior to SLOOS data	0.27	0.44
Crisis Period	Dummy variable: Period of 2007:Q3–2009:Q4	0.09	0.29
Bank Characteristics			
Large Bank	Share of banks with mean total assets > $10 billion	0.28	0.45
Log (Bank Assets)	Log of total bank assets (in billions of $)	1.92	1.57
Bank Capitalization	Ratio of bank equity to total bank assets	0.07	0.03
Bank-Quarter Observations	13,589		

Notes: The dependent variables are based on the average values for each bank in each quarter of the Survey of Terms of Business Lending (STBL). The macroeconomic data come from various sources (drawn from Fred II at the Federal Reserve Bank of St. Louis) and the bank characteristics come from the Consolidated Report of Condition and Income (the "Call Report"). All values are reported as sample means and standard deviations. The sample covers 1982:Q3–2009:Q4. All dollar values are in 2007 dollars.

commitment loans and spot loans fund different kinds of operations. The STBL does not identify the use of a loan, but it is reasonable to think that floating-rate and shorter-term loans are more likely to be used for working capital while fixed-rate and longer-term loans are used more for discrete projects. As shown in table 1, there is little difference in the share of floating-rate loans across commitment and spot loans: 67 percent of commitment loans are fixed rate and 60 percent of spot loans are fixed rate.[11] However, spot loans have a longer maturity than commitment loans (a difference of 0.42 years). This means that there may be some differences in how spot and commitment loans are used. Our methodology assumes that even if the uses of spot and commitment loans are different, demand for both types of loans changes in the same way with monetary policy. To the extent that this is not true, it affects how our results should be interpreted.

Our primary macroeconomic variable is our measure of monetary policy, which is the real federal funds rate (referred to as the "funds rate"). The credit channel implies loan supply is related to real interest rates, so we adjust the nominal funds rate for expected inflation. We use current inflation as the forecast of the next quarter's inflation. The real federal funds rate is therefore the nominal federal funds rate net of current inflation, where the nominal federal funds rate is the quarterly average of the daily effective federal funds rate and inflation is the quarterly growth rate in the core CPI (that is, the CPI net of food and energy prices). Our results are robust to using business fixed investment (BFI) prices and ex post inflation as alternative measures of expected inflation. The other macroeconomic control variables are described in the methodology.

The STBL identifies the bank originating each loan, which allows us to match the STBL data to the quarterly Call Report data for each lender. We focus on total bank assets as the primary bank characteristic in our empirical specification. Using these data, we can consider whether bank size is related to the relative importance of the bank lending channel. It is also possible that the prevalence of commitment loans could depend on the size of the bank making the loan, so we include the natural log of a bank's total assets as a

[11] Percentages are based on dollar amount.

control. Lastly, the STBL match with bank identities allows us to use a bank-specific fixed-effects specification.

4. Empirical Methodology: Identifying Changes in Loan Supply

The theory of the credit channel provides predictions about the changes in loan supply in response to monetary policy. In our methodology, commitment lending serves as a baseline for measuring changes in the demand for spot loans, with changes in spot lending relative to commitment lending helping to identify changes in bank loan supply following changes in monetary policy.

Loan commitments limit the ability of banks to control the amount of lending in a given period, so a firm with an existing line of credit can borrow against this line whenever it has a demand for credit.[12] This gives the firm, rather than the bank, control over the amount of commitment lending. Although some commitment loans are drawn shortly after commitment contracts are signed, our data indicate that most drawdowns occur months after the signing of a commitment.[13] Thus, we assume that a bank has limited influence over the amount of commitment lending it does in the short run.[14] Based on this, changes in commitment lending can be used as a measure of changes in demand for loans under commitment.

There is evidence that the effects of monetary policy on commitment lending over a short period of time reflect changes in loan demand, not loan supply. Beginning in the second quarter of 2003, the STBL data include the date on which the commitment contract underlying a loan was signed. To test for a relationship between commitment signing and the funds rate, we regress the log of the average

[12]As noted above, commitments typically allow firms to borrow on demand, with credit line reductions during the recent financial crisis being an exception.

[13]Starting in the second quarter of 2003, we have data on the date a commitment was signed if a loan is made under commitment. These data show that only 25 percent of commitment borrowings are from commitment agreements that were signed in the three months prior to the drawdown, with 57 percent over six months old and 31 percent over one year old.

[14]This assumption becomes weaker over longer periods of time. However, if banks reduce new commitments over time, it will reduce the difference between spot and commitment loans, reducing the power of our tests.

time since commitments were signed for each bank in each quarter on the real funds rate and a time trend. The coefficient on time-since-signed is insignificant (results not shown). This suggests that the *signing* of commitments—the main ways banks can increase the supply of loans drawn under commitment—is not strongly responsive to changes in the real funds rate, because there is not a greater *amount* of commitment lending as rates are rising (rising rates should lead borrowers to seek more new commitment contracts). However, to the extent that changes in commitment lending reflect changes in loan supply, our methodology will under-estimate changes in supply and over-estimate changes in demand.

The difference in the adjustability of loan supply for spot loans and commitment loans allows us to use commitment lending as a baseline against which to measure changes in the supply of loans.[15] We assume that the demand for spot loans responds similarly to monetary policy as the demand for commitment loans, which implies that changes of the same direction and magnitude in spot lending and commitment lending should reflect changes in demand. If spot lending decreases relative to commitment lending, we interpret this as a reduction in the supply of loans. On the other hand, an increase in spot lending relative to commitment lending is interpreted as an increase in the supply of loans.

4.1 Baseline Specification

We aggregate the loan-level data to bank-quarter observations to measure the characteristics of spot and commitment loans made by a bank in a quarter. Our baseline model is

$$\begin{aligned} Y_{i,t} = \alpha_i &+ \Sigma_{j=0}^{4}\beta_{1,j}(\mathit{Monetary\ Policy})_{t-j} + \Sigma_{j=0}^{4}\beta_{2,j}(\mathit{Baa-Aaa\ Spread})_{t-j} \\ &+ \Sigma_{j=0}^{4}\beta_{3,j}(\mathit{Yield\ Curve\ Slope})_{t-j} + \Sigma_{j=0}^{4}\beta_{4,j}(\mathit{GDP\ Growth})_{t-j} \\ &+ \Sigma_{j=0}^{4}\beta_{5,j}(\mathit{Unemployment})_{t-j} + \beta_6(\mathit{SLOOS\ Net\ Tightening})_t \\ &+ \beta_7(\mathit{Pre\text{-}SLOOS})_t + \beta_8(\mathit{Crisis\ Period})_t + \beta_9(\mathit{Bank\ Assets})_{i,t} \\ &+ \beta_{10}(\mathit{Bank\ Capitalization})_{i,t} + \beta_{11}(\mathit{Time\ Trend})_t + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

[15] One possible issue is the bank capital constraint. A bank which has large drawdowns on its commitments might reduce its spot lending in an effort to limit the change in total lending. However, commitment lending and spot lending are positively correlated at the bank level, indicating that the two are not first-order substitutes.

where the dependent variable, Y_{it}, measures characteristics of bank lending. Our first dependent variable is *total lending*, which is the total dollar amount of either spot or commitment lending for a bank in a quarter.[16] We then analyze *loan maturity* and *loan size* as dependent variables to analyze distributional changes in loan supply in response to changes in monetary policy. Loan maturity is the average maturity of a bank's loans in a quarter, weighted by dollar amount, and loan size is the average dollar amount of a bank's loans in a quarter.[17] Our final dependent variable is the *product* of total lending and loan maturity. Each of these four dependent variables is measured in logs.[18] Lastly, as shown in equation (1), the macro variables include the contemporaneous value and four lags.[19] For these variables, the results are reported as the sum of the coefficients (e.g., Funds Rate (Sum)).

In our baseline specification, we use the real federal funds rate to measure monetary policy, with a higher rate indicating a policy tightening (Bernanke and Blinder 1992). Negative coefficients on the funds rate indicate that lending decreases with the tightness of monetary policy. Based on the assumptions stated above, a change in commitment lending will reflect a change in loan demand and we can measure loan supply changes by examining the difference between the coefficients on the funds rate variable in a regression with spot loans as the dependent variable and one with commitment loans as the dependent variable.[20]

To address concerns about the endogeneity of the federal funds rate, we have also estimated our model using Taylor residuals as the measure of monetary policy (Taylor 1993). By controlling for the predicted value of the federal funds rate based on economic

[16] The term "total lending" refers to each bank's total C&I lending in the STBL data.

[17] Individual loan maturity is capped at thirty years.

[18] We add one to all dependent variables prior to the log transformation.

[19] Havranek and Rusnak (2013) document the transmission lags of monetary policy. Our results are qualitatively the same when we exclude the contemporaneous values of all macro variables including the funds rate or when we use fewer lags.

[20] We also examined the probability of a loan being made under commitment. The results using this alternative specification, which included additional loan-level controls, produced similar results regarding changes in loan supply in response to monetary policy (see Black and Rosen 2009).

conditions, the Taylor residuals measure the "discretionary" component of monetary tightness or looseness relative to a basic policy rule. This measure of monetary policy has been used in other studies of the credit channel, including Maddaloni and Peydro (2011). In our analysis, the results based on Taylor residuals (shown in the robustness section) are qualitatively similar to the results based on the funds rate itself.

To control for other macroeconomic factors that can influence loan supply and demand, we include the Baa–Aaa spread, the yield-curve slope, GDP growth, unemployment, and a time trend in our baseline model. Because we are using a lag structure, quarterly averages are constructed from the weekly Baa–Aaa spread, the daily yield-curve slope, and the monthly unemployment rate. The Baa–Aaa spread controls for the overall level of risk in the economy. To the extent that loan commitments provide insurance against widening interest rate risk spreads on loans, we expect that commitment lending might increase when the risk spread is larger. The yield-curve slope controls for expectations of the future path of the funds rate, which partially addresses the potential for debt market timing. Overall economic conditions for loan demand are captured through GDP growth and the unemployment rate. The time trend picks up the systemic change in the shares of commitment and spot lending during our sample period.

Our analysis includes two additional controls to highlight aspects of the economy that might influence lending patterns. The recent financial crisis affected banks in many ways, including their lending practices. We examine whether this changed the proportion of commitment lending by including a crisis dummy that is one for the period from the third quarter of 2007 through the fourth quarter of 2009, inclusive. It is also possible that changes by banks in the terms and conditions (including covenants) of the loans they issue can change the incentives for a firm to choose a spot loan versus a commitment loan. We do not have information on additional loan characteristics, but we use the average value in a quarter for the net percentage of banks that report tightening the terms and conditions on commercial and industrial loans from the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS) as a control.[21] Since

[21] We use the value for "large and middle market firms" in the survey.

this question has been asked on the SLOOS only since 1990, we include a pre-SLOOS dummy for the dates before 1990.

It is possible that the coefficients on the federal funds rate might be sensitive to the combination of macroeconomic factors included in the regression. To test the robustness of our results to this concern, we varied the combination of macroeconomic factors (results not shown). In particular, we tried isolating the effects of the financial macroeconomic variables (Baa–Aaa spread and yield-curve slope), the real macroeconomic variables (GDP growth and unemployment), and the bank macroeconomic variables (SLOOS net tightening and pre-SLOOS). Our results are generally robust to alternative combinations of these variables.

We include bank size and capitalization as important bank characteristics. Bank size (the log of bank assets) is an essential control because C&I lending technologies and opportunities differ with bank size (Berger and Black 2011), making it possible for bank size to be correlated with the shares of a bank's total assets used for commitment and spot lending. The strength of a bank may affect the types of loans it makes, so we include the capital-to-asset ratio of the bank as a control (Kishan and Opiela 2000). We also include bank fixed effects to control for systematic differences in lending across banks; therefore, the other variables explain changes within a given bank over time.

4.2 The Response of Loan Supply to Changes in Monetary Policy

We use our four dependent variables to examine the potential responses of loan supply to monetary policy. The first step is to examine the effect of monetary policy of total lending. However, this is only a first step because total lending measures the flow of loans, while loan supply is the stock of lending. To get a picture of the stock of lending, we need to examine how loan maturity changes with monetary policy. A reduction in the stock of loans during periods of tight monetary policy, implied by the bank lending channel, can occur indirectly via a reduction in the average maturity of bank loan supply. A bank that reduces the maturity of loans it originates while keeping the amount of originations constant will gradually reduce the size of its loan portfolio over time.

In addition, we can use our framework to test whether the balance sheet channel is operative. If it is, banks will reallocate loan supply toward higher-net-worth firms during periods of tight monetary policy. The theory predicts that a reduction in firms' net worth due to a monetary contraction causes the risk of smaller firms to increase more than larger firms, causing banks to shift their loan supply toward larger firms. The STBL does not have borrower information, so we use loan size as a proxy for firm size in our test.

To determine the overall effect of monetary policy on loan supply, we combine the effects on the amount of total lending and loan maturity. To do this, we use the *product* of total lending and loan maturity. As noted above, our data measure *flow* effects but we want the effect on the *stock* of loans. Using the product of total lending and loan maturity allows us to connect flows and stocks. As an example, assume a bank that goes from supplying a \$1,000, five-year loan every quarter to supplying two \$1,000, three-month loans during a quarter. Total lending—the supply flow—increases from \$1,000 per quarter to \$2,000 per quarter, but the steady-state quantity of loans outstanding for the bank decreases from \$20,000 (\$1,000 × 5 years × 4 quarters) to \$2,000 (\$2,000 × 1 quarter). As the example indicates, changes in total lending multiplied by loan maturity gives the steady-state stock of loans outstanding. We use this measure as our proxy for the loan stock.

5. Results: The Effect of Monetary Policy on Lending

Tables 2 and 3 present the results for the baseline model using the full sample of loans.[22] In these tables, we examine how each bank's quarterly commitment and spot lending is affected by monetary policy. Table 2 contains the regression results for each of our dependent variables: total lending, loan maturity, loan size, and the product of total lending and maturity (each in logs). The odd-numbered columns show the results for commitment loans, and the even-numbered columns show the results for spot loans. Table 3

[22] All the reported standard errors in the regressions are robust and are corrected for bank-level clustering. Note that the sample sizes are different because not all banks make both commitment loans and spot loans in every quarter.

Table 2. The Effect of Monetary Policy on Bank Loan Supply: Regression Estimates

	Total Lending		Loan Maturity		Loan Size		Total Lending * Loan Maturity	
	(1) Commit	(2) Spot	(3) Commit	(4) Spot	(5) Commit	(6) Spot	(7) Commit	(8) Spot
Real Funds Rate (Sum)	−0.053*	0.052	0.031***	−0.002	0.002	0.026**	0.124***	0.042
	(0.029)	(0.034)	(0.006)	(0.010)	(0.010)	(0.013)	(0.031)	(0.027)
Baa–Aaa Spread (Sum)	0.105	−0.192	0.118***	0.043	0.075*	−0.140**	0.606***	0.099
	(0.128)	(0.180)	(0.035)	(0.062)	(0.044)	(0.066)	(0.166)	(0.151)
Yield Curve Slope (Sum)	−0.067*	0.049	0.016	−0.009	0.001	0.035**	0.003	0.016
	(0.038)	(0.047)	(0.010)	(0.018)	(0.012)	(0.018)	(0.043)	(0.046)
GDP Growth (Sum)	0.201***	−0.009	0.059***	0.046	−0.025	−0.032	0.445***	0.136
	(0.068)	(0.086)	(0.019)	(0.036)	(0.024)	(0.033)	(0.087)	(0.087)
Unemployment (Sum)	−0.156***	0.026	0.000	−0.022	−0.014	0.007	−0.099**	−0.055
	(0.034)	(0.045)	(0.009)	(0.219)	(0.012)	(0.018)	(0.040)	(0.043)
SLOOS Net Tightening	−0.004***	−0.002	−0.001	−0.001*	−0.001***	−0.000	−0.006***	−0.004**
	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Pre-SLOOS	−0.224***	0.029	−0.005	0.050	−0.006	−0.046	−0.173*	0.126
	(0.082)	(0.124)	(0.022)	(0.041)	(0.028)	(0.038)	(0.096)	(0.105)
Crisis Period	0.063	0.048	−0.136***	−0.020	0.034	0.066	−0.517***	−0.120
	(0.152)	(0.209)	(0.037)	(0.067)	(0.042)	(0.065)	(0.193)	(0.193)
Log(Bank Assets)	0.785***	0.973***	0.034	−0.005	−0.015	0.175***	0.962***	0.748***
	(0.098)	(0.164)	(0.024)	(0.038)	(0.038)	(0.056)	(0.106)	(0.112)
Bank Capitalization	1.965	−1.050	0.241	−0.122	−0.396	−0.475	3.264	0.833
	(2.095)	(3.040)	(0.525)	(0.825)	(0.742)	(1.245)	(2.733)	(1.781)
Time Trend	−0.010**	−0.028***	0.007***	0.003	−0.001	−0.004**	0.015***	−0.011**
	(0.005)	(0.006)	(0.001)	(0.002)	(0.001)	(0.002)	(0.005)	(0.005)
Observations	12,821	11,499	12,821	11,499	12,821	11,499	12,821	11,499
Adj. R-squared	0.793	0.598	0.398	0.322	0.629	0.518	0.681	0.423

Notes: This table reports regression estimates for equation (1), with each column showing the results for a different dependent variable. All dependent variables are in logs. "Commit" refers to commitment loans and "Spot" refers to spot loans. "Sum" indicates the sum of the contemporary and lagged coefficients. The robust standard errors clustered by bank are shown in parentheses with *, **, and *** indicating significance at 10 percent, 5 percent, and 1 percent, respectively.

Table 3. Effect of Monetary Policy on Bank Loan Supply: Difference in Coefficients on the Real Funds Rate

Regression	Spot Coefficient − Commit Coefficient
Total Lending	0.105**
	(0.045)
Loan Maturity	−0.033***
	(0.012)
Loan Size	0.023
	(0.016)
Total Lending * Loan Maturity	−0.082**
	(0.041)

Notes: Tests are based on coefficients in table 2. We report the difference between the coefficients on the real funds rate in the spot loan regressions and the coefficients in the commitment loan regressions. The standard error of a test for whether that value is significantly different from zero is shown in parentheses. *, **, and *** indicate significance at 10 percent, 5 percent, and 1 percent, respectively.

shows the difference in the coefficients on monetary policy across commitment and spot loans for each dependent variable.

5.1 Baseline Results

The regression results for total lending are shown in the first two columns of table 2. When commitment lending is the dependent variable, the sum of the funds rate coefficients, our measure of monetary policy, equals –0.053, which is significantly different from zero at the 10 percent level. This indicates that loan demand decreases somewhat in response to tighter monetary policy, which is consistent with the interest rate channel. The effect of monetary policy on spot lending is less clear. When spot lending is the dependent variable, as reported in column 2, the sum of coefficients on the funds rate variable, 0.052, is not significantly different from zero. To identify the effect on loan supply, we discuss the difference in these coefficients in table 3.

The other coefficients in the first two columns, when significant, are consistent with expectations. The real economy variables—GDP growth and unemployment—show that commitment lending increases when economic growth is high and unemployment is low. Commitment lending also tends to be lower with a steeper yield curve and the increased tightening of bank underwriting standards. Not surprisingly, the evidence is consistent with larger banks originating more total loans. The coefficients on the time trend show that the amount of spot lending is decreasing relative to commitment lending over time.

The results in columns 3–6 in table 2 suggest that monetary policy affects the average maturity of loans and average loan size. The coefficients reported for the loan maturity regressions are consistent with tighter monetary policy leading firms to draw longer-maturity commitment loans (the sum of the funds rate coefficients in column 3 is 0.031) but to take weakly shorter-maturity spot loans (the funds rate coefficient sum is –0.002 in column 4). When loan size is the dependent variable, the coefficients on the federal funds rate for spot loans indicate that tighter monetary policy leads to larger spot loans. If loan size serves as a reasonable proxy for firm size, monetary policy may have some effect on the allocation of credit across firms of different sizes.

To estimate the net effect of a change in monetary policy on loan supply, we use the product of total lending and loan maturity as the dependent variable. We discuss this further below, but for now, columns 7 and 8 show the results of the baseline model using this as the dependent variable. Tighter monetary policy increases commitment lending but has no effect on spot lending.

5.2 Banks' Spot Lending Relative to Commitment Lending

Although the above results are of interest, our analysis is focused primarily on the differences between the spot and commitment loan regressions. Following our identification strategy, we use these differences to estimate of the effect of monetary policy on bank loan supply. For a given variable, the coefficients from the spot loan regression minus the coefficients on the commitment loan regression is our estimate of the marginal effect on supply of a change in that variable. The marginal supply effects are shown in table 3, for each of the four dependent variables.

We find that the banks increase total lending when monetary policy tightens. The difference between the spot and commitment coefficients on the federal funds variables in the regressions in columns 1 and 2 in table 2, reported in the first row in table 3, is 0.105, which is significantly different from zero at the 5 percent level. This implies, perhaps surprisingly, that the flow of lending banks that are willing to supply increases when monetary policy tightens (consistent with the findings of den Haan, Summer, and Yamashiro 2007, for C&I lending). But, if tighter monetary policy reduces the maturity of loans banks supply, then an increase in the *flow* of lending may not lead to an increase in the *stock* of loans outstanding.

Our results indicate that, indeed, loan maturity decreases significantly when monetary policy tightens. Specifically, the difference between the spot and commitment coefficients in the loan maturity regressions is –0.033, which is statistically significant at the 1 percent level. This can be thought of as an inward shift in the loan supply curve along the dimension of maturity rather than quantity, which is consistent with a bank lending channel. This finding is consistent with the liquidity version of the lending channel in Diamond and Rajan (2006). The result is also economically significant—a 1-percentage-point increase in the federal funds rate reduces the average maturity of loan supply by 3.3 percent.

The increase in total lending is not because banks are more willing to make larger loans. We do not find a significant difference in the real funds rate coefficients for spot and commitment lending for the loan size regression. If loan size serves as a reasonable proxy for firm size, this implies that there is not a significant redistribution of loan supply across small and large firms. Based on this proxy, the loan size results would suggest that the balance sheet channel is relatively weak.

The results with total lending times loan maturity as the dependent variable are reported in columns 7 and 8 in table 2 and the final row in table 3. Focusing on the final row in table 3, we find that the monetary policy coefficients are significantly smaller in the spot loan regression than in the commitment loan regression, with a difference of –0.082. The difference in coefficients on the funds rate variables can be interpreted as the percent change in bank loan supply with a 1-percentage-point change in the (steady-state) funds rate. So, a 1-percentage-point increase in the funds rate would decrease bank loan supply by 8.2 percent. Thus, changes in monetary policy have economically significant effects on loan supply.

This last set of results (the product of total lending and loan maturity) is particularly important, because it gives the most complete picture of the effect of monetary policy on bank loan supply. Unlike total lending, which only captures the dollar amount of bank lending, this measure captures the amount and *duration* of lending. The negative difference in coefficient suggests that loan supply at a typical bank contracts with monetary tightening even if the flow of new loans does not shrink. The key factor appears to be the change in loan maturity since banks react to tightening by reducing loan maturity. We believe these results highlight an effect of monetary policy on bank loan supply that is not directly observable in total lending. Our evidence for a bank lending channel in C&I lending extends beyond prior work by providing evidence on how monetary policy affects the allocation of loan supply *within* C&I lending.

5.3 Robustness

In this subsection, we address two possible concerns about the robustness of our results. Our baseline results could be affected by debt market timing and the potential endogeneity of the federal funds rate. Based on additional analysis of the data, we find that our results are robust.

One potential limitation to our approach would be changes in firms' demand for fixed- versus floating-rate debt, known as debt market timing. Firms' relative demand for fixed-rate debt has been shown to move with the term structure of interest rates and with bond risk premia (Baker, Greenwood, and Wurgler 2003; Vickery 2008). To see whether it matters if the interest rate on a loan is fixed, we split our sample into fixed- and floating-rate loans and analyze spot lending relative to commitment lending within each subsample. The results are shown in table 4. We find that the supply of fixed-rate loans is sensitive to monetary policy but the supply of floating-rate loans does not change much, either in a statistical or economic sense, when monetary policy changes. In particular, when monetary policy tightens, fixed-rate loan maturity shortens and there is a shift in the flow of lending from fixed-rate loans to floating-rate loans.

Table 4. Effect of Monetary Policy on Bank Loan Supply, by Type of Loan

Regression	Fixed Rate: Spot Coefficient − Commit Coefficient	Floating Rate: Spot Coefficient − Commit Coefficient
Total Lending	0.083**	0.079
	(0.038)	(0.051)
Loan Maturity	−0.075**	−0.019
	(0.030)	(0.013)
Loan Size	0.002	0.062***
	(0.011)	(0.022)
Total Lending * Loan Maturity	−0.128***	0.009
	(0.036)	(0.039)

Notes: This table reports results based on regression estimates for equation (1) where the sample is split into fixed-rate and floating-rate loans. The regressions include the same variables as in table 2. We report the difference between the coefficients on the real funds rate in the spot loan regressions and the coefficients in the commitment loan regressions. The standard error of a test for whether that value is significantly different from zero is shown in parentheses. *, **, and *** indicate significance at 10 percent, 5 percent, and 1 percent, respectively.

This may occur because when monetary policy tightens, firms are more likely to put off large, discrete projects (presumably financed with fixed-rate loans) than they are to significantly reduce working capital (often financed with floating-rate loans). Since roughly two-thirds of lending in our sample is fixed rate (table 1), the changes are consistent with the significant effect on supply we report in the full-sample results in tables 2 and 3.

We use the real federal funds rate as our baseline measure of U.S. monetary policy because it directly indicates the decisions of the Federal Open Market Committee (FOMC) during our sample period. However, as shown by the Taylor rule, monetary policymakers respond to economic conditions, potentially making the target funds rate an endogenous variable (Taylor 1993). The Taylor rule is a policy rule for modeling the relationship of the funds rate to the inflation and output gaps. To address the endogeneity concern, we have also run our regressions using the Taylor residuals as our

Table 5. Effect of Monetary Policy on Bank Loan Supply Using Taylor Residuals

Regression	Spot Coefficient − Commit Coefficient
Total Lending	0.076
	(0.053)
Loan Maturity	−0.076**
	(0.035)
Loan Size	−0.031
	(0.020)
Total Lending * Loan Maturity	−0.119**
	(0.053)

Notes: This table reports results based on regression estimates for equation (1) where Taylor residuals are used as the measure of monetary policy. The regressions include the same variables as in table 2. We report the difference between the coefficients on the real funds rate in the spot loan regressions and the coefficients in the commitment loan regressions. The standard error of a test for whether that value is significantly different from zero is shown in parentheses. *, **, and *** indicate significance at 10 percent, 5 percent, and 1 percent, respectively.

measure of monetary policy.[23] This is an alternative approach to Jimenez et al. (2012), who use monetary policy determined outside the country. See Maddaloni and Peydro (2011) for a similar approach.

Table 5 shows the results for the difference in coefficients on Taylor residuals for spot loans and commitment loans. The Taylor residuals provide exogenous variation in the stance of monetary policy by measuring the difference between the actual federal funds rate and the funds rate predicted by the Taylor rule. In other words, a positive residual indicates that the funds rate is higher than the Taylor rule would predict. We find that the results are qualitatively similar to our baseline results.

[23] Our Taylor residual regressions are only run through 2008:Q3, which is when the nominal federal funds rate reached zero. A simple Taylor rule does not account for the zero lower bound. Results for the Taylor-rule regressions run for our entire sample period are qualitatively similar in magnitude to those reported but with weaker statistical significance.

6. Differences in the Strength of the Credit Channel across Banks

The credit channel literature has focused on bank size as an important factor in determining the sensitivity of loan supply to monetary policy. However, despite the number of empirical articles comparing lending sensitivities across bank sizes, the theoretical prediction for a small-versus-large bank comparison is not well established. Small banks likely face greater information frictions on the liability side of their balance sheet, while large banks likely face greater information frictions on the asset side of their balance sheet. On the liability side, Stein (1998) shows that uninsured forms of bank finance are subject to adverse selection. Therefore, smaller banks, which tend to be less transparent than large banks, may face greater costs of raising external funds during periods of tight monetary policy. This implies that small-bank loan supply should be more sensitive to changes in monetary policy. On the asset side, Stiglitz and Weiss (1981) show that agency problems in lending increase with the interest rate charged to borrowers, which implies that agency problems are greater during periods of tight monetary policy. Stein (2002) shows that large banks are not as effective as small banks at overcoming agency problems in lending. This could mean that large-bank loan supply is also sensitive to changes in monetary policy.

The difference in the transmission of monetary policy through large and small banks could reflect differences in large- and small-bank characteristics. For instance, bank capital and deposit funding could play a key role in the credit channel (Diamond and Rajan 2006, 2011), as shown empirically in papers such as Kishan and Opiela (2000) and Black, Hancock, and Passmore (2007). Kashyap and Stein (2000) analyze the effect of balance sheet liquidity, building on earlier work that analyzes the sensitivity of bank lending to monetary policy for different bank sizes under the hypothesis that large banks face lower costs of external financing (Kashyap and Stein 1995). We focus on bank size as a basic proxy for other forms of bank heterogeneity.

To test whether a bank's size affects the way it reacts to monetary policy changes, we split our sample between large and small banks. "Small" banks have average total assets over the sample period of less than or equal to \$10 billion, while all other banks are considered

Table 6. Effect of Monetary Policy on Bank Loan Supply, by Bank Size: Regression Estimates

	Commitment Loans	Spot Loans
	Funds Rate Coefficient	**Funds Rate Coefficient**
Small Banks		
Total Lending	0.001	0.013
Loan Maturity	0.037***	0.011
Loan Size	0.016	0.012
Total Lending * Loan Maturity	0.117***	0.029
Large Banks		
Total Lending	−0.133***	0.078
Loan Maturity	0.026***	−0.015
Loan Size	−0.015	0.036
Total Lending * Loan Maturity	0.136**	0.046

Notes: This table reports the coefficients on the real federal funds rate for equation (1) split by bank size. "Small" banks have average total assets over the sample period of less than or equal to $10 billion, while all other banks are considered "large" banks. The dependent variables listed in the first column are in logs. "Spot" refers to spot loans and "Commit" refers to commitment loans. "Funds Rate Coefficient" refers to the coefficients labeled as Real Funds Rate (Sum) in table 2, with *, **, and *** indicating significance at 10 percent, 5 percent, and 1 percent, respectively. The small-bank regressions have between 5,169 and 7,115 observations, while the large-bank regressions have between 4,756 and 5,706 observations.

"large" banks.[24] We use a more restrictive definition of large banks than is common. The $10 billion threshold allows us to ensure that the large banks in our sample have the low-cost access to financing present in the arguments of Kashyap and Stein (1995) and Stein (1998). In our full sample, there are 143 small banks and 87 large banks.

Tables 6 and 7 present results of the baseline regressions with the sample split into small and large banks. To simplify the presentation, in table 6, we give the coefficients for the federal funds rate variable

[24] A bank is either small or large for the entire sample. Asset size is based on real assets in 2007 dollars.

Table 7. Effect of Monetary Policy on Bank Loan Supply, by Bank Size: Difference in Coefficients on the Real Funds Rate

Regression	Small Banks	Large Banks
	Spot Coefficient − Commit Coefficient	**Spot Coefficient − Commit Coefficient**
Total Lending	0.012	0.211**
	(0.042)	(0.084)
Loan Maturity	−0.027	−0.041**
	(0.018)	(0.016)
Loan Size	−0.004	0.051*
	(0.014)	(0.031)
Total Lending * Loan Maturity	−0.088**	−0.090
	(0.041)	(0.077)

Notes: Tests are based on coefficients in table 6. We report the difference between the coefficients on the real funds rate in the spot loan regressions and the coefficients in the commitment loan regressions, and the standard error of a test for whether that value is significantly different from zero. This is done separately for small and large banks.

only, but the underlying regressions include all the controls used in the prior regressions. These results are provided primarily for reference, because our methodology focuses on the differences between spot and commitment lending. Table 7 reports the results of tests on the difference between the spot and commitment coefficients on the real federal funds rate for each of the dependent variables.

For both small and large banks, the pattern is qualitatively similar to the full-sample results. As can be seen in table 7, there is an increase in lending and a shortening in the average maturity of banks' loan supply when monetary policy tightens, although the differences are only significant for large banks. Our overall result, the product of total lending and loan maturity, shows a decline in the availability of credit with a tightening of monetary policy, but this time the result is only significant for small banks (but the magnitudes are virtually the same for large banks as for small banks).

Our results for small banks are generally consistent with previous findings indicating that small banks are sensitive to the credit channel (Kashyap and Stein 1995, 2000; Zaheer, Ongena, and van Wijnbergen 2013). To compare our results more directly with Kashyap and Stein (2000), we also interacted the federal funds rate with each bank's ratio of liquid assets to total assets. We find that the interaction does not have a significant effect on our measure of overall loan supply for either small or large banks.

Our results for large banks illustrate the importance of considering effects on loan maturity. The large-bank results based on total lending suggest that large banks increase their loan supply when monetary policy is tightened; however, this hides the reduction in the maturity of loans supplied. Our analysis shows that results based on total lending can hide significant shifts in credit allocation over the monetary policy cycle.

7. Conclusion

We find that changes in monetary policy have an effect on bank loan supply and the distribution of banks' loan supply. A contribution of the paper is the identification of a *redistribution* in loan supply across loans of different maturities. In response to a monetary tightening, banks reduce the average maturity of their loan supply, which effectively reduces loan supply over time. This is consistent with the liquidity theory of Diamond and Rajan (2006), who predict that long-term lending is sensitive to monetary policy due to banks' short-term funding. A 1-percentage-point increase in the federal funds rate—our primary measure of monetary policy tightening—reduces the average maturity of loan supply by 3.3 percent, contributing to an 8.2 percent decline in the steady-state loan supply at a typical bank. Therefore, our paper shows that loan maturity is an important transmission mechanism of monetary policy through the bank lending channel.

In addition, we find evidence that the distribution of loan supply at both small and large banks is sensitive to monetary policy. In particular, we show that the channel is not limited to small banks. This suggests that these effects will continue to play an important role even with the ongoing consolidation of the banking system.

In the context of the recent financial crisis, our results show that monetary loosening can have a mitigating effect on a "credit crunch." We find that lowering the federal funds rate increases the average maturity at which credit is made available. This can improve the availability of financing for projects at longer maturities, which can have a large impact on the real activity of firms.

The results also suggest that monetary tightening can have a dampening effect on bank loan supply. Banks appear to reduce the amount of maturity transformation through the banking sector when the federal funds rate increases. This implies that future rate increases during an economic recovery should be undertaken with an acknowledgment of the potential reduction in credit availability over time, especially at longer maturities.

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Shoe-Leather Costs in the Euro Area and the Foreign Demand for Euro Banknotes*

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We estimate the shoe-leather costs of inflation in the euro area using monetary data adjusted for holdings of euro banknotes abroad. While we find evidence of marginally negative shoe-leather costs for very low levels of the nominal interest rate, our estimates suggest that the shoe-leather costs are non-negligible even for relatively moderate levels of anticipated inflation. We conclude that, despite the increased circulation of euro banknotes abroad, in the euro area the inflation tax is still predominantly borne by domestic agents, with transfers of resources from abroad remaining small.

JEL Codes: E41, C22.

1. Introduction

It is estimated that as much as 25 percent of the euro currency circulates outside the euro area (European Central Bank 2011, 2013). Bartzsch, Rösl, and Seitz (2013a) estimate that this share could be as high as 45 percent for the euro banknotes issued in Germany, given the important role of the Deutsche Bundesbank in servicing large banks active in the global currency market. The fact that a significant share of the euro currency circulates abroad may have

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implications for the calculation of the "shoe-leather" costs of inflation. These are the inflation-related welfare costs arising when agents inefficiently manage their money holdings for transaction purposes because of the tax on monetary balances implied by expected inflation.[1] Bailey's (1956) traditional methodology to compute the shoe-leather costs consists of measuring the area underlying the inverse money demand function, which in turn represents the lost consumer surplus that could be gained by reducing the steady-state nominal interest rate from a positive value to zero. The intuition is that anticipated inflation leads to higher opportunity costs of holding money via its impact on the nominal interest rate, thereby driving the demand for monetary balances below its optimal level.

Widespread circulation of a currency abroad can affect the accuracy of Bailey's welfare cost measures since, as noted by Schmitt-Grohé and Uribe (2012), in an economy characterized by strong foreign demand for its domestic currency, the inflation tax is to a large extent borne by foreign rather than domestic residents, which implies transfers of real resources from abroad. Consistently with this observation, Calza and Zaghini (2011) show for the United States that failure to control for the amount of U.S. dollars abroad may lead to over-estimating the shoe-leather costs borne by domestic residents. More precisely, using M1 data adjusted for the circulation of U.S. dollars abroad, they obtain significantly lower estimates of the shoe-leather costs than previous studies (such as Fischer 1995, Gillman 1995, Lucas 2000, and Ireland 2009).[2] In addition, the authors find that in the United States the shoe-leather costs are minimized—at *negative* levels—for moderate inflation rates close to the values currently targeted by the Federal Open Market Committee members, rather than for the deflation rate implied by the Friedman rule.

The aim of this paper is to apply Bailey's approach to estimate the shoe-leather costs of inflation for the euro area, using monetary

[1] See Driffill, Mizon, and Ulph (1990) and Fischer (1995) for a comprehensive analysis of inflation-related sources of welfare costs (e.g., high risk premia, the interaction between inflation and the tax code, inefficient distraction of resources from production of goods to financial activities).

[2] In particular, Calza and Zaghini (2011) estimate the costs of a 10 percent inflation rate at just 0.05 percent of GDP per year in perpetuity and the welfare gains from moving from 10 percent inflation to price stability at about 0.1 percent of annual GDP.

data adjusted for euro banknotes in circulation abroad. In particular, we are interested in assessing whether the foreign demand for euro banknotes is large enough to generate substantial transfers of resources from abroad. To preview our results, we find that on the one hand, the shoe-leather costs in the euro area are non-negligible even at moderate levels of the nominal interest rate; on the other hand, the transfer of resources from abroad, while leading to marginally negative shoe-leather costs of inflation, are not able to offset the distortionary impact of inflation so that the tax on monetary balances stemming from euro-area inflation continues to be borne predominantly by domestic agents.

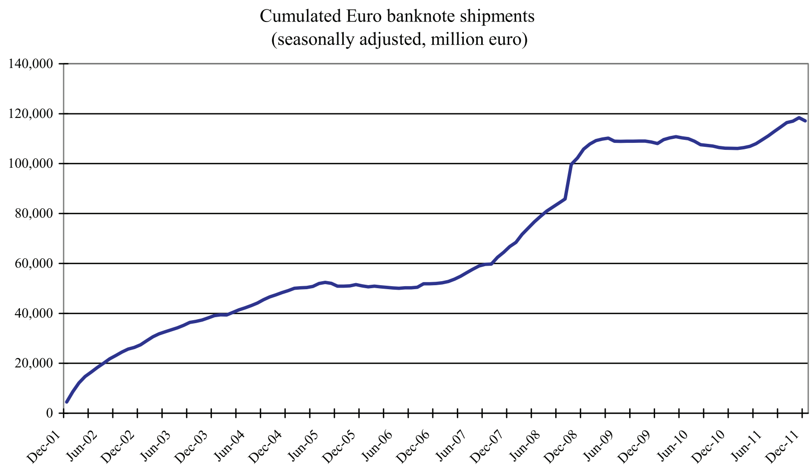
2. Euro Banknotes Abroad

The empirical exercise is based on estimates of the demand for the narrow monetary aggregate M1 adjusted for the circulation of the euro currency abroad over the period between the introduction of the euro banknotes and coins in 2002 and 2011. Official data on the notional stock of M1 are available at the monthly frequency and on a seasonally adjusted basis from the Statistical Data Warehouse of the European Central Bank (ECB). These official data include all currency in circulation, regardless of the country of residence of the holder, and therefore over-estimate the holdings of currency by domestic agents. In order to correct the data for this measurement error, we need an equally long time series of the estimated value of the euro currency circulating abroad.

The ECB publishes monthly estimates of the amount of the euro currency held by non-euro-area residents using the shipments-proxy method proposed by Feige (1994, 1997).[3] This method focuses on the cumulated flows of net shipments abroad of domestic banknotes through the banking sector. In the case of the euro area, total net shipments are given by the sum across the area's member countries of net shipments by monetary and financial institutions (MFIs) to non-euro-area countries. According to the data on net shipments, Germany accounts for the largest share (76 percent) of total net

[3]See ECB (2013). The Federal Reserve Board has also implemented the shipments-proxy method to provide estimates of U.S. dollars circulating abroad in its Flow of Funds Accounts.

Figure 1. ECB Estimates of the Euro Currency Held Abroad



Source: ECB, own calculations.

exports of euro banknotes, followed by France (14 percent) and Italy (6 percent). The main net importer is Austria, with a negative share of around 30 percent.

As figure 1 shows, the estimated amount of euro currency circulating abroad has tended to rise over the past few years. In particular, it increased gradually after the cash change-over in 2002 and then stabilized over the period 2005–6. The demand for euro currency from abroad significantly increased right after the outbreak of the financial crisis in the summer of 2007 and stabilized again at just below EUR 110 billion after the collapse of Lehman Brothers. However, in 2011 the further deterioration of the financial crisis led to a new increase of shipments of euro notes abroad, probably as a result of the relatively larger deterioration of trust in local currencies in some Eastern and Central European countries (see Beckmann and Scheiber 2012).

At the end of 2011, the estimated share of euro banknotes in circulation outside the euro area amounted to 14 percent of the total. Nevertheless, ECB (2013) warns that the estimates of euro currency abroad based on the net-shipments approach represent lower-bound figures, since MFIs are only one among a number of channels through which euro banknotes are shipped outside the euro area. Indeed, anecdotal evidence suggests that other channels, such as tourism or workers' remittances, are often more important. Overall, ECB (2011, 2013) estimates that the actual share of euro currency abroad could be as high as 25 percent, with the highest use in the Western Balkans and significant amounts in Russia and in Northern African countries.[4] This figure is broadly consistent with estimates by Bartzsch, Rösl, and Seitz (2013a, 2013b) showing that around 45 percent of all banknotes issued by Germany (which accounts for the very large majority of net shipments of euro banknotes outside the euro area) are held by non-euro-area residents.

3. Shoe-Leather Costs and Money Demand

Before presenting the results of the empirical exercise, we briefly recall Bailey's (1956) approach to measuring the shoe-leather costs of inflation. This approach consists of calculating the integrals of the inverse money demand function (i.e., expressed as a function of the nominal interest rate, r) on the interval $[0, r]$, to measure the consumer surplus lost by agents who inefficiently forgo monetary services because of anticipated inflation. These welfare triangles are calculated net of seigniorage revenues.

A limitation of the Bailey's methodology is that it follows a partial equilibrium approach, which does not allow to show how the demand for monetary assets can be endogenously derived as a function of technology and preferences. However, Cysne (2009) shows that Bailey's formula can be obtained as an exact general equilibrium measure of the welfare costs of inflation under the assumption of quasi-linear preferences. Cysne (2011) extends this result to an economy with several types of money.

Calza and Zaghini (2011) argue that in the presence of foreign holdings of the domestic currency, the correct specification of the welfare triangle $w(r)$ becomes

[4]Similarly, a recent study by Feige (2012) using the net-shipments approach estimates the share of U.S. currency abroad at around 30–37 percent. However, a study by Judson (2012) using several alternative methods concludes that the actual figure is half or slightly more than half of total U.S. currency. Using various methods, Leung, Ng, and Chan (2010) estimate that between 50 percent and 70 percent of the Hong Kong dollar in circulation in 2009 was held abroad.

$$w(r) = \int_0^r m^h(x)dx - rm(r), \tag{1}$$

where $m^h(x)$ denotes the inverse money demand function of domestic residents, r stands for the nominal policy interest rate, and $rm(r)$ indicates total seigniorage revenues (including also the revenues stemming from currency holdings abroad). If the money demand functions are specified in terms of money-to-income ratios, $w(r)$ can be interpreted as the fraction of income forgone by agents because of a steady-state non-zero nominal interest rate r.[5]

The key difference compared with the standard specification of the welfare triangles (which assumes that all money is held domestically) regards the distinction between the domestic measure of money ($m^h(x)$) used to compute the inflation-related utility losses and the total aggregate used to calculate the seigniorage revenues ($m(x)$).[6] Indeed, domestic residents incur utility losses only to the extent that their demand for monetary services is distorted by inflation. However, the government obtains seigniorage revenues from the entire amount of money that is issued, regardless of the country of residence of its holders.

It should be noted that the welfare triangle (1) is derived assuming that money is entirely non-remunerated, though the deposits included in money are typically (implicitly or explicitly) interest rate bearing. Due to unavailability of statistics on the own rate of M1, we maintain this assumption in the empirical analysis. However, Cysne and Turchick (2010) show that, under certain conditions, failure to account for interest-rate-bearing deposits may induce some upward bias in the estimates of the shoe-leather costs.[7]

In order to compute the welfare measures, in the next section we estimate the equilibrium money demand equation from euro-area domestic residents. Consistent with the literature (see Sriram 2000;

[5]See Lucas (2000). Cysne (2009) shows that this interpretation of $w(r)$ is consistent with Bailey's (1956) original definition.

[6]The standard formula abstracts from foreign holdings of domestic currency and assumes that money is entirely held by the home residents: $m^h(.) = m(.)$.

[7]We assume that the money demand adjusted for currency abroad is entirely used for transactions purposes. However, as noted by an anonymous referee, some of the cash may be hoarded (see Bartzsch, Rösl, and Seitz 2013a, 2013b), while some of the deposits may be demanded as investment instruments. We are grateful to the referee for pointing this out.

Duca and Vanhoose 2004), we estimate the relationship in a cointegration analysis framework, in which long-run domestic demand for real balances (m^h) is typically assumed to be a function of a reference interest rate (r) and a measure of the volume of real transactions (y). More precisely, our money demand equation is specified in a semi-logarithmic form:

$$\ln(m^h) = \ln(B) + \beta \ln(y) - \xi r, \tag{2}$$

where $B > 0$ is a constant, β is the elasticity with respect to the transaction variable, and ξ denotes the absolute value of the interest rate semi-elasticity.

4. Empirical Analysis

4.1 Money Demand Estimates

For the purpose of the estimation, we use monthly seasonally adjusted data on notional stocks of M1 adjusted for currency abroad sourced from the ECB as our measure of money (m^h). The volume of transactions is measured by GDP sourced from Eurostat and converted from the quarterly to the monthly frequency using the Chow-Lin interpolation procedure based on euro-area industrial production. Both nominal GDP and the monetary data are deflated by the GDP deflator. Two different interest rates are considered: the Euro Overnight Index Average (EONIA) and the three-month Euro Interbank Offered Rate (EURIBOR). Prior to the crisis, most empirical studies used the EURIBOR rate as a proxy for the ECB policy rate. In the course of the crisis, concerns have emerged about the accuracy and reliability of this rate. Therefore, we also consider the EONIA, an effective rate which has been seen in the past as an implicit operational target for the implementation of monetary policy in the euro area.

As a preliminary step, the statistical properties of the variables (both in level and in log format) are examined using standard unit-root tests (augmented Dickey-Fuller and Phillips-Perron) as well as the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test. The results—not reported for the sake of brevity—suggest that over the sample period from January 2002 to December 2011 all the variables can be modeled as I(1) in levels.

Table 1. Phillips-Ouliaris Cointegration Test

$\ln(m^h) = \ln(B) + \beta\ln(y) - \xi r$					
$\hat{\beta}$	$\hat{\xi}$	$\hat{\rho}$	q	Z_ρ	Z_t
A. EONIA					
3.2953	6.3573	0.7653	4	−26.702**	−3.717**
			5	−28.051***	−3.806***
			6	−29.883***	−3.924***
			7	−30.514***	−3.964***
			8	−31.636***	−4.034***
B. EURIBOR					
3.6337	6.2845	0.8032	4	−22.273*	−3.498*
			5	−22.790*	−3.534**
			6	−23.885**	−3.610**
			7	−24.264**	−3.636**
			8	−24.626**	−3.661**

Notes: *, **, and *** denote statistical significance at the 15 percent, 10 percent, and 5 percent critical level, respectively. The panels show the estimated coefficients using OLS, the slope coefficient $\hat{\rho}$ from an OLS regression of the error term on its own lagged values, and the Phillips-Ouliaris statistic for $\rho = 1$ corrected for autocorrelation in the residual with the Newey-West procedure for various values of the lag truncation parameter q. Critical values as in case 3, tables B.8 and B.9 of Hamilton (1994).

We then test for the existence of an equilibrium money demand relationship using the residual-based cointegration tests by Phillips and Ouliaris (1990). These tests are conducted by applying the Phillips-Perron Z_ρ and Z_t unit-root tests to the residuals of the equilibrium equation (2) estimated with OLS (with the test statistics computed for different values of the truncated lag q in the Newey-West estimator of the error covariance matrix). Under the null hypothesis ($\rho = 1$) the residuals contain a unit root and the equation fails to represent a cointegrating relationship. The results of the tests reported in table 1 provide evidence of cointegration at the conventional significance levels for the specification using the EONIA (at the 5 percent significance level for values of the truncated lag q equal to or greater than 5 and at the 10 percent level for $q = 4$). The evidence of cointegration is slightly weaker (at the 10 percent

Table 2. Estimated Long-Run Interest Rate Coefficients

$\ln(m^h) = \ln(B) + \beta\ln(y) - \xi r$		
	$\hat{\beta}$	$\hat{\xi}$
EY(1)	3.2949***	6.0446***
	(0.001)	(0.822)
DOLS(4,4)	3.5133***	6.1936***
	(0.074)	(0.215)
GLS(1)	2.2208***	5.0109***
	(0.301)	(0.513)

Notes: Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10 percent, 5 percent, and 1 percent critical levels, respectively. Number of lags (and leads for DOLS) in levels are reported next to the estimator. The lag specification of the models (as well as of the leads in the case of the dynamic OLS) is based on the Schwarz and Hannan-Quinn information criteria.

critical level for $q \geq 5$) when the EURIBOR rate is used instead. Nevertheless, the results of the analysis are overall supportive of the hypothesis of cointegration.

Based on the results of the cointegration analysis, we focus on the specification using the EONIA rate and proceed to estimate the equilibrium relationship between the real monetary balances (adjusted for currency abroad), the real transaction variable, and the nominal interest rate using three alternative estimators: (i) Engle and Yoo's (1991) "three-step" approach to the Engle-Granger estimator, (ii) the dynamic OLS (DOLS) method by Saikkonen (1991), and (iii) the generalized least squares (GLS) estimator corrected as in Choi, Hu, and Ogaki (2008).

The estimated long-run coefficients for both the scale variable and the interest rate are statistically significant at the conventional levels, regardless of the estimation procedure used (table 2). In addition, the signs of the coefficients are consistent with the interpretation of the cointegrating vectors as equilibrium money demand relationships.[8] The estimated coefficients tend to be consistent across estimators, suggesting that the results are fairly robust to the choice

[8]In the rest of the exercise, the value of the intercept B is calibrated as in Lucas (2000) so that it equals the average value over the sample of $my^{\beta}e^{-\xi r}$.

of econometric methodology. The application of Nyblom tests for parameter constancy of the cointegrating vector as extended to cointegrated systems by Hansen and Johansen (1999) suggest that the long-run parameters are fairly stable over the sample period considered.[9] In the rest of this paper, we will use the DOLS estimates for the computation of the welfare measures.

4.2 Shoe-Leather Costs of Inflation

After substituting the estimated parameters into (1) and solving the integral, the welfare cost measure for a given level of r takes the following form[10]:

$$w(r) = \frac{\widehat{B}}{\widehat{\xi}} y^{\widehat{\beta}-1}\left(1 - e^{-\widehat{\xi} r}\right) - rm(r). \tag{3}$$

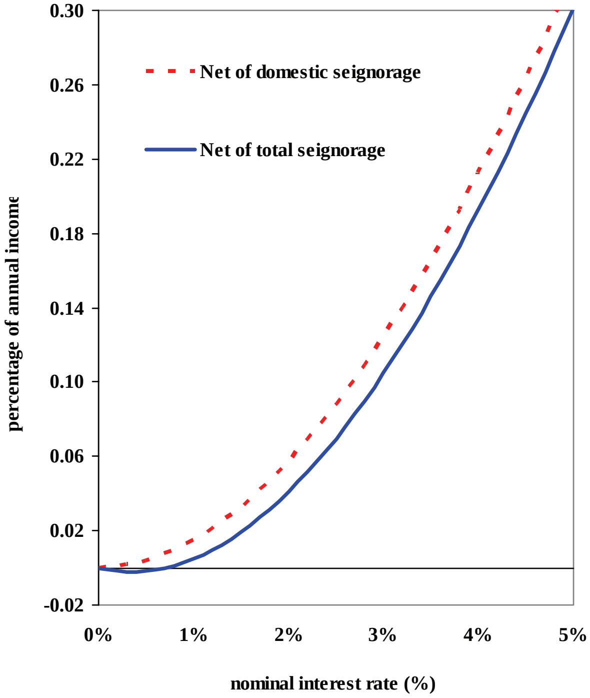
When the elasticity of money with respect to the transaction variable (β) is statistically different from one (as is the case in our estimates), a value of the transaction variable must be specified so as to calculate the welfare costs (Gillman 1995). In order to ensure that the welfare calculations at different inflation levels are time independent, the level of the transaction variable is usually set at its average value over the sample period.[11] Before presenting the results, it should be mentioned as a caveat that the sample period for the analysis covers a period in which anticipated inflation and nominal interest rates remained at relatively low levels. For instance, the EONIA averaged 2.2 percent. Therefore, the estimated shoe-leather function may be less appropriate to assess the welfare impact of high inflation and nominal interest rates.

[9]The null hypothesis of the tests—which are respectively based on the mean (Mean) and the maximum (Sup) of a weighted LM-type statistic over the sample period—is the joint stability of the parameters of the cointegrating vector. The Mean and Sup test statistics yield 0.26 (p-value = 0.33) and 1.14 (p-value = 0.17), respectively. The distributions of the tests are bootstrapped using 1,000 replications. The computations are performed using the program Structural VAR, version 0.19, by Anders Warne (downloadable from http://www.texlips.net/svar).

[10]Note that in order to compute the seigniorage revenues, we also need to substitute in (1) the parameters of $m(r)$, the money demand estimated over the same time period for the whole M1 (i.e., including currency abroad). DOLS coefficients are used in the paper, but results are robust to the estimation method employed.

[11]The results are not affected when alternative reference values are used.

Figure 2. Estimated Shoe-Leather Costs



The continuous line in figure 2 shows the shoe-leather costs net of total seigniorage revenues as a function of the nominal interest rate. As usual, the shoe-leather costs are convex in the nominal interest rate and increase rather steeply for values of the steady-state nominal interest rate r above 2 percent. At the same time, the shoe-leather cost function is rather flat at around 0 percent for values of r within the [0,1] interval.[12] While the function lies below the x-axis for some points within this interval—thereby signaling negative shoe-leather costs—the deviations from zero are very limited in size.

[12]The steady-state nominal interest rate can be translated into the equivalent inflation rate, provided that an estimate of the natural rate of interest is available. Mésonnier and Renne (2007) estimate that the natural rate of interest in the euro area was very low—at around 0.5 percent—just before the crisis, suggesting that values of the nominal interest rate within the [0,1] interval may be close to a zero-inflation regime.

These results for the euro area somewhat differ from those in Calza and Zaghini (2011), who provide evidence of small but persistently negative shoe-leather costs in the United States for values of the nominal interest rate up to 11 percent. In the case of the United States, the negative shoe-leather costs can be explained by the fact that in the presence of substantial foreign demand for the U.S. dollars, the consumer loss because of the inflation-related money demand distortions is more than compensated by the seigniorage revenues extracted from the foreign holders of U.S. dollars.

Our results suggest that in the euro area, where foreign demand for the euro currency (as a proportion of the total aggregate) is still significantly lower than in the United States, the seigniorage revenues extracted from foreign residents are significant enough to drive the shoe-leather costs function below zero for a narrow range of values of the interest rate, but not large enough to offset in a meaningful way the disutility to euro-area agents stemming from positive inflation. In order to illustrate this result, the dotted line in figure 2 represents the shoe-leather costs under the counterfactual of no foreign demand for euro banknotes.[13] The relatively limited gap between the two lines in figure 2, which provides an estimate of the amount of resources transferred from abroad, suggests that in the euro area the inflation tax continues to be borne almost entirely by the domestic agents. The estimated shoe-leather costs do not significantly change when the data set is extended to include data for 2012 and early 2013.

These estimates can also be used to illustrate the impact of the financial crisis on the shoe-leather costs in the euro area. Between the introduction of the euro banknotes in 2002 and the start of the crisis in the summer of 2007, the EONIA rate averaged about 2.7 percent, equating to a shoe-leather cost of 0.08 percent of annual GDP in perpetuity. At the peak of the crisis, the EONIA rate stood at 4.3 percent and the corresponding shoe-leather cost rose to 0.22 percent of the euro area's output per year. As a result of a number of

[13]This counterfactual is equivalent to treating the euro area as a closed economy and focusing only on the seigniorage revenues extracted from domestic residents' home (instead of total seigniorage revenues) to compute the shoe-leather costs of inflation. In practice, we estimate this shoe-leather cost function by substituting $m^h(r)$ for $m(r)$ in the second term of (1).

policy interventions, the EONIA rate fell by the end of 2009 below 0.4 percent, therefore implying shoe-leather costs close to nil.

5. Concluding Remarks

This paper presents estimates of the shoe-leather costs of inflation in the euro area using M1 data adjusted for the circulation of currency abroad over the sample period between the introduction of the euro banknotes in 2002 and 2011. Our results suggest that the adjusted shoe-leather costs of inflation in the euro area are non-negligible even for levels of the nominal interest rate that are relatively modest. Although we find evidence of marginally negative shoe-leather costs for the nominal interest rate in the restricted interval between 0 percent and 1 percent, our results are not as striking as those in Calza and Zaghini (2011) for the United States, who show that the shoe-leather costs of inflation in the United States are persistently and more significantly negative for a much broader interval of values of the nominal interest rate (up to 11 percent).

This difference between the euro area and the United States can be mainly explained by the relatively wider circulation abroad of U.S. dollars compared with euro banknotes. Indeed, the widespread circulation of U.S. dollars abroad implies large transfers of real resources from foreign residents, which more than compensate for the consumer losses borne by domestic agents because of inflation-related money demand distortions. While the circulation of euro banknotes abroad has risen since their introduction, it is not yet so large as to significantly offset the distortionary impact of inflation on the monetary holdings of euro residents.

Our results suggest that, as far as the shoe-leather costs of inflation are concerned, the results for the euro area may not be qualitatively different from those obtained under the assumption of a closed economy. As a caveat, it should be noted that we use estimates of the foreign hoardings of euro banknotes that may under-estimate the true amount of euro banknotes abroad. In addition, it is worth noting that we have focused only on one specific source of inflation-related welfare costs and that policy conclusions may vary when other sources are taken into consideration.

Future research should try to assess the robustness of our findings to estimates of foreign holdings of euro currency obtained using different methods (such as those used for U.S. dollars by Porter and Judson 1996 and for euro banknotes issued in Germany by Bartzsch, Rösl, and Seitz 2013a, 2013b).

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How to Measure the Unsecured Money Market: The Eurosystem's Implementation and Validation Using TARGET2 Data*

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This paper develops a methodology, based on Furfine (1999), to identify unsecured interbank money-market loans from transaction data of the most important euro processing payment system, TARGET2, for maturity ranging from one day (overnight) up to one year. The implementation has been verified with (i) interbank money-market transactions executed on the Italian trading platform e-MID and (ii) individual reporting by the EONIA panel banks. The type 2 (false negative) error for the best performing algorithm setup is equal to 0.92 percent. The different stages of the global financial crisis and of the sovereign debt crises are clearly visible in the interbank money market, characterized by significant drops in the turnover. We find aggregated interest rates very close to EONIA but we observe high heterogeneity across countries and market participants.

JEL Codes: E42, E44, E58, G01.

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1. Introduction

An efficient interbank money market is essential for the stability of the financial system and plays a critical role in the transmission of monetary policy. After the failure of Lehman Brothers in the fall of 2008, banks became increasingly reluctant to lend liquidity to each other, due to higher perceived counterparty risk (Heider, Hoerova, and Holthausen 2009). To compensate for this increased uncertainty, lenders demanded higher credit risk premia or high-quality collateral (European Central Bank 2010). At the same time, liquidity-short banks were reluctant to ask for interbank deposits to avoid being perceived as illiquid, due to the so-called stigma effect (Cappelletti et al. 2011). In many cases banks stopped lending to their counterparties and preferred turning to the European Central Bank's (ECB's) overnight deposit to store their liquidity surplus. This resulted in a significant decrease of the turnover in the unsecured interbank money market and a significant increase of the ECB's overnight deposit facility. Furthermore, interbank money-market trading has shifted from the unsecured to the secured market (Cappelletti et al. 2011; European Central Bank 2012), which allows the interposition of the central counterparty to mitigate risks. Since the contagion of the sovereign debt crisis among European periphery countries, the segmentation in the interbank money market has increased significantly. Banks located in the so-called periphery countries (Greece, Ireland, Italy, Portugal, and Spain) faced increased sovereign risk premiums while cross-border liquidity flows to these countries declined (Bank for International Settlements 2012).

In response to the crisis, the Eurosystem has introduced unconventional monetary policy measures to ease the strain in several markets, such as the interbank money market, which hampered the smooth transmission of the monetary policy impulses. (European Central Bank 2010; van Riet 2010).[1] The effect of these actions and

[1]Unconventional monetary policy measures included fixed-rate full allotment since October 2008; swap agreements with other central banks (e.g., Federal Reserve, Swiss National Bank); extension of the collateral framework; extension of the duration of the refinancing operations (e.g., year tenders starting July 2009 and three-year tenders starting December 2011); the introduction of the Covered Bond Purchase Program (May 2009), the Securities Market Program (May 2010), and the Outright Monetary Transactions (September 2012).

especially of switching to fixed-rate full-allotment monetary policy tenders has been that banks no longer need to rely on each other to fund their liquidity needs. Liquidity-short banks can always obtain the desired amount of liquidity from regular ECB monetary policy operations, against collateral from a wide range of eligible assets. Liquidity-rich banks can always deposit their excess at the ECB's overnight deposit facility instead of lending it to a market counterparty, as long as they accept the implicit opportunity cost.

To evaluate the efficiency of the transmission of the (unconventional) monetary policy impulses, it is essential to have reliable and complete information on the interbank money market. Normally, however, central banks, including the ECB, have to rely on partial information. In the Eurosystem this information contains the following sources: (i) reporting by the major banks in the euro area on their overnight lending rates and volumes (which make up the Euro OverNight Index Average, EONIA); (ii) data on individual exchanges on the Italian electronic trading platform e-MID; (iii) data on individual trades on the Spanish domestic market MID; and (iv) data on domestic and cross-border lending and borrowing for Greek banks.[2] EONIA panel data only refer to the aggregated daily overnight transactions of the major money-market actors in the euro area. e-MID data account for less than 20 percent of overall interbank transactions in the euro area and are, especially since mid-2011, mainly representative of Italian banks. Similarly, MID and Greek data mainly reflect the Spanish and Greek interbank markets. The residual over-the-counter (OTC) money-market transactions are not directly available to the Eurosystem. However, the majority of these transactions will be settled in the most important euro large-value payment system (LVPS), TARGET2.

The main research question of this paper is, therefore, how to identify euro-area unsecured interbank loans, with maturities ranging from one day up to one year, using payment data from TARGET2. To find the loan-refund combination from LVPS data,

[2]Besides the fact that each of the four sources only gives partial information on the money market, there are also restrictions on the availability of the data for confidentiality reasons: EONIA data are available only to the European Banking Federation (EBF) and to the ECB for monetary policy purposes, e-MID data to Banca d'Italia in its financial markets' supervisory function, and correspondingly MID and Greek data to Banco de España and to the Bank of Greece, respectively.

we employ and expand the method of Furfine (1999). He developed an algorithm to identify interbank loans for the U.S. money market, using Fedwire data. This algorithm assumes a round value transferred from bank A to bank B at time t and the same value plus a plausible interest rate amount from bank B to bank A at time $t + 1$. The minimum value of a payment has been set to 1 million U.S. dollars with increments of 100,000 U.S. dollars. The interest rate is considered plausible if it lies within 50 basis points above or below the federal funds rate. Demiralp, Preslopsky, and Whitesell (2004) extended the algorithm to capture smaller-size loans and excluded any transaction whose interest rate does not correspond to a market quote for interest rates in units of 1/32 percentage points or in whole basis points.

Subsequently, several authors have applied Furfine's method to payment data from several payment systems. Millard and Polenghi (2004) applied Furfine's algorithm to the British LVPS (CHAPS) data, using a threshold of 1 million pounds sterling. Hendry and Kamhi (2007), studying the Canadian Large Value Transfer System (LVTS), follow the approach of Demiralp, Preslopsky, and Whitesell (2004) by only including interest rates in units of half a basis point as eligible. Akram and Christophersen (2010) have implemented an algorithm for the Norwegian market. They determined that some money-market trades can occur at rates below the overnight deposit rate, which is usually the lower bound of the interest rates traded in the market, as at that rate banks can turn to their central bank for depositing their excess liquidity as long as they have access to the standing facility of the central bank. The authors argued that foreign banks which do not have access to the overnight deposit facilities of the Norges Bank may in fact lend their excess liquidity in Norwegian krones at rates even below the deposit rate.

The aforementioned papers have in common that they focus solely on the overnight money market. Heijmans, Heuver, and Walraven (2010), Guggenheim, Kraenzlin, and Schumacher (2011), and Kuo et al. (2013) implemented an algorithm for maturities up to one year for the U.S., Swiss, and Dutch markets, respectively. The main difference between the first two papers and the third paper is the way longer-term loans are matched. Guggenheim, Kraenzlin, and Schumacher (2011) and Kuo et al. (2013) start by identifying the one-day loans. When a loan-refund match has been found, the two payments that have been matched are excluded from the search for the following maturity. Conversely, Heijmans, Heuver, and Walraven (2010) do not exclude any loan-refund candidates when looking at longer maturities. Thus, the same payment may be matched to different refunds and vice versa. Multiple matches may arise both within the same maturity and between different ones. The alternative candidates stemming from these multiple matches are then selected according to the most plausible match. This approach avoids the a priori matching imposed by the order in which the algorithm processes the payments.

Following a similar approach, we enhance the algorithm to reduce the uncertainty of the results. Moreover, with respect to other works, the results have been validated against two external data sources: (i) individual EONIA panel contributions and (ii) e-MID transaction-level data. To the authors' best knowledge, this is the most comprehensive validation exercise yet carried out with reference to a Furfine implementation. The validation enables us to quantify the type 2 (false negative) and type 3 (mismatch) errors. Further, it shows that our algorithm's performance is considerably reassuring, particularly in the overnight segment. This result is in sharp contrast with the recent paper by Armantier and Copeland (2012) assessing the quality of Furfine's algorithm implemented at the Federal Reserve Bank of New York against a data set of bilateral transactions between two large U.S. dealers.[3]

The outline of this paper is straightforward. Section 2 presents the data used in our analysis. Section 3 describes the algorithm, whereas its validation against e-MID and EONIA panel data is provided in section 4. That section also describes the level of uncertainty of the algorithm and presents the most suitable corridor for the euro

[3]They find very discouraging results, namely average type 1 and type 2 errors equal to 81 percent and 23 percent, respectively, between 2007 and 2011. In addition, they also argue that these errors may not subside if the algorithm's output is aggregated. This confirms the validity of our implementation and underscores that a "plain-vanilla" version of the Furfine algorithm without a deep knowledge of the underlying data and technical details of the system may lead to misleading and potentially spurious results. This study also aims at providing the Eurosystem with a database of euro-area money-market transactions to serve monetary policy, financial stability, and research purposes. Kovner and Skeie (2013) find evidence that the estimates extracted from the data are statistically significantly correlated with banks' federal funds borrowing as reported on the FR Y-9C.

money market. Finally, section 5 concludes and makes some policy recommendations.

2. Data

The data sources we use for this paper comprise (i) payments settled in TARGET2, the main euro-area LVPS; (ii) individual interbank loans settled in the Italian electronic money-market trading platform e-MID; and (iii) individual reporting by the banks participating in the EONIA panel.

2.1 TARGET2

TARGET2, Trans-European Real-time Gross settlement Express Transfer, is the Eurosystem real-time gross settlement system (RTGS) for large-value payments in euro in central bank money. Currently, all euro-area countries and six non-euro-area countries are connected to TARGET2.[4] The system processes the transactions of roughly 4,500 credit and other financial institutions which meet the access criteria, directly or indirectly. As TARGET2 is an RTGS, each transaction is settled immediately (real time), individually (gross), and irrevocably. Besides transactions between (in)direct participants and transactions related to monetary policy implementation, it is also used for settlement of many other ancillary systems (Kokkola 2010). For the purpose of this paper, two important systems which settle in TARGET2 are the Italian e-MID and the Spanish MID, i.e., the only trading platforms for unsecured money-market transactions operating in the euro area (see section 2.2).

Every transaction in TARGET2 involves two participants (mainly banks) and/or one (domestic) or two (cross-border) national central banks (NCBs). The participants' list comprises mainly euro-area credit institutions and several large non-euro-area banks (notably the United Kingdom and the United States). Each account of every participant is assigned to one of the NCBs. Although banks are free to choose a reference central bank in the Eurosystem, most

[4]The six non-euro-area countries are Bulgaria, Denmark, Latvia, Lithuania, Poland, and Romania (status at the end of October 2012).

banks choose the central bank of the country where their headquarters are located and opt for two or more reference central banks only as specific business needs arise. For non-euro-area participants, the location of branches and/or subsidiaries has determined the choice of reference central bank. This is relevant and should be kept in mind when studying domestic and cross-border developments in the euro interbank money market.

Money-market transactions may be settled also through EURO1, the second LVPS system in euro, which is a privately owned payment system for domestic and cross-border payments in commercial bank money. The system numbers sixty-five participating (mainly large) euro-area banks. Although banks participating in this system have the option to settle interbank money-market loans in EURO1, the majority of money-market transactions are assumed to be settled in TARGET2: in the latter, the daily turnover is close to 3,000 billion euros, whereas in EURO1 it is below 250 billion euros.[5]

2.2 e-MID

e-MID, electronic Mercato Interbancario dei Depositi, is a privately owned electronic money-market system for interbank loans, created in 1990 from a joint initiative of the Italian banking community and the Banca d'Italia. Money-market trades that are executed on this platform do not differ significantly from OTC transactions, as e-MID offers three different trading opportunities: (i) the multilateral trading facility, where orders entered by participants are visible to the entire market and are binding vis-à-vis other participants; (ii) the request for quote facility, where banks have the opportunity to trade with a restricted group of counterparties; and (iii) the direct order dealing option, where banks agree bilaterally on money-market trades. These last two trading options closely resemble the features of OTC transactions.

Since the launch of the euro and until the start of the financial crisis, e-MID experienced continuous growth in trading and increasing participation by non-Italian banks. At the beginning of 2007,

[5]See https://www.ebaclearing.eu/Statistics-on-EURO1%2fSTEP1-N=E1_Statistics-L=EN.aspx.

more than 60 percent of participants were non-Italian institutions from nineteen countries. In that year, e-MID represented 20 percent of the overall interbank transactions in Europe (European Central Bank 2012). As of August 2007, and especially in the aftermath of Lehman's collapse, the daily average traded volumes declined, most likely as a result of higher perceived counterparty risk and a potential stigma effect for banks having to disclose their liquidity needs on a transparent electronic platform like e-MID (Cappelletti et al. 2011). Cross-border flows decreased significantly too, as of 2008. Nevertheless, according to Monticini and Ravazzolo (2011), e-MID was still representative for the whole euro-area money market in 2008, as loans involving at least one non-Italian counterparty accounted for 42 percent of the total turnover and foreign participants represented 42 percent of the total number of active traders (179). Although the share of non-Italian trading fell to 20 percent in 2009 and to 10 percent in 2010, e-MID prevailing market conditions remained anchored to the euro-area money market, as witnessed by the low spread between the overnight interest rate traded in e-MID and EONIA. Thus, e-MID can be regarded as a benchmark of the euro-area money market and a suitable support in validating Furfine's algorithm, especially at the beginning of the analyzed period and for the overnight maturity.[6]

Unlike one-day transactions, longer-term maturities traded on e-MID have been quite rare since the outbreak of the crisis. Therefore, the extension to the entire data set of validation results for these maturities is less straightforward. The e-MID market shifted towards shorter-term maturities in the aftermath of the subprime crisis. From June 2008, one-day transactions (overnight, tomorrow-next, spot-next)[7] accounted for more than 90 percent of total transactions. Until mid-2009 loans with maturity up to three months

[6]Only since the contagion of the sovereign debt crisis in Italy (August 2011) has the market become mainly Italian and the spread between the EONIA and e-MID widened, reflecting an increased national segmentation of the euro-area money market. Thus, the information content of e-MID loans as a benchmark for the overnight euro-area money market has, since then, deteriorated (Cappelletti et al. 2011).

[7]In an overnight loan, the dates of agreement and settlement coincide, whereas in a tomorrow-next or spot-next transaction, the agreement date is, respectively, one day or two days before the settlement date.

(excluding one-day transactions) represented 5 percent of the overall turnover. Although infrequent, e-MID longer trades are the only readily available source of individual money-market transactions which can be used to assess the goodness of fit of the Furfine-like algorithm in the euro area at longer maturities.

2.3 EONIA Panel

EONIA is an effective overnight interest rate computed as the weighted average of all overnight unsecured loans reported by the contributing euro-area panel banks.[8] Soon after the closing of the day-trade phase in TARGET2, each panel bank sends to the ECB the sum of all lending transactions carried out during the business day and the corresponding weighted average rate. There are a number of lending transactions that panel banks have to exclude from their report: loans to counterparties belonging to the same banking group (intragroup), money-market transactions settled on behalf of customers, and tomorrow-next and spot-next transactions, the last ones not being agreed upon on the reporting business day.

The data set comprises the daily individual volume and the corresponding weighted average rate for all the reporting banks during the period in analysis. The EONIA panel includes banks in EU countries participating in the euro from the beginning, banks in EU countries not participating in the euro from the beginning, and large international banks in non-EU countries but with important euro-area operations. All banks contributing to EONIA hold an RTGS account in TARGET2.

3. The Algorithm Setup

Our implementation of the unsecured interbank loans identification algorithm in the euro area using TARGET2 payments data is characterized by the following elements: (i) the input data, (ii) the loan value and increment, (iii) the areas of interest rate plausibility, (iv) a further criterion for plausible interest rates, (v) the procedure to

[8]In October 2012 the panel of banks contributing to EONIA consisted of forty-three banks. The list of current panel banks can be found at http://www.euribor-ebf.eu/euribor-eonia-org/panel-banks.html.

deal with multiple matches, and finally (vi) the identification of the maximum reliable duration. This section concludes by summarizing the algorithm implementation.

3.1 TARGET2 Data

As we are interested in identifying unsecured loans settled in TARGET2 between commercial banks in the euro area, our input data set is composed solely of bank-to-bank (interbank) transactions.[9] Starting from the total TARGET2 database, interbank transactions are identified excluding payments from or to accounts belonging to central banks and national treasury accounts. In addition, we exclude transactions from and to accounts belonging to the same legal entity. Some banks (or a group of banks) have more than one account in TARGET2 (within one central bank for administrative reasons and/or across several central banks within the euro area): we deem it admissible to consider them together because usually these accounts are controlled by the credit institution's head office. As we want to assess the overall money-market transactions in the euro area, executed both over the counter and electronically, we also include ancillary system transactions stemming from the electronic money-market platforms e-MID (Italy) and MID (Spain). Transactions from all other ancillary systems in the euro area are discarded. Finally, we need to point out that, due to data unavailability, the matches are based on the TARGET2 settlement banks and not on the originator and final beneficiary of the transactions. This may introduce substantial noise into analyses at bank level. The TARGET2 data we use in this paper ranges from June 1, 2008 until October 31, 2012.

3.2 Loan and Increment Values

In the seminal version of the algorithm, Furfine (1999) adopts 1 million U.S. dollars as the minimum loan value and a fixed increment of 100,000 U.S. dollars for the U.S. federal funds market. Demiralp,

[9]The algorithm can be used to analyze customer payments as well: these are excluded from our input data set, as the focus of the present work is on the interbank money market, not the lending and borrowing activity involving customers.

Preslopsky, and Whitesell (2004) also describe the U.S. market using 50,000 U.S. dollars as the lower bound and as increment. Heijmans, Heuver, and Walraven (2010), investigating the Dutch part of the euro-area market, used 100,000 euros as minimum loan and increment value. Guggenheim, Kraenzlin, and Schumacher (2011) for the Swiss market use a minimum loan value of 500,000 Swiss francs and increment value of 100,000 Swiss francs. All the papers available in the literature adopted minimum loan values ranging between 50,000 and 1 million of the local currency unit, with increment values of between 50,000 and 100,000 units. Nevertheless, none of the existing papers provide hard evidence to support their choices.

To choose the optimal setup for the euro area, a two-phased approach was adopted. First, a survey was conducted among the euro-area central banks to assess national practices in the euro-denominated money market.[10] The survey revealed (i) that the minimum loan value is 1 million euros with increments ranging from 10,000 euros to several million euros, depending on the loan size, (ii) that payment splitting (which would make it almost impossible to identify individual money-market transactions) almost never occurs, and (iii) that rollovers (automatic renewal of loans) are frequent in certain euro-area countries.[11] In addition, the e-MID database confirms that 1 million euros is a good choice as minimum loan value, although the platform does allow smaller trades under specific conditions.[12]

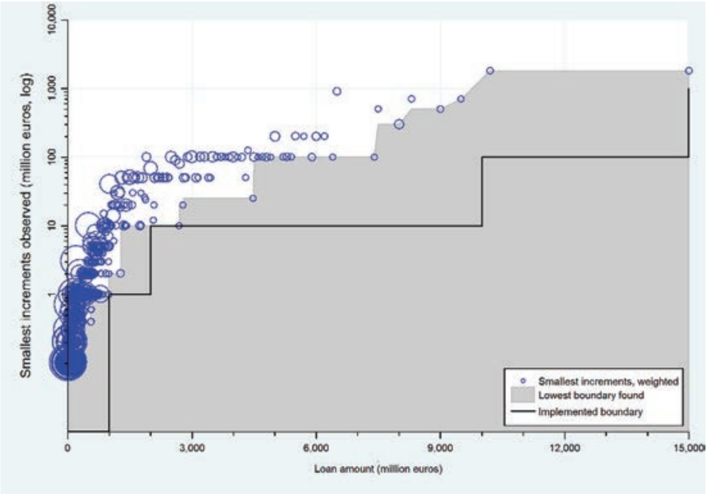
The analysis of the number of unique matches obtained by imposing a minimum increment threshold of 10,000 euros shows that setting the increments depending on the loan amounts is the optimal strategy: too-low increments could lead to an increase of false positives, whereas too-high thresholds would not capture effective money-market transactions (false negatives; see section 4.1). Figure 1 depicts the scatter plot of the increment with respect to the loan

[10]The survey was jointly conducted by the Working Group Oversight (WGO) and the Working Group TARGET2 (WGT2) of the Eurosystem.

[11]This applies in France, Portugal, and Spain.

[12]In e-MID, banks are required to quote proposals at least equal to 1.5 million euros. Nevertheless, if after being hit by an order that partially covers the proposed quantity, the residual quantity is lower than the minimum amount, the proponent can still negotiate such a residual amount. In fact, e-MID trades below 1 million euros represent only 0.1 percent of all e-MID transactions, by volume.

Figure 1. Observed Smallest Increments to the Next Higher Loan Amount



amount for all unique matches captured by the algorithm that uses the 10,000 euros increment rule. The size of the circles is weighted with the number of identified transactions for a given loan amount and a given increment. The black line, representing the increment threshold below which no unique matches were found, led us to adopt a step function for the minimum increment amount, as follows:

- 10,000 euros for transactions below 1 billion euros;
- 1 million euros for transactions between 1 billion and 2 billion euros;
- 10 million euros for transactions between 2 billion and 10 billion euros;
- 100 million euros for transactions between 10 billion and 15 billion euros;
- 1,000 million euros for transactions greater than 15 billion euros.

3.3 Areas of Plausibility

Matching two transactions as being an interbank loan and its refund requires assumptions regarding plausible interest rates. Furfine

(1999) uses a corridor ranging from 50 basis points below the minimum of the three published federal funds rates—the 11:00 a.m. rate, the closing rate, and the value-weighted funds rate—and the Federal Reserve's target rate to 50 basis points above the maximum of these four rates. Demiralp, Preslopsky, and Whitesell (2004) use a corridor of 100 basis points in order to capture loans that potentially differ more noticeably from brokered federal funds trades. They use a minimum interest rate of 1/32. Heijmans, Heuver, and Walraven (2010) use a corridor of 50 basis points centered on the EONIA or EURIBOR rate (depending on the maturity) for most of the investigated period. After the failure of Lehman Brothers, they increase the lower bound to 100 basis points, because some banks were able to attract liquidity at unusually low interest rates. Guggenheim, Kraenzlin, and Schumacher (2011) set the corridor to 15 basis points around the respective LIBOR rate for most of the days. On days of high volatility, they use a band width that is a function of the intraday volatility.

To find the optimal area of plausibility for the euro area, we investigate five different corridors. The first plausibility area (ECB0) is equal to the ECB corridor of marginal lending and overnight deposit rates. However, evidence from the literature and from the e-MID data shows that rates both below the deposit rate and above the marginal lending rate do occur.[13] Therefore, a second plausibility area widens the ECB corridor by 25 basis points below and above (ECB25). However, the ECB corridor represents a benchmark for overnight money-market transactions but not for longer-term ones. Better reference rates for longer-term money-market transactions might therefore be derived from the EURIBOR yield curve. Therefore, we also investigate corridors around EONIA for overnight transactions and around EURIBOR for maturities starting from one week. Unlike the ECB key policy rate, which is the center of the first type of plausibility areas, the EURIBOR is not an actual rate but only a quoted one, which means that effective longer-term maturities may depart significantly from the relative fixing. Like Furfine

[13]Banks may borrow at rates higher than the ECB marginal lending rate if, e.g., they lack collateral to guarantee their overdraft; banks may also borrow and lend at rates outside the ECB corridor if they do not have access to the Eurosystem standing facilities.

(1999), we choose to set a corridor around this reference rate of 25 (EONIA25), 50 (EONIA50), and 100 basis points (EONIA100).

3.4 Plausible Interest Rates

The corridor approach excludes implausibly high or low interest rates but may still match payments that yield implausibly complicated interest rates. Anecdotal evidence collected from market operators as well as the e-MID minimum rate tick rule suggests that banks do not agree on interest rates that are not rounded to a particular number of decimals.

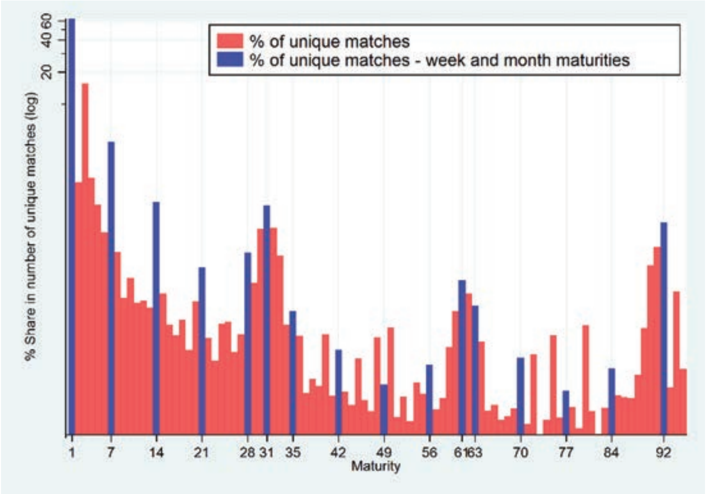
Demiralp, Preslopsky, and Whitesell (2004) were the first to employ such an additional criterion on the interest rate: they filtered out any repayments that did not imply an interest rate in units of 1/32 percentage points or in whole basis points. Similarly, we only include matched transactions with implied interest rates of multiples of half a basis point, i.e., the third decimal must be either 0 or 5. In other words, a returning payment that leads to a 4.345 percent rate is included in the output data set, whereas one resulting in a 4.343 percent rate is not considered a plausible match and is therefore discarded. Treasurers at several commercial banks have confirmed this hypothesis.[14]

3.5 Multiple Matches

The algorithm described so far matches all transactions that represent possible loan advances with all payments that qualify as potential repayments. As a consequence, a single transaction can be matched with several other payments (multiple matches or collisions). Two different types of multiple matches can occur: (i) intraday and (ii) interday multiple matches. The first case occurs when one or more potential reimbursements match with one or more transactions on the same day. In this case the wrong choice of match may lead to an error in the estimated rate if the amounts of the

[14] In this paper we have only implemented the 360-day year convention for rate calculation. However, we have found evidence that some trades (in some parts of the Eurosystem), follow the 365-day year convention. This is probably due to the British banks holding TARGET2 accounts: the United Kingdom follows the 365-day convention.

Figure 2. Observed Frequency of Maturity of All Unique Matches



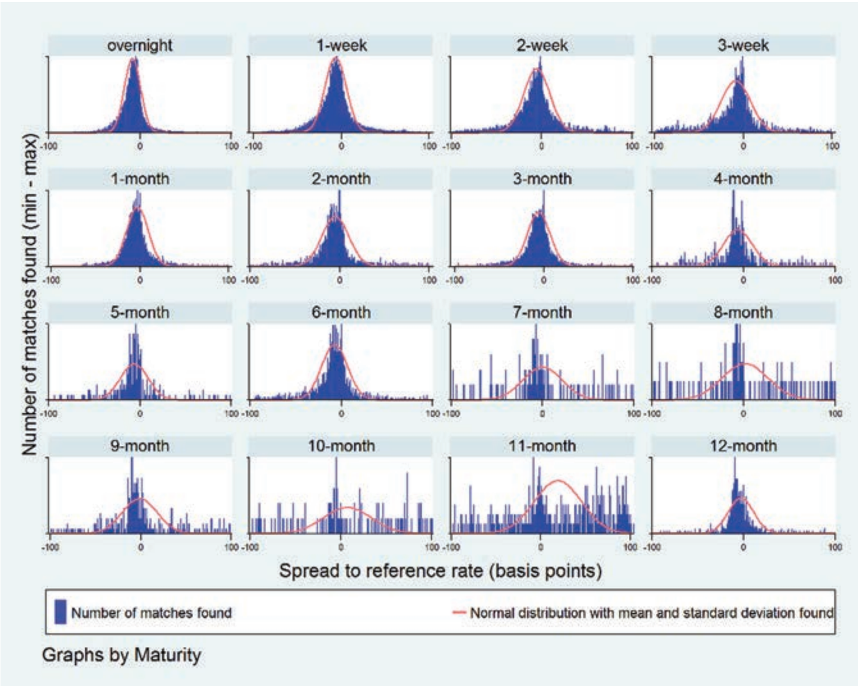
reimbursements differ. The second case occurs when one or more reimbursements on different days match with one or more setup transactions; in this case the error affects both the maturity and the rate. Obviously, the two can also occur simultaneously.

In the case of an intraday maturity collision, the choice of match is made randomly since the first implied interest rate is assessed to be as plausible as the second one. In the case of interday maturity collision, we choose the most plausible duration according to the observed frequency of the maturities of uniquely matched TARGET2 loans (see figure 2). The chart shows that where an identified loan advance matches with two opposite transactions, one six and the other seven days later, our rule will consider it as a seven-day maturity loan. In most cases, maturities counted in whole weeks and months occur with higher frequency than all other adjacent maturities.

3.6 Maximum Reliable Duration

The longer the loan maturity, the larger the area of plausibility is in an absolute sense. Where the corridor is wider, it is more likely that a matched loan-refund combination is in fact a pair of two unrelated transactions. In other words, the amount of noise (falsely

Figure 3. Type 1 Error: Frequency of Spreads vs. the Reference Rate at Increasing Maturity



Notes: The light gray line (red in the online version) represents the fitted normal distribution using the mean and standard deviation of the sample.

identified loans) will increase with maturity. Figure 3 shows for sixteen different maturities the distribution of all unique loans found by our algorithm. As the stochastic error becomes larger, the algorithm become less reliable. The validation exercise of section 4.2 confirms this. Therefore, we assume that our algorithm is most reliable for identified TARGET2 loans up to three months.

3.7 Summary of the Algorithm

The elements of the algorithm are the following:

(i) Input:
- Interbank payments (MT202) and selected ancillary systems transactions (e-MID and MID)

- Only transactions between different bank identifier codes (BICs) (no liquidity transfers)

(ii) Loan and increment:
- The minimum loan value is 1 million euros.
- The loan increment follows the following criteria:
  - 10,000 euros for transactions below 1 billion euros;
  - 1 million euros for transactions between 1 billion and 2 billion euros;
  - 10 million euros for transactions between 2 billion and 10 billion euros;
  - 100 million euros for transactions between 10 billion and 15 billion euros;
  - 1,000 million euros for transactions greater than 15 billion euros.

(iii) Plausible corridors are centered either on EONIA/EURIBOR rates or on ECB standing facilities corridor rates. In the first case, EONIA is used for loans up to four days and the corresponding closest EURIBOR is used for loans of five days or longer.

(iv) Interest rates must be multiples of half a basis point, i.e., the third decimal digit is either 0 or 5.

(v) Multiple matches:
- In the case of multiple interday matches, the most plausible duration is chosen on the basis of the maturity frequencies for unique matches.
- In the case of multiple intraday matches, the algorithm chooses randomly.

(vi) Post-processing of transactions to distinguish between intragroup and extragroup loans based on the SWIFT BIC directory information. For this purpose the field Parent BIC code is considered to consolidate the group of accounts.

(vii) In the case of multiple intraday matches, the algorithm chooses randomly.

4. Validation

To evaluate the robustness of the algorithm and to choose the best-performing corridor, the identified TARGET2 loans were validated against external sources of money-market transactions which represent a subset of the total market. For this purpose, e-MID transaction-level data and aggregated EONIA data were used. This section describes the validation of the algorithm outcome. Section 4.1 explains the three different types of uncertainties inherent in the algorithm. Sections 4.2 and 4.3 present the validation of the algorithm with e-MID and EONIA data, respectively.

4.1 Uncertainties in the Algorithm

The algorithm as described above is not free of errors, as it identifies money-market transactions simply by matching two payments given certain boundary conditions. The algorithm does not "know" whether the coupled payments really represent a money-market loan, nor if the two payments refer to the same money-market exchange or stem from two different money-market transactions. In the estimated database, three different types of errors may occur:

(i) A type 1 error, or false positive, occurs when the algorithm identifies a money-market transaction which in fact is not composed of a loan and a repayment, but of two unrelated money-market transactions. This error can typically occur if the corridor is too wide, because the larger the corridor, the higher the probability that two random transactions match as a loan-refund combination. This happens especially when matching longer maturities, because there the plausibility area is wider in absolute terms. It is also possible that the algorithm matches some secured transactions (repos). However, the majority of repos are traded in electronic platforms and settled via central clearing counterparties (CCPs) and/or central securities depositories (CSDs). As we excluded all transactions originated by CCPs and CSDs, only over-the-counter traded and manually settled in TARGET2 repos may be captured by our algorithm. Finally, the algorithm may capture money-market trades made on behalf of other banks.

Such loans made via correspondent banking relationships may be considered a type 1 error only when the focus is on individual counterparties, as at the aggregate level they are pure interbank transactions. Loans made on behalf of customers, such as corporations or other financial institutions excluding banks, are not captured by our algorithm, as we excluded all customer payments (MT103).

(ii) A type 2 error, or false negative, occurs when the algorithm fails to identify a money-market transaction. This can happen for the following reasons: (i) the transaction is not present in the TARGET2 initial data set—for example, because the money-market exchange is not settled in TARGET2 but in EURO1 or on commercial bank accounts; or (ii) the algorithm is not able to find the transaction, because the loan does not satisfy the conditions embedded in the parameters of the algorithm. This is particularly likely to happen if the interest rate of the exchange lies outside the corridor (if the algorithm looks for loans with an interest rate between 1 percent and 2 percent, it will fail to pick up money-market exchanges executed at 2.1 percent or 0.95 percent), if the amount of the loan transaction does not respect the increment rule, or if the implied rate is not a multiple of half a basis point.

(iii) A type 3 error relates to the so-called wrong match or multiple match. Two types of these matches can be distinguished. First, a loan can be matched with several repayments executed on the same day, i.e., a loan transaction at $t = D$ may match with more than one plausible refund payment on $t = D + x$. Since only one of these has to be randomly selected, the algorithm may choose a wrong one, thus impairing the statistics on the executed rates. The second kind of multiple match occurs if the algorithm couples a loan with several repayments executed on different days: this happens when a loan at $t = D$ has a plausible refund at $t = D + x$ but also at $t = D + y$. As the algorithm will select one, according to the unique-matches duration probabilities described in section 3.5, it may select the wrong match, discarding the correct one. The wrong matches are directly connected to false positive errors and can be considered as a subset of false positive errors, i.e., each wrong match is connected to a false negative transaction but not vice versa.

The increase of wrong matches may stem from the fact that in a wider corridor the algorithm is more likely to find multiple matches, including the correct one. If the corridor is too narrow, the algorithm finds a smaller number of multiple matches, possibly missing the correct one: here the false negative error rate may be higher. On the other hand, the wider the corridor, the more likely the data set will be to include false positives, which however will be difficult to estimate or even to approximate. The choice of corridor width is therefore a compromise between the false negative and estimated false positive error rates.[15] The trade-off between false negatives and positives is amplified for longer maturities for which the overlap between corridors of subsequent maturities increases as the maturity increases and, accordingly, the probability of "collision" (see section 3.5).

4.2 Comparison with e-MID

The validation of the identified TARGET2 loans with e-MID data employed two different strategies, given the two different settlement procedures in e-MID, (i) automatic settlement and (ii) manual settlement. The first strategy is applied to automatically settled trades. This typically occurs when both counterparties have joined the automated facility that allows the electronic platform e-MID to send the deal directly to TARGET2. The transactions submitted automatically by e-MID to TARGET2 are identified in the TARGET2 database with a code which allows matching uniquely the originating transaction and the reimbursement of a single e-MID deal. However, not all e-MID participants have joined the automated facility, and when at least one counterparty of a money-market contract has not, the deal must be sent to TARGET2 directly by the participants (manual settlement). Those e-MID transactions do not allow

[15] Needless to say, increasing the maturity spectrum over which the algorithm is run will increase, ceteris paribus, the false positive error rate. This is because each bilateral transaction is matched with a greater number of potential reimbursements, thus increasing the likelihood of spurious matches.

straightforward matching of the loan and the connected repayment. In this case the validation process has to revert to e-MID nominative individual transactions collected by Banca d'Italia for supervisory purposes.

4.2.1 Validation of e-MID Trades Settled Exclusively with Automatic Settlement Facility

The automatic settlement facility is adopted by all Italian banks, whereas most non-Italian banks do not use this feature; therefore, the validation with automatically settled e-MID transactions concentrates on loans between Italian banks. We compare the e-MID labeled loans in the TARGET2 data (settlement date, settlement banks, maturity, amount, and rate) with money-market transactions identified by our Furfine procedure. The validation shows three different matching possibilities:[16]

(i) *Perfect Match:* A loan with identical settlement date, settlement banks, maturity, amount, and rate in TARGET2 and e-MID data.[17]

(ii) *False Negative:* A loan in the e-MID data set not found in the Furfine data set, which can either be
  - a false negative because the interest rate of the transaction lies outside of the assumed corridor;
  - a false negative for other reasons.

(iii) *Wrong Match:* e-MID transactions identified by the algorithm but with different rate and/or duration.

Table 1 presents the results for the different corridors on maturities between 1 and 370 calendar days carried out on all automatically

[16] A false positive is not a match possibility in the strict sense: the e-MID data set does not comprise the whole universe of unsecured money-market trades where at least one counterparty is Italian. That is, our algorithm may identify legitimate unsecured loans traded bilaterally and for this reason not recorded in the e-MID data set. Thus, it is not possible to quantify the incidence of false positives from the validation with e-MID data.

[17] The perfect match may include some correspondent banking.

Table 1. First Validation Method (e-MID transactions with amount > 1 million euros)

	Total Automatically Settled e-MID Trades (A)	Matched Transactions (B)	Validation Rate (C=B/A)	False Negatives Rate (Interest Rate out of Range) (D)	False Negatives Rate (Other Reasons) (E)	Total False Negative Rate (F=D+E)	A Component of Total False Negatives: Wrong Matched (G=γF)
ECB0	222,568	211,613	95.1%	2.76%	2.16%	4.92%	0.47%
ECB25	222,568	220,513	99.1%	0.68%	0.25%	0.92%	0.26%
EONIA25	222,568	194,464	87.4%	12.53%	0.10%	12.63%	1.08%
EONIA50	222,568	212,436	95.4%	4.46%	0.10%	4.55%	1.08%
EONIA100	222,568	218,201	98%	1.81%	0.15%	1.96%	0.73%

Notes: Error rates are in terms of number of transactions. γ is the fraction of matches that is a multiple match.

settled e-MID transactions from June 2008 up to and including June 2012 with a size exceeding 1 million euros.[18] For each corridor, false negative and wrong match rates (type 2 and 3 errors) with respect to the total number of e-MID automatic transactions are shown. The outcome shows that the algorithms searching over the corridors ECB25 (overall error rate 0.92 percent) and EONIA100 (overall error rate 1.96 percent) yield better results compared with the implementations based on other corridors. In terms of traded amounts (not reported in table 1), the false negative rate is always below 0.015 percent for all five corridors. Nevertheless, as the corridor width for ECB25 and EONIA100 is quite large in both cases, the majority of unidentified transactions is due to the fact that the rate is outside the plausible corridor. Increasing the corridor width improves the type 3 error rate (wrong match), which is a special kind of false negative error.

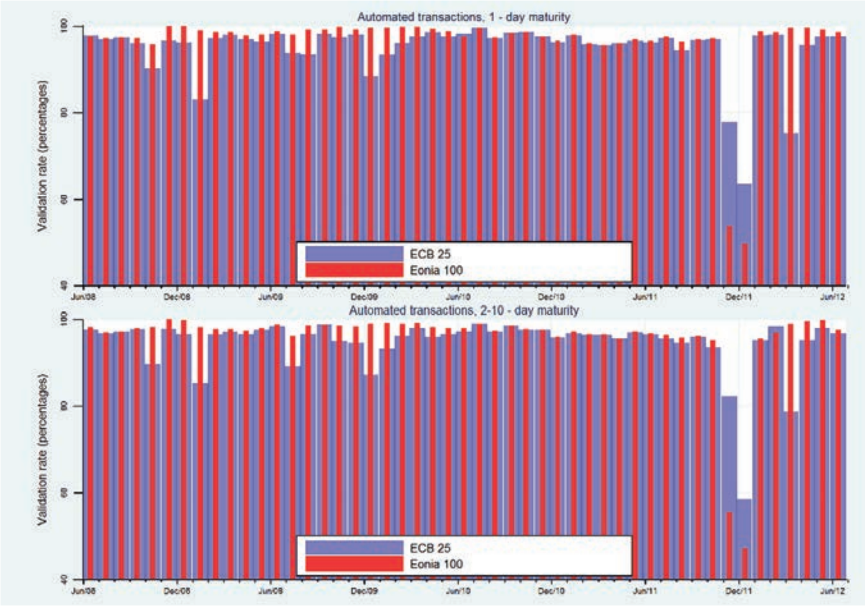
Figure 4 shows the time series of the false negative rates for different maturities. The evolution of the false negative error over time shows that both the ECB25 and EONIA100 corridors work remarkably well between 2008 and 2010 and in 2012 (error rate below 0.6 percent). However, during 2011 the error rate increases significantly (7.8 percent for EONIA100 and 2.75 percent for ECB25). This is due to the high rates agreed upon by the Italian banks sometimes exceeding our corridors towards the end of the year, during the Italian sovereign debt crisis until the ECB's first three-year long-term refinancing operation.

4.2.2 Validation of Automatically and Manually Settled e-MID Trades Based on e-MID Archive Data

Apart from e-MID loans, which are settled automatically, there are two other options: (i) loans between two counterparties that are not settled in TARGET2 because they are settled through the same settlement bank (on-us transactions) and (ii) loans that are settled in TARGET2 but involve at least one e-MID participant that has not joined the automated settlement. Comparing

[18]The extension of the maturity to 370 calendar days aims at capturing one-year money-market exchanges whose effective duration is longer than 365 days because of intervening weekend days and holidays that shift the repayment date.

Figure 4. Results of the e-MID Validation for Automatically Settled Loans



the Furfine-identified transactions with the e-MID archive data conveys important insights on both of these categories which cannot be inferred from e-MID automatically settled loans in the TARGET2 database. The second validation method is carried out separately for loans between Italian banks and for loans involving at least one foreign counterparty.

On the one hand, on the automatic settlement platform, used directly or through a settlement agent by virtually all Italian banks, the error rates of the validation exercise should be interpreted as a mix of

- the algorithm's inability to identify the real trades from the settlement data;
- difficulties in matching the identified TARGET2 loan with the correct e-MID trade because it has been indirectly settled (through correspondent banking relationship), as in

the e-MID archives the settlement banks are not recorded (type 2);
- missing identification due to the fact that two banks trading in e-MID settle their obligations through the same TARGET2 direct participant (*on-us* transactions) (type 3).

In comparison to the previous validation method, the last two sources of uncertainty yield a slightly lower validation rate for Italian participants. This is not due to the algorithm, which is invariant under both methods. The uncertainties could be removed if we had detailed information about the original sender and beneficiary across the TARGET2 data.

On the other hand, when it comes to deals involving non-Italian participants, there is an additional error factor related to the different market practices the trading banks may choose to adopt. In fact, while market players cannot affect the settlement of their automatically settled e-MID trades, TARGET2 loans involving at least one non-Italian bank do not necessarily match exactly the traded quantity. Banks may, for example, not settle their money-market transactions on a gross basis exchanging a unique loan amount and a unique repayment ("one-to-one basis"), as inferred from anecdotal evidence, but may split their obligations into several chunks, e.g., by repaying the principal and the interest separately. Furthermore, market operators may offset some intermediate payments against each other in the case of a rollover, a market practice that from the outcome of the money-market survey seems to be infrequently used.

As the first validation method already outlined the superiority of the ECB25 and EONIA100 corridors, the second validation methodology focuses directly on them: the results are shown in table 2. A first by-product of the second validation approach is a measure of the incidence of *"on-us"* transactions on total unsecured money-market trading, which yields reassuring results. According to the e-MID data, only a small percentage, around 3 percent, of trades carried out between domestic counterparties are not settled in central bank money and thus escape detection because they are not included in the payment data. More specifically, the incidence of internalized transactions on total money-market trades executed between Italian counterparties seems relatively low, across all maturities, with higher

Table 2. Second Validation Methodology

	Maturity	Total	Total e-MID Trades with Amount > 1 Million Euros (A)	On-Us (B)	Total e-MID Trades without On-Us Transactions (C=A–B=D+E+F)	Matched (D)	False Negatives because Interest Rate Is Out of Range (E)	False Negatives for Other Reasons (F)	Validation Rate (D/C)	False Negatives Error Rate (E+F)/C
ECB25	All Maturities	226,439	226,162	7,158	219,004	213,011	1,522	4,471	97.3%	2.7%
	1 Day	166,552	166,325	4,736	161,589	158,193	602	2,794	97.9%	2.1%
Domestic	2–10 Days	52,735	52,692	2,014	50,678	49,216	287	1,175	97.1%	2.9%
	11–33 Days	5,185	5,179	305	4,874	4,239	267	368	87%	13%
	34–94 Days	1,621	1,620	79	1,541	1,134	292	115	73.6%	26.4%
	94–370 Days	346	346	24	322	229	74	19	71.1%	28.9%
	All Maturities	11,516	11,515	38	11,477	10,490	4	987	91.4%	8.6%
	1 Day	8,898	8,897	16	8,881	8,169	1	712	92%	8%
Foreign	2–10 Days	2,427	2,427	11	2,416	2,177	0	239	90.1%	9.9%
	11–33 Days	163	163	2	161	131	2	30	81.4%	19.9%
	34–94 Days	21	21	9	12	8	0	4	66.7%	33.3%
	94–370 Days	7	7	0	7	5	1	2	71.4%	42.9%
EONIA100	All Maturities	226,439	226,162	7,158	219,004	210,928	4,057	4,019	96.3%	3.7%
	1 Day	166,552	166,325	4,736	161,589	156,253	2,708	2,628	96.7%	3.3%
Domestic	2–10 Days	52,735	52,692	2,014	50,678	48,756	894	1,028	96.2%	3.8%
	11–33 Days	5,185	5,179	305	4,874	4,323	290	261	88.7%	11.3%
	34–94 Days	1,621	1,620	79	1,541	1,306	146	89	84.8%	15.2%
	94–370 Days	346	346	24	322	290	19	13	90.1%	9.9%
	All Maturities	11,516	11,515	38	11,477	10,547	16	930	91.9%	8.2%
	1 Day	8,898	8,897	16	8,881	8,191	15	690	92.2%	7.9%
Foreign	2–10 Days	2,427	2,427	11	2,416	2,209	0	207	91.4%	8.6%
	11–33 Days	163	163	2	161	133	1	28	82.6%	18%
	34–94 Days	21	21	9	12	8	0	4	66.7%	33.3%
	94–370 Days	7	7	0	7	6	0	1	85.7%	14.3%

Notes: Error rates are in terms of number of transactions.

maturities exhibiting higher ratios.[19] The incidence of the *"on-us"* transactions appears ten times smaller in the case of cross-border money-market deals, around 0.3 percent, again with higher maturities exhibiting higher ratios. Always bearing in mind the caveats due to lower representativeness of the sample of the e-MID cross-border transactions compared with the OTC transactions executed in the euro area, this result is not surprising, as we expect that small and medium banks are less likely to establish correspondent relationships across national borders.

The comparison between our estimated Furfine data set and the e-MID native archives enables us to quantify the ratio of unmatched transactions to the total e-MID loans (type 2 error rate) that, as expected, is lower for loans carried out between Italian counterparties than for loans involving at least one non-Italian bank, thanks to the availability of a richer data set.[20]

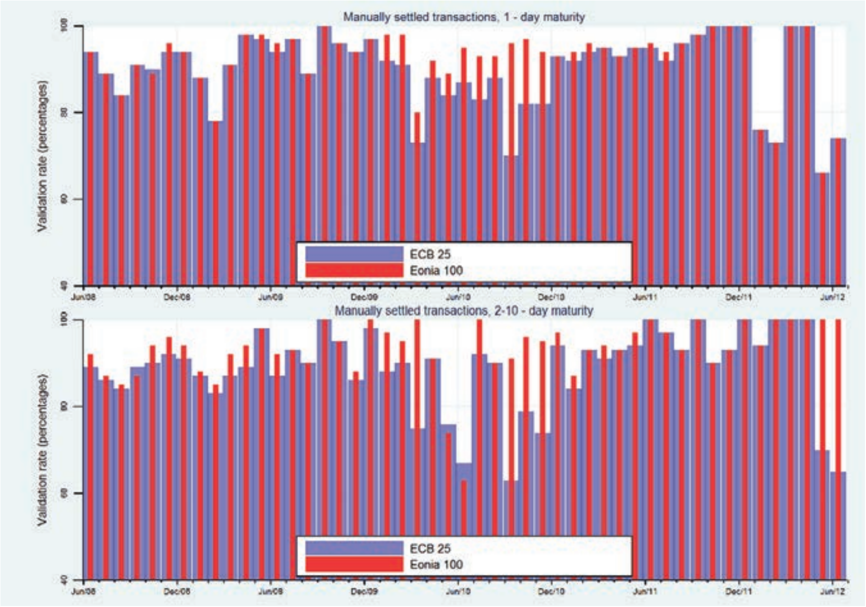
At the domestic level, the ratio of non-matched transactions is relatively small (2.7 percent for the ECB25 corridor and 3.7 percent for the EONIA100 corridor), increasing quite substantially with rising maturities. The two corridors perform differently across the maturity range: for the short maturities (up to one month) the ECB25 corridor exhibits slightly better validation rates; the opposite holds for longer ones, at which for domestic deals the error rate of the ECB25 corridor peaks at 29 percent above three months, whereas the error rate of the EONIA100 corridor never exceeds the 20 percent threshold. For money-market deals executed on a cross-border basis, the validation rates exhibit a similar pattern, but they are lower across the entire range of maturities for both corridors.[21] While for domestic transactions the error rates are negligible throughout the whole reference period, except for the dramatic fall recorded in late

[19]It is worth mentioning that the *"on-us"* rates could be improved if future analysis aimed at detecting *who settles for whom* in TARGET2, especially for foreign participants. This analysis could also shed light on the settlement practices followed by the market and help improving the accuracy of the algorithm.

[20]In the ECB25 corridor the overall type 2 error rate for trades between Italian banks is 2.7 percent, while the one for trades involving at least one non-Italian participant is 8.6 percent. In the EONIA100 corridor the percentages are very similar (3.7 percent and 8.2 percent, respectively).

[21]The only exception is the period November–December 2011, when such relationship reversed, as cross-border exchanges involve also non-Italian banks not affected by the sovereign debt tensions.

Figure 5. Results of the e-MID Validation for Manually Settled Loans



2011 due to the Italian sovereign debt crisis, the evolution of the error rates for cross-border transactions appears more erratic, with validation rates dropping below 80 percent on several occasions.[22] Figure 5 shows the time series of the false negative rates for different maturities for manually settled loans.

4.3 Comparison with EONIA

Despite its granularity and the availability of longer-term money-market transactions in the e-MID data, which allows

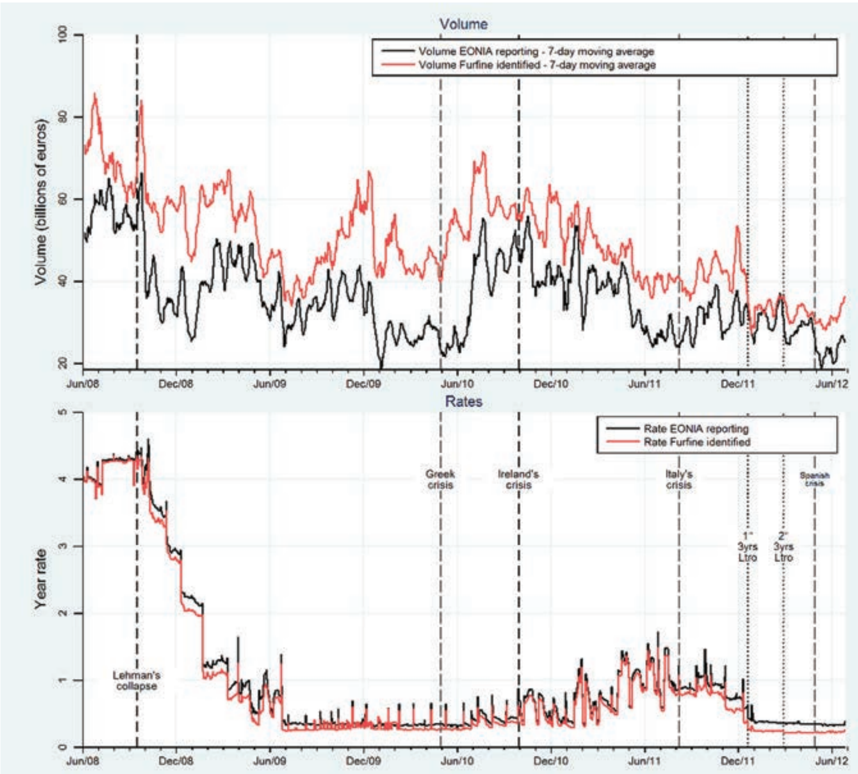
[22]The results obtained by our Furfine procedure have been compared for the overnight transactions with those of the original Furfine methodology. As for the e-MID comparisons, both algorithms obtain about the same error rates, whereas for the comparison with the EONIA data set the original one clearly over-estimates the reported volumes: the estimated turnover ranges from 93 percent to 430 percent and first and second quartiles are 134 percent and 180 percent, respectively.

transaction-by-transaction cross-checking, the analysis is somehow lacking a euro-wide context since from the start of the crisis e-MID data has concentrated on money-market trades between Italian participants. The need for validation against more euro-wide representative data calls for a cross-check also with the EONIA data. As already noted, every bank in the EONIA panel reports daily (i) the aggregate volume and (ii) the corresponding weighted average rate of lending transactions made on its own behalf. The use of the EONIA data set provides valuable reference material for the euro-area market going beyond and complementing the e-MID validation. The results reported in the following are based on the comparison between the overnight interbank loans identified using the Furfine algorithm for the EONIA panel banks and the actual daily aggregate reported values and rates of EONIA. The validation considers a dynamic panel reflecting the changing composition of the reporting banks in the sample under analysis.

The results of the comparison are reassuring. We start by looking at the difference between the total value reported and the total value identified with the Furfine algorithm. Figure 6 depicts the reported and identified turnovers for the EONIA panel banks using the EONIA100 corridor. The two series show similar trends, with the identified turnover ranging from 98 percent to 250 percent (first and third quartile are 120 percent and 160 percent, respectively) of the reported one. This does not imply that EONIA is not valid. In fact, the differences in the two series can be due to several reasons:

- Identified volumes can be larger than reported by EONIA due to:
  - possible over-identification;
  - tomorrow-next and spot-next transactions, not reported in EONIA;
  - rollovers, not reported in EONIA unless both parties are actively involved in the issue of a new contract;
  - intragroup transactions, excluded in EONIA reporting but not always possible to distinguish and discard in the TARGET2 data set;
  - transactions concluded on behalf of clients;
  - some secured loans may be captured, but so far we do not have evidence of this.

Figure 6. Results of the EONIA Cross-Check for the Corridor EONIA100



- Identified volumes can be lower than the reported EONIA rate due to
  - transactions settled outside TARGET2, e.g., on accounts of a commercial bank (correspondent banking);
  - loans settled via another payment system such as EURO1.

For example, for some banks we identified that they were very active in the tomorrow-next and spot-next markets. In other cases, we identified regular lending to other banks, and a deeper analysis showed that the sending and/or receiving banks are not always the beneficiary but act on behalf of another bank. Such transactions of course introduce a bias in the implied rate and an upward bias in the volume estimation. Finally, one bank reporting in the EONIA panel opened an account in TARGET2 only a few months after the beginning of our sample. The lending transactions of this bank were obviously settled outside TARGET2, either via a different payment system or on its books.

With regard to the rates (see figure 6, bottom panel), the reported and the implied rates lie close together. It is reassuring that the matching of interest rate spikes occurring at the end of a maintenance period, due to the increase in the cost of interbank borrowing. The mean and median spread are equal to 9 and 8 basis points, respectively. Finally, the implied rate is almost always lower than the reported rate and the difference is larger around interest rate decisions. This may be due to unidentified intragroup loans, which usually take place at rates well below the EONIA rate, and possible identified repos, most of the time traded at rates below unsecured benchmarks.

5. Conclusions

This paper developed an algorithm to identify unsecured interbank money-market loans from TARGET2 data, which is suitable for the whole euro area. This algorithm improves on the version developed by Furfine (1999), who was the first to develop such an algorithm for overnight loans only, and the one by Heijmans, Heuver, and Walraven (2010), who first developed an algorithm for a subset of the euro-area money market. With respect to the original algorithm, several enhancements have been implemented. The algorithm has been extended mainly in three ways: (i) It identifies money-market loans with maturity up to one year. (ii) It incorporates criteria for the implied interest rates: inclusion of the rate in a plausibility corridor and rounding to half a basis point. Specifically, we investigated two plausible corridors: one centered on the EONIA rate for loans up to four days and on the respective EURIBOR rate for other maturities and the other using the ECB standing facility corridor bounded by the overnight deposit facility rate and the marginal lending rate. Each corridor was tested at several sizes. (iii) It includes a procedure to efficiently select the correct loan in case of multiple plausible matches. Where such multiple plausible matches have the same maturity, the “correct” loan is determined randomly; where the maturities differ, the choice is made on the basis of the most plausible duration within maturity distribution inferred from the uniquely matched TARGET2 loans.

In contrast to the literature, our data set of identified interbank loans has been compared with real data sources, namely EONIA panel data and e-MID transaction-level data. The validation against EONIA panel data has been carried out for overnight identified TARGET2 transactions. Results show that the average interest rate found by the algorithm matches very well with the reported EONIA rate. The average deviation with the EONIA rates are 9 basis points, with highest deviation in the period September 2008 to June 2009. The turnover, however, is roughly 50 percent higher than that quoted by EONIA. Differences between estimated and reported turnover appear due to transactions that are not reported by EONIA panel banks: (i) intragroup transactions, (ii) transactions settled on behalf of other banks, (iii) rolled-over transactions, and (iv) spot-next and tomorrow-next loans.[23] On the other hand, a source of misidentification are loans reported by EONIA panel banks not settled in TARGET2 but in commercial bank money or in other payment systems (e.g., EURO1).

The second and more sophisticated validation method was used against the e-MID data set. This method was applied to all maturities, transaction by transaction, and allows to compute the number of unidentified loans (false negative, type 2 error) and the wrongly matched loans (real loans but with incorrect rates and/or maturities, type 3 error). Limits of this validation technique are the impossibility to estimate the false positive error (type 1) and the fact that e-MID data are not representative for the entire euro money market during the whole analyzed period. The best-performing corridor setup is the one centered on the EONIA and EURIBOR rates and 200 basis points wide: type 2 error rate is 1.96 percent while type 3 error rate is 0.73 percent. Analysis of the error rates per maturity shows that the algorithm is more reliable for transactions up to three months. It can be used for loans up to one year, using extra caution with respect to the uncertainties of the loans found. Our findings are in sharp contrast with Armantier and Copeland (2012),

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[23] This is because our algorithm works on the settlement dates and cannot distinguish between different trading dates.

who validate the algorithm developed for Fedwire transaction. They find an estimate of 81 percent type 1 and 23 percent type 2 errors, which are significantly larger.

The current setup of our algorithm can be further improved by (i) a more theoretically correct assignment of a multiple match and (ii) also looking at loans which follow the 365-day year convention for calculating the rate, as there are also, e.g., British banks which follow this convention. Finally, although our algorithm performs well, and with the inclusion of these improvements may even perform better, it would be beneficial for both research and policy purposes to have money-market loans flagged in TARGET2.

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