Volume 2, Number 2 June 2006

IJCB

INTERNATIONAL JOURNAL OF CENTRAL BANKING

IJCB International Journal of Central Banking

Volume 2, Number 2 June 2006

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The *International Journal of Central Banking* is published quarterly (ISSN: 1815-4654). Online access to the publication is available free of charge at **www.ijcb.org**. Individual print subscriptions are available at an annual rate of $100 (USD).

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International Journal of Central Banking
Publications Fulfillment, MS-127
Federal Reserve Board
Washington, DC 20551

Phone: 202-452-3245
Fax: 202-728-5886
E-mail: editor@ijcb.org

ISSN: 1815-4654

Global Bond Portfolios and EMU*

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This paper examines the bilateral composition of international bond portfolios for the euro area and the individual EMU member countries. I find considerable support for euro-area bias: EMU member countries disproportionately invest in one another relative to other country pairs. Another striking pattern is the positive connection between trade linkages and financial linkages in explaining asymmetries across EMU member countries in terms of their outward bond investments vis-à-vis external counterparties. My empirical results underline the impact of currency union on financial integration and support the notion that financial regionalization is the leading force underlying financial globalization.

JEL Codes: E42, F41, G15.

1. Introduction

Financial globalization is a key force that is reshaping the nature of the linkages across the major economic zones in the world economy. One dimension of globalization is the rising share of financial assets and liabilities held by foreign investors.[1] However, it is by no means the case that the pattern of foreign ownership is uniformly globalized in the sense that the national identity of investors has ceased to matter. Rather, the "international investor base" significantly differs across countries and regions, reflecting variation in both aggregate

*I am grateful to the editors, the referees, and Frank Warnock for helpful suggestions. This paper was prepared by the author under the Lamfalussy Fellowship Program sponsored by the European Central Bank. Any views expressed are only those of the author and do not necessarily represent the views of the ECB or the Eurosystem. I thank Vahagn Galstyan and Agustin Benetrix for excellent research assistance and the IRCHSS and the HEA-PRTLI grant to the IIIS for financial support; e-mail: plane@tcd.ie.

[1]See, for instance, Lane and Milesi-Ferretti (2003).

economic fundamentals (i.e., some countries are more attractive than others to all investors) and also bilateral linkages (i.e., the demand by an investor in region i for the financial assets issued by region j may be influenced by bilateral economic variables and also common institutional and cultural ties).

Such heterogeneity in the investor base potentially matters for two reasons. First, the cost of capital and the stability of international demand for the assets issued by a given country or region will depend on the characteristics of its international investor base. Second, the bilateral pattern of investment holdings will in itself influence the transmission of financial shocks and the nature of international risk sharing and also potentially affect exchange rate regime choices.[2]

In this paper, I investigate these issues by analyzing the bilateral patterns in international bond holdings, with a particular emphasis on European Monetary Union (EMU). I ask various questions about EMU: Do EMU members disproportionately invest in other EMU member countries, relative to other destinations? With respect to external financial linkages, is there systematic heterogeneity in the external bond portfolios of the individual EMU member countries? By addressing such questions, the contribution of the paper is to build a profile of the role of the euro in shaping global bond portfolios.

At an empirical level, I address these questions by exploiting the International Monetary Fund's Coordinated Portfolio Investment Survey (CPIS), which reports the portfolio holdings of sixty-seven investor countries in 220 destination territories. The availability of the CPIS data set represents a considerable advance relative to previous studies that relied on smaller samples and used data on transactions rather than holdings (see, for example, Portes, Rey, and Oh 2001).

This work builds on a number of recent contributions. Lane and Milesi-Ferretti (2004) develop a general empirical modeling approach for the study of bilateral investment positions, with an application to the international equity holdings for a large sample of investor nations. In related work, Lane and Milesi-Ferretti (2005) investigate

[2]On the latter, see Devereux and Lane (2003) for some suggestive evidence.

the international equity holdings of euro-area investors. In terms of the empirical analysis of bond portfolios, Portes, Rey, and Oh (2001) study the geography of gross bond flows between the United States and forty partner countries, while Burger and Warnock (2004) analyze the international bond holdings of U.S. investors. Another related contribution is the analysis of bank asset portfolios by Aviat and Coeurdacier (2005). Finally, Anderton, di Mauro, and Moneta (2004); Baele et al. (2004); Geis, Mehl, and Wredenborg (2004); and Pagano and Von Thadden (2004) each provide useful surveys of recent developments in European financial markets and the growth in euro-denominated securities issued by international participants in global capital markets.

The structure of the rest of the paper is as follows. I briefly discuss the relevant theoretical issues in thinking about the geography of bond portfolios in section 2. Section 3 introduces the Coordinated Portfolio Investment Survey (the source of the data on international bond holdings) and, taking a euro-area perspective, describes some broad patterns in the data. A range of empirical questions concerning EMU and the importance of the euro area in international bond holdings are addressed in the econometric analysis in section 4. Finally, directions for future research and some concluding remarks are offered in section 5.

2. A Conceptual Framework

In a benchmark finance model (e.g., the International Capital Asset Pricing Model, or ICAPM), investors should hold the bonds of each issuer in proportion to its share of global bond market capitalization.[3] This is the case to the extent that there are no real or financial imperfections that distort international trade in goods or assets, such that the optimal allocation rule is independent of the nationality of the investor. However, the segmentation of product and capital markets, plus informational asymmetries and differences in institutions (such as tax and legal systems) across countries, means

[3] See Lane and Milesi-Ferretti (2004) for a more formal treatment and detailed literature review of international asset allocation, with an application to international investment patterns in equity markets. See also the discussion in Burger and Warnock (2004).

that the world is far distant from this benchmark. The presence of such frictions means that the optimal portfolio allocation strategy plausibly varies with the nationality of the investor.

The incompleteness of financial markets also means that international diversification strategies may vary across countries. In a multicurrency world, hedging against nominal currency risk is costly, such that there may be a preference for bonds issued in the investor's home currency.[4] In addition, to the extent that a group of countries shares a common financial infrastructure, this should raise intragroup financial trade relative to other destinations that may involve higher transactions costs (Martin and Rey 2000). These two factors are especially relevant for the euro area, to the extent that the single currency has both eliminated nominal exchange rate risk among the member countries and lowered transactions costs by improving liquidity through a deepening and broadening of the consolidated euro-area bond market, relative to the individual national bond markets that operated prior to the launch of EMU.

In terms of other factors, much recent research has emphasized that information sets vary greatly across investors. This is a popular rationalization of home bias in portfolios. The multicountry version of this argument is that bilateral investment patterns should correlate with the strength of informational linkages between different country pairs. Again, it may be argued that the single currency has substantially integrated the financial market of the euro area and thereby improved the information flow among member countries.[5]

An additional consideration is that investors in different countries face different "endowment" risks (e.g., nondiversifiable shocks to labor income or tax rates). The basket of international assets that offers the best hedge against these risks may vary on a bilateral

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[4]Our data do not permit us to distinguish between the nationality and currency denomination of a bond issue. However, Burger and Warnock (2004) report that local-currency bonds represent 93 percent of total bonds outstanding for developed-country markets and 78 percent of total bonds outstanding for emerging markets. For advanced-country destinations, there is likely to be a strong overlap between the nationality of the issuer and the currency of issue; for developing-country destinations, in contrast, external investors primarily hold the foreign-currency bonds issued by these countries.

[5]See also Baele et al. (2004) for a recent review of the integration of the European financial markets. Pagano and von Thadden (2004) provide an extensive study of recent developments in the euro-area bond market.

basis.[6] In addition, with regard to the segmentation of product markets, there are several reasons to believe that trading partners should receive a higher weight in portfolios. A basic reason is that the volume of trade is a good predictor of the level of bilateral exchange rate volatility (Devereux and Lane 2003, Broda and Romalis 2003). As such, currency risk is minimized by preferring the bonds of major trading partners.

Along another dimension, Obstfeld and Rogoff (2001) show that the more investors are exposed to consumption risk through fluctuations in the supply of imported goods, the more the incentive to hold state-contingent foreign assets is increased. At the extreme, a country that just purchases domestic goods is not exposed to external shocks to its level of consumption and so need not be concerned with hedging against this risk. Lane and Milesi-Ferretti (2004) generalize this argument to an N-country setting, with the prediction that bilateral portfolio shares should be positively related to import shares in order to minimize consumption risk. Although these authors focused on international equity portfolios, analagous reasoning may apply to bond allocations. For instance, holding the domestic-currency bonds issued by a trading partner provides a natural hedge against bilateral real exchange rate movements: if the relative price of the import good rises, this is offset by the increased real return for the domestic investor from holding the foreign bond.[7]

I build my empirical specifications in the econometric work in section 4 on the basis of these theoretical arguments that provide some hypotheses as to why the composition of international bond portfolios may deviate on a country-by-country basis.

3. The Coordinated Portfolio Investment Survey (CPIS)

In this section, I first discuss some features of the CPIS, before presenting an overview of the broad patterns in the data on

[6] See Davis, Nalewaik, and Willen (2001) for a formal treatment of this point.

[7] Whether the hedged return on a foreign bond positively or negatively co-moves with the real exchange rate (or the terms of trade) is ambiguous. In general, it depends on the source of the relative price shock and the relative importance of nominal risk versus credit risk in determining the value of the foreign bond. See also a related example in Obstfeld (2004).

international bond portfolios, with a primary focus on the euro area as a source and destination for cross-border bond investments.

3.1 Data Issues

The source of data on bond holdings is the CPIS, which is organized by the International Monetary Fund. After a smaller survey in 1997, the annual survey since 2001 has included sixty-seven source countries and 220 destination territories.[8] I mainly focus on the 2004 cross-section in this study.[9] However, I also examine the changes in bond portfolios between 1997 and 2004 in seeking to establish the impact of EMU.

While the CPIS represents a major advance in availability of data on bilateral investment positions, Lane and Milesi-Ferretti (2004, 2005) point out that the survey is imperfect. First, holdings are surely underreported by some countries due to incomplete coverage or the complexities of tax-driven asset management structures.[10] Second, the bilateral data can be distorted by third-party holdings to the extent that final ownership of assets is not properly traced. This is a larger problem for those countries that primarily surveyed custodians rather than end investors. Third, in relation to debt securities, the survey offers relatively little information on the currency denomination of bonds.[11] Finally, the CPIS does not report the domestic holdings of investors; therefore, it does not provide a complete profile of the composition of portfolios but rather only details the geographical breakdown of the cross-border component of investment positions.

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[8]The 1997 survey did not include some important investor nations (e.g., Germany) as source countries, severely limiting its usefulness in examining the investment patterns of the aggregate euro area. However, in the next section, I will compare changes in investment patterns between 1997 and 2001 in order to assess whether EMU membership has influenced portfolio allocations.

[9]In an earlier draft, I considered the 2001 cross-section. The release of the 2004 data in March 2006 has allowed me to take a longer time span in considering the impact of the euro on bond portfolios.

[10]For instance, the German survey did not cover holdings by households.

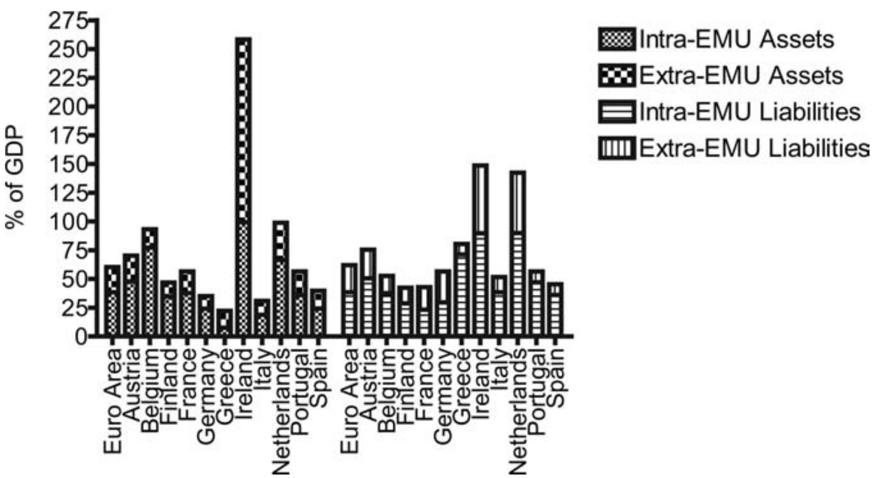
[11]See the analysis in Geis, Mehl, and Wredenborg (2004). Even for those countries that do report the breakdown across the major currencies, these data are provided only in the aggregate, rather than on a destination-by-destination basis.

It is also important to understand that the CPIS reports only aggregate holdings. It does not provide the decomposition in terms of whether securities are issued (or held) by public or private institutions and/or the relative holdings of individual investors versus financial intermediaries. Moreover, it does not give details as to the "age profile" of the holdings in terms of whether particular assets were recently acquired or have been held for a long time. For these reasons, the CPIS, while useful, by no means provides a complete profile of the investor base in international bond markets.

3.2 Broad Patterns

I begin in figure 1 by looking at the total international bond holdings of EMU member countries at the end of 2004.[12] The euro-area aggregate holdings amount to $5.7 trillion in cross-border assets, or 60.3 percent of GDP. Of these, 63.8 percent are invested in

Figure 1. International Bond Holdings of EMU Member Countries: End of 2004



Source: Author's calculations, based on CPIS data.

[12]Throughout the paper, we focus on the data for long-term debt securities. The CPIS does provide some information on short-term debt securities, but there are many more missing observations for this category.

other member countries, with extra-EMU bond holdings representing \$2.1 trillion, or 22 percent of GDP. Of the individual countries, figure 1 does not include Luxembourg. Its cross-border bond holdings amount to 2,733 percent of its GDP, with the distribution between intra- and extra-area destinations similar to that for the aggregate. Clearly, this extraordinarily large bond portfolio reflects Luxembourg's status as a major financial center for European asset management and also highlights that a major proportion of these holdings have not been traced back to the end investor. Albeit to a lesser extent, Ireland also shows up as a major financial center, with a bond portfolio valued at 258 percent of its GDP.[13] At the other end of the distribution, Greece has by far the lowest ratio of international bond assets to GDP at 22.3 percent, with most of the other countries in the 30–60 percent range. Another noteworthy feature is that only Greece and Ireland devote more than 50 percent of their portfolios to territories outside the euro area, with the other countries exhibiting much higher levels of euro-area bias in the allocation of their international bond holdings.

In terms of external destinations, the United States and the United Kingdom are by far the two most popular individual destinations, although there is considerable heterogeneity across the member countries. With respect to external bond liabilities, Japan is the single biggest bond investor in the euro area, with the United Kingdom a close second and the United States and Switzerland also significant sources of total inward investment into the euro area. In the next section, I attempt to tease out some of the determinants of these various patterns in the relations between the euro area and global bond markets.

4. EMU and Cross-Border Bond Portfolios

I begin this section by analyzing whether a euro-area bias is evident in the data. Subsequently, I investigate the external bond holdings of the euro area, in order to establish whether there are systematic

[13] Ireland set up the International Financial Services Center (IFSC) in 1987, which has attracted many international firms to establish both back-end and front-end asset management operations there.

differences in the external bond portfolios (of assets and liabilities) of the individual EMU member countries.

4.1 Do EMU Member Countries Invest Disproportionately in Each Other?

Do EMU member countries invest disproportionately in each other? To address this question, I consider a sample of source countries that includes eleven EMU member countries and eleven other high-income countries from outside the euro area, to form a sample of twenty-two source countries.[14] By contrasting the behavior of members and similar nonmembers, I can investigate whether a country pair where both are members of the euro area has a different investment pattern than other country pairs.

The general specification is

$$\log(BOND_{ij}) = \phi_i + \phi_j + \rho EURO_{ij} + \gamma \log(IMP_{ij}) + \beta Z_{ij} + \varepsilon_{ij}$$
$$i = \{HIGH - INC\}, \tag{1}$$

where the dependent variable is the level of source-country j's bond holdings in host-country i. I include a pairwise dummy $EURO_{ij}$ that takes the value of 1 if both the source and host countries are members of the euro area and 0 otherwise. To the extent that the various control variables capture the natural variation in bilateral bond investment patterns, the pairwise $EURO$ dummy variable will measure the impact of joint membership of the euro area "over and above" the other linkages that tie together the various pairings among EMU member countries. The inclusion of country dummies for each source and host country means that I control for all characteristics that determine a country's general propensity to invest externally and to be a recipient of inward investment, respectively (see Lane and Milesi-Ferretti 2004 for an extended discussion of this

[14]The eleven nonmember countries I consider are the United States, the United Kingdom, Denmark, Sweden, Switzerland, Norway, Japan, Canada, Iceland, Australia, and New Zealand. These countries are advanced economies that are structurally similar to the EMU member countries and, as such, form a natural comparator group. Luxembourg is excluded as a source country due to its special status as an offshore center.

specification).[15] As such, I rather seek to explain portfolio asymmetries: why does country A disproportionately invest in destination X, whereas country B relatively overweights destination Y?

The inclusion of double fixed effects means that the list of regressors is confined to bilateral variables that vary across country pairs (i, j). In addition to the volume of imports, I consider in a range of specifications a set of other variables that may proxy for informational linkages, the scope for diversification, and institutional similarities between country pairs. Finally, since there are a large number of zero or small-value bilateral holdings in the data (in terms of bond holdings in the smaller developing countries), I restrict attention to positions in excess of \$1 million.[16]

I also provide some time-series evidence on this question by looking at changes in portfolio allocation between 1997 and 2004. The number of investor countries is reduced, since the 1997 survey covered a smaller number of countries. From this high-income group, two EMU members (Germany and Greece) and one important non-member (Switzerland) are excluded.[17] Table 1 shows the growth in foreign bond holdings for each member country between 1997 and 2004. In most cases, the growth in holdings in other member countries far exceeds the growth in the aggregate portfolio. The differential is especially striking for Finland, Italy, and Spain.

In order to conduct a more formal investigation, I adopt the specification

$$\begin{aligned}\Delta \log(BOND_{ij}) = \phi_i + \phi_j + \rho EURO_{ij} + \gamma\Delta \log(IMP_{ij}) + \beta_1 \Delta Z^1_{ij} \\ + \beta_2 Z^2_{ij} + \varepsilon_{ij} \qquad i = \{HIGH - INC\}, \qquad (2)\end{aligned}$$

where Z^1 is a set of regressors that are entered in first differences and Z^2 are entered in levels.[18]

[15]If the set of source countries was restricted to just the euro-area members, a *EURO* dummy could only be included by dropping the double-fixed-effects specification and employing a panel version of the specification similar to equation (3) below. It turns out that a *EURO* dummy is highly significant in such a specification. However, since it is not possible to include source- and host-country dummies, this alternative approach cannot rule out that omitted factors correlated with EMU membership are responsible for its significance.

[16]However, results are very similar if I include these data points.

[17]These countries are still included as host countries in the survey.

[18]I still include the double fixed effects in this specification.

Table 1. Changes in Holdings for EMU Member Countries: 1997 to 2004

	World	Euro Area
Austria	417.2	654.8
Belgium	278.8	425.6
France	461.8	729.8
Italy	202.6	835.8
Netherlands	394.8	385.6
Finland	1,013.1	2,771.9
Ireland	694.5	617.7
Portugal	568.9	883.2
Spain	1,495.5	3,425.1

Note: This table shows the percentage of growth in each country's international bond holdings: aggregate and in other euro-area countries.

The empirical results are shown in table 2. Columns 1–3 report levels specifications, while the findings from the differences specifications are displayed in columns 4–6.[19] In column 1, I just include the *EURO* dummy as the sole bilateral regressor (in addition to the fixed source- and host-country dummies). The dummy variable is highly significant, both statistically and economically. This basic specification suggests that the level of cross-border bond investment between two members of the euro area is 426 percent higher than between any other country pair in the sample.

In column 2, I include those bilateral variables that are most plausibly correlated with the joint membership of the euro area: the volume of bilateral imports, the level of bilateral exchange rate volatility, and joint membership in the European Union. In addition, I include some popular gravity-type variables: distance, a colonial dummy, a border dummy, and a common language dummy. I also add the correlation of output growth rates between the source and host countries and a tax treaty dummy to the specification. The former is intended to capture the scope for bilateral risk diversification, to the extent that output growth is a good proxy for bond returns.[20]

[19]Due to its offshoring role, I exclude Luxembourg from this exercise.

[20]See Chen (1991) and Ilmanen (1995). Data on bond returns are only available for a fairly small subset of the countries in the sample.

Table 2. Is there a Euro Bias?

	(1) Level	(2) Level	(3) Level	(4) Diff.	(5) Diff.	(6) Diff.
EURO Dummy	1.66 (9.9)***	1.21 (5.93)***	1.19 (5.99)***	0.68 (3.6)***	0.58 (2.15)**	0.77 (2.68)***
Log(Imports)		0.17 (2.99)***	0.27 (3.55)***		0.07 (1.88)*	0.11 (2.87)***
VOL(ER)		−0.1 (1.41)	−0.12 (1.66)		−0.22 (2.45)**	−0.13 (1.27)
EU Dummy		−0.37 (1.65)	0.29 (1.23)		−0.32 (1.14)	0.19 (.62)
Border		−0.23 (1.16)	−0.18 (1.08)		−0.23 (.98)	−0.02 (.08)
Log(Distance)		−0.59 (5.04)***	−0.24 (1.91)*		0.05 (.48)	0.27 (2.28)**
Colony		0.09 (.5)	0.16 (.85)		−0.11 (.46)	−0.21 (.76)
Common Language		0.29 (1.85)*	−0.005 (.03)		0.18 (.9)	−0.13 (.55)
Correl (Growth Rates)		−0.14 (.76)	0.35 (1.56)		−0.32 (1.21)	−0.33 (1.09)
Tax Treaty		0.33 (2.39)**	0.39 (2.25)**		0.37 (1.77)*	0.4 (1.68)*
Common Legal Origin			0.39 (3.3)***			0.31 (2.16)**
Number of Observations	1,230	1,108	716	764	701	526
Number of Sources	22	22	21	19	19	18
Number of Destinations	114	100	48	95	88	48
Adj R2	0.81	0.85	87	0.29	0.46	0.49
Marginal R2	0.05	0.21	0.33	0.02	0.06	0.10

Note: Estimation is by pooled least squares, with double fixed effects. Heteroskedasticity-corrected t-statistics are in parentheses. ***, **, and * refer to 1, 5, and 10 percent significance levels, respectively. Marginal R2 is the explanatory power of the bilateral variables in explaining the residuals from an "only fixed effects" regression. See appendix 2 for the definitions and data sources for the variables.

Despite the inclusion of these controls, the *EURO* dummy remains highly significant. In terms of magnitude, it now implies a 235 percent euro bonus in terms of bilateral bond investment. The fact that the *EURO* dummy remains significant even with the inclusion of these regressors indicates that the effect is not simply attributable to the elimination of exchange rate volatility among the member countries, the high level of intra-EMU trade, or common membership in the EU.

In turn, this indicates that the explanation for the euro effect lies in the institutional impact of EMU in terms of the unification of the euro-area bond market and the importance of "truly zero" currency risk in determining the composition of bond portfolios. At one level, EMU acts to reduce transactions costs due to the greater liquidity of the unified market and the elimination of currency conversion and hedging costs. At another level, EMU has altered the basic properties of the bonds issued by governments and corporations in the member countries; these now are much closer substitutes due to the absence of currency risk.

Finally, at the cost of a major reduction in sample size (in effect, the set of host countries now comprises only major industrial and middle-income countries), I include a dummy variable for "common legal origin" in column 3. This variable is intended to capture a basic level of institutional similarity between the source and host countries and has been found to have some explanatory power for bilateral patterns in equity investments (see Lane and Milesi-Ferretti 2004). Although the estimated coefficient for the *EURO* dummy does fall in value in column 3, it still indicates that cross-border bond investment is 229 percent larger among euro-area member countries than among other country pairs.

With respect to the other explanatory variables, the level of imports and distance are highly significant in both columns 2 and 3. As was discussed in section 2, there are multiple hypotheses as to why portfolio holdings are skewed toward trading partners and geographically proximate destinations. Regarding the role of trade, this may reflect an optimal risk-diversification strategy; alternatively, trade in goods may also be a good information vehicle. Regarding distance, this also has an information interpretation but may also proxy for institutional similarity or lower transactions costs. Further research is required to discriminate between these various hypotheses.

The other individually significant regressors are colonial relationship (positive) and common language (positive). Each of these variables has the expected sign. In addition, the common legal origin variable is highly significant in column 3, indicating that institutional similarity may be important in determining bilateral holdings. The border variable is now also significant, albeit with a negative sign. However, the colonial and common language dummies are not individually significant in this smaller sample, perhaps suggesting that these variables are more relevant in explaining allocations across less-advanced economies that are not included in this smaller sample.

I turn to the time-series evidence in columns 4–6 by looking at changes in portfolio allocation between 1997 and 2004. As mentioned before, the number of investor countries is reduced, since the 1997 survey covered a smaller number of countries. From this high-income group, two EMU members (Germany and Greece) and one important nonmember (Switzerland) are excluded.[21] As previously noted, table 1 shows the growth in foreign bond holdings for each member country between 1997 and 2004. In most cases, the growth in holdings in other member countries far exceeds the growth in the aggregate portfolio: the differential is especially striking for Finland, Italy, and Spain.

The basic specification that is reported in column 4 of table 2 shows that bond holdings indeed grew significantly more quickly between members of the euro area than between other country pairs: the estimated coefficient indicates intra-EMU bilateral holdings grew by an additional 97 percent. It turns out that the inclusion of the other regressors in columns 5 and 6 only slightly reduces the estimated coefficient, with the estimated magnitude in the range of [79, 116] percent.

With regard to the control variables, the growth in imports and the tax treaty dummy are also significantly positive in both columns 5 and 6. The only other individually significant results are that exchange rate volatility reduces holdings in column 5, while those countries that are farther apart and those that share a common

[21] These countries are still included as host countries in the survey.

legal origin experienced faster growth in bilateral bond holdings in the specification in column 6. Taken together with its negative sign in the levels specifications, the positive sign on distance in the differences regression suggests that the propensity to invest in closer destinations is weakening over time.

Overall, the results in table 2 strongly indicate that the extent of bilateral financial integration is stronger between EMU member countries than between other country pairs. Of course, this finding requires more extensive testing by exploring other specifications and econometric techniques, but these initial steps establish a benchmark for such future empirical investigations.[22]

4.2 What Drives Variation in the External Bond Portfolios of Individual Member Countries?

In this subsection, I explore heterogeneity across euro-area members in terms of their external bond holdings. The exposure of member countries to external country risk is asymmetric to the extent that such heterogeneities are important. As in table 2, I again employ the double-fixed-effects specification

$$\log(BOND_{ij}) = \phi_i + \phi_j + \gamma \log(IMP_{ij}) + \beta Z_{ij} + \varepsilon_{ij} \quad i \in \{EMU\}, \tag{3}$$

where the set of source countries is restricted to members of the euro area, and the set of host countries now includes only destinations outside the euro area.[23] The results are reported in columns 1–3 of table 3.

I begin in column 1 by including just imports as a bilateral regressor. This variable is highly significant: the greater the import

[22]As one robustness check, I entered distance in a nonlinear (quadratic) format. This was done in view of the close geographic proximity of EMU member countries (relative to other country pairs). In general, the results are very similar for the *EURO* dummy.

[23]I exclude Luxembourg as a source country, in view of its predominant role as an offshore center. The external investment pattern for Luxembourg-associated holdings is reasonably similar to the euro-area average, with the exception that a lower weight is attached to the United Kingdom and a higher weight to "other Europe." The results are also essentially unchanged if Ireland (the other main euro-area offshore center) is excluded.

Table 3. Heterogeneity in the External Bond Portfolios of EMU Member Countries

	(1) Out	(2) Out	(3) Out	(4) In	(5) In	(6) In
Log(Imports)	0.57 (13.0)***	0.63 (11.6)***	0.71 (7.55)***	−0.05 (.49)	0.01 (.07)	0.14 (.95)
Log(Distance)		−0.03 (.35)	−0.14 (1.02)		−0.32 (.71)	−0.35 (.63)
Colony		−1.84 (3.95)***	−0.85 (1.63)		−1.31 (1.07)	−0.91 (.79)
Common Language		1.12 (3.35)***	0.67 (1.59)		−0.55 (1.13)	0.35 (.63)
Correl (Growth Rates)		0.5 (1.57)	1.09 (2.42)**		0.95 (1.27)	0.67 (.8)
Tax Treaty		0.84 (3.51)***	0.79 (2.28)**		−0.79 (1.9)*	−0.77 (1.83)*
Common Legal Origin			−0.08 (.3)			0.07 (.22)
Number of Observations	592	539	292	402	372	287
Number of Sources	11	11	11	51	48	38
Number of Destinations	99	90	36	11	11	11
Adj R2	0.27	0.41	0.43	0.52	0.55	0.55
Marginal R2	0.15	0.29	0.10	0.81	0.83	0.84

Note: Estimation is by pooled least squares, with double fixed effects. Heteroskedasticity-corrected t-statistics are in parentheses. ***, **, and * refer to 1, 5, and 10 percent significance levels, respectively. Marginal R2 is the explanatory power of the bilateral variables in explaining the residuals from an "only fixed effects" regression. See appendix 2 for the definitions and data sources for the variables.

dependence of a member country on a given external destination, the greater the level of bond holdings in that country. I expand the specification to include some gravity-type variables, plus the correlation in growth rates and the tax treaty dummy in column 2. Finally, again at the cost of a major reduction in sample size, I include a dummy variable for common legal origin in column 3. The imports variable remains highly significant in these broader specifications, and its magnitude slightly increases to [88, 103] percent. It is important to emphasize that the import variable is largely unaffected by the inclusion of these gravity variables, despite their importance in explaining bilateral trade patterns. This suggests that the volume of trade per se is important in determining bond investment patterns, as opposed to imports merely proxying for these other informational variables.

Among the other explanatory variables, the tax treaty dummy is significantly positive in both columns 2 and 3. Again, this is best interpreted as an indicator of institutional similarity. The colonial dummy is significantly negative and the common language dummy significantly positive in column 2. Their loss of significance in column 3 may be explained by the greater importance of these variables in explaining allocations to developing-country destinations that are featured more heavily in the sample in column 2 than in column 3.[24] Distance is not significant: since the euro-area countries are close to one another, differences in the distances to particular external partners are relatively small, such that this variable may not have much marginal explanatory power. The fact that the correlation in growth rates enters in a significantly positive manner is, on the surface, puzzling—a diversification motive should point to lower allocations to those countries that share a business cycle with the home country.[25]

4.3 External Bond Investment in EMU Member Countries: Sources of Heterogeneity

In columns 4–6 of table 3, I examine which bilateral factors are important in determining asymmetries in the distribution of inward

[24]The colonial dummy actually enters with a negative sign. Its loss of significance in column 3 may also be related to the inclusion of the common legal origin dummy, which is highly correlated with the colonial dummy.

[25]As noted earlier, we have inadequate data on bond returns to study in more detail the relation between the co-movements in bond returns and allocations. In related work, Couerdacier and Guibaud (2005) argue that the apparent positive association between the bilateral co-movements in equity returns and bilateral equity holdings can be explained by reverse causation: an increase in bilateral portfolio holdings in equilibrium raises the correlation in equity returns.

investment across the individual member countries of the euro area. For this purpose, I again use a double-fixed-effects specification:

$$\log(BOND_{ij}) = \phi_i + \phi_j + \gamma \log(IMP_{ij}) + \beta Z_{ij} + \varepsilon_{ij} \quad j \in \{EMU\}. \tag{4}$$

Here, the set of source countries is restricted to nonmembers of EMU, and the set of host countries now includes only member countries.[26]

As before, I start in column 4 by just including imports as a regressor. Similarly to columns 2 and 3, I then expand the specifications in columns 5 and 6 to include a larger number of regressors, with an attendant reduction in sample size.

The only variable that turns out to be individually significant is the tax treaty dummy. In contrast to the pattern for the outward portfolio allocations of the EMU member countries, a tax treaty exerts a negative effect on the level of inward bond investment from a nonmember country to a member country, such that the tax treaty seems to have a highly asymmetric impact. The most sensible interpretation of the lack of significant variables in these specifications is that the bonds issued by EMU member countries are viewed as very close substitutes by external investors.

5. Conclusions

This paper has exploited the International Monetary Fund's Coordinated Portfolio Investment Survey to build a profile of the euro area as both a source and destination for international bond investment. I have documented the importance of the aggregate euro area in global bond markets but highlighted that there are substantial asymmetries in the external patterns of outward and inward investment with respect to the individual member countries.

My results are strongly indicative that EMU has had a substantial impact on global bond portfolios. In both levels and differences, cross-investment among euro-area members is substantially greater than among other country pairs, even controlling for other characteristics that may generate strong investment linkages across the euro area.

[26] I exclude Luxembourg as a host country.

In terms of understanding the sources of the euro bias, more research is required. In contrast to the literature that investigates the impact of EMU on trade in goods, there are two factors at work in terms of its impact on bond trade that are not easily separated: EMU both reduces bilateral trading costs and, by fundamentally altering the risk and payoff profiles of the bonds issued by the individual member countries, also changes the elasticity of substitution between these bonds.[27]

A second message from my empirical work is that there are asymmetries across member countries in terms of the bilateral composition of their bond assets. Another extension of this line of research is to push the analysis further by examining the extent to which the observed asymmetries in portfolios across euro-area members and between the euro area and the rest of the world materially contributes to asymmetries in wealth dynamics across these countries and regions. In this regard, the Argentina default provided an interesting localized example (Italian retail investors were among the main European financial casualties in that episode.) However, in the event of a more widespread crisis in international financial markets, such asymmetries may pose a more serious problem at both the European and global levels in terms of the optimal design of policy responses.

Finally, another direction for future research is to understand the implications for EMU for asset pricing and the degree of financial development. A unified market for euro-denominated securities with lower transactions costs raises the value of these assets, reducing required yields and the cost of capital.[28] In addition, an increase in cross-holdings increases the correlation in returns across countries, altering the international transmission mechanism for financial shocks. Accordingly, the macroeconomic and financial impact of greater financial integration within the euro area (and between the

[27]See Lane (2006) for an overview of the impact of EMU on goods trade. Anderson and van Wincoop (2004) provide a general survey of the impact of shifts in trading costs on the volume of goods trade; this relation turns on the elasticity of substitution between home and foreign goods (which is typically assumed to be a fixed parameter). Martin and Rey (2004) study the impact of a reduction in cross-border trading costs on asset trade but, again, take the elasticity of substitution between assets to be fixed.

[28]See, for example, Martin and Rey (2000, 2004).

euro area and the rest of the world) presents an exciting research agenda for economists.

Appendix 1. Countries and Regions Participating in the Coordinated Portfolio Investment Survey

Argentina, Aruba, Australia, Austria, the Bahamas, Bahrain, Belgium, Bermuda, Brazil, Bulgaria, Canada, Cayman Islands, Chile, Colombia, Costa Rica, Cyprus, Czech Republic, Denmark, Egypt, Estonia, Finland, France, Germany, Greece, Guernsey, Hong Kong SAR of China, Hungary, Iceland, Indonesia, Ireland, Isle of Man, Israel, Italy, Japan, Jersey, Kazakhstan, Republic of Korea, Lebanon, Luxembourg, Macao SAR of China, Malaysia, Malta, Mauritius, Netherlands, Netherlands Antilles, New Zealand, Norway, Panama, Philippines, Poland, Portugal, Romania, Russian Federation, Singapore, Slovak Republic, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, Ukraine, United Kingdom, United States, Uruguay, Vanuatu, Venezuela.

Appendix 2. Data Sources

This paper largely draws upon the data bank constructed by Lane and Milesi-Ferretti (2004). Other data sources include the following:

Long-Term Debt Securities: Issued by host-country residents and held by source-country residents. Source: 2004 Coordinated Portfolio Investment Survey.

Source-Country Imports: Imports of goods by source countries from host countries. Source: International Monetary Fund, Direction of Trade Statistics.

Distance: The logarithm of Great Circle distance in miles between the capital cities of the source and host countries. Source: Rose and Spiegel (2004).

Correlation in Growth Rates: The correlation between the GDP growth rate in the source and host countries. Source: Author's calculations based on World Bank, World Development Indicators.

Common Legal Origin: A dummy variable that takes the value of 1 if the source and host countries have a legal system with a common origin (common law, French, German, or Scandinavian).

Source: Author's elaborations based on La Porta, López de Silanes, and Shleifer (2006).

Exchange Rate Volatility: Exchange rate data are from *International Financial Statistics.* Exchange rate volatility is measured as the standard deviation of the monthly log difference in the bilateral nominal exchange rate over 1994–97 and 1999–2004.

Tax Treaty: A dummy variable that takes the value of 1 if the source and host countries have a tax treaty enacted prior to 1999. Source: Lane and Milesi-Ferretti (2004), based on treaty data taken from www.unctad.org.

Common Language: A dummy variable that takes the value of 1 if the source and host countries share a common language. Source: Rose and Spiegel (2004).

Colony Dummy: A dummy variable that takes the value of 1 if the source and host countries ever had a colonial relationship. Source: Rose and Spiegel (2004).

EURO Dummy: A dummy variable that takes the value of 1 if the source and host countries are both members of the euro area.

EU Dummy: A dummy variable that takes the value of 1 if the source and host countries are both members of the European Union.

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Anticipation of Monetary Policy and Open Market Operations*

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Central banking transparency is now a topic of great interest, but its impact on the implementation of monetary policy has not been studied. This paper documents that anticipated changes in the target federal funds rate complicate open market operations. We provide theoretical and empirical evidence on the behavior of banks and the Open Market Trading Desk. We find a significant shift in demand for funds ahead of expected target rate changes and that the Desk only incompletely accommodates this shift in demand. This anticipation effect, however, does not materially affect other markets.

JEL Codes: E5, E52, E58.

1. Introduction

Through time, the Federal Reserve has been perceived as becoming more open and transparent. For example, explicit announcements of changes in the target federal funds rate began in 1994. With predictable changes in monetary policy, financial markets move *before* the Federal Reserve, not just in reaction to it. Lange, Sack, and Whitesell (2003) find empirical evidence of an anticipation effect in

*The views expressed are those of the authors and do not necessarily reflect those of the Board of Governors, the Federal Reserve System, or other members of the staff. We thank Kristin van Gaasbeck, James Hamilton, Mark Gertler, seminar participants at the Board of Governors of the Federal Reserve System, and staff at the Open Market Trading Desk at the Federal Reserve Bank of New York for their invaluable comments. Author contact: Carpenter: Mail Stop 59, 20^{th} and C Street NW, Washington, DC 20551; e-mail: scarpenter@frb.gov. Demiralp: Department of Economics, Koc University, Istanbul, Turkey; e-mail: sdemiralp@ku.edu.tr.

the market for Treasury securities in the months prior to changes in monetary policy.

In this paper, we investigate whether a similar type of anticipation effect exists in the federal funds market, the overnight loans of balances on deposit at the Federal Reserve. The supply of balances in this market is influenced by the Open Market Trading Desk at the Federal Reserve Bank of New York in order to push trading in the market toward the target rate determined by the Federal Open Market Committee (FOMC). On the one hand, because this market is the most directly affected by monetary policy, one might think that an anticipation effect would more likely be present in this market. On the other hand, supply is controlled by the Desk to offset any rate pressures. As a result, deviations from the target could reflect constraints that the Desk faces in accomplishing its goal. Predictable changes in the target rate could therefore have implications for the conduct of open market operations. In addition, an anticipation effect is related to, but distinct from, changes in the funds rate that are a result of an announcement by the Federal Reserve. Demiralp and Jorda (2002) and Hanes (2005) analyze these so-called open-mouth operations by looking at the movement of the funds rate *after* a target change announcement, not prior to it.

In this paper, we look into why an anticipation effect in the federal funds market exists and what the broader implications are. We present evidence that the federal funds rate tends to move in the direction of an anticipated change in policy prior to that change. We estimate econometric models of the federal funds market at a daily frequency in the spirit of Hamilton (1997, 1998) and Carpenter and Demiralp (forthcoming) to filter out the systematic variation in the funds rate and to estimate the movement that is attributable solely to the anticipation effect. Turning from the price side to the quantity side, we present results on the supply of reserve balances that suggest that the Desk increases the supply of balances in response to the anticipation effect. The fact that federal funds trade away from the current target, however, suggests that the change in supply is not sufficient to achieve the target. Indeed, in its annual report for 2004, the Desk acknowledged that it has attempted to offset only partially a shift in demand, because fully offsetting the demand could lead to unwanted volatility in the federal funds market. We attempt to assess this rationale based on our results.

Because the anticipation effect is the result of a shift in demand, we present an optimizing, dynamic programming model of a representative bank's demand for daily reserve balances to explain the shift in demand.[1] The model indicates that demand is shifted by a finite amount, suggesting that a full offset to the shift in demand is possible. First, we discuss the open market operations that would be necessary to counteract this effect. We conclude that it is possible that fully offsetting the rise in rates before fully anticipated moves could result in a substantial decline in the funds rate relative to the target following the FOMC meeting in question. We then document that over the period studied, there has been no significant increase in volatility surrounding the meetings. Lastly, we show that there has been little spillover from the funds market to other financial markets.

2. Data and Econometric Evidence

To examine the anticipation effect, we turn to the market for Federal Reserve balances. Reserve requirements, based on banks' customers' reservable deposits, are satisfied either with vault cash or with balances at the Federal Reserve. These balances are called *required reserve balances.* In addition, banks may contract with the Federal Reserve to hold more balances to facilitate the clearing of transactions through their accounts. These balances are called *contractual clearing balances.* Holdings of required balances—the sum of required reserve balances and contractual clearing balances—are averaged over a fourteen-day period called a *maintenance period.* Any balances held beyond the required level are called *excess balances.* The market for balances is discussed in more detail in section 3.

We use business-day data from February 1994 through July 2005. The starting date reflects the Federal Reserve's adoption of a policy of announcing changes in the target federal funds rate. We specify an equation with the deviation of the effective federal funds rate from its target as the dependent variable, and we specify an equation with the level of daily excess reserves as the dependent variable. For each equation, we include a lagged dependent variable to capture the

[1] In this paper we frequently use the generic word "bank" to represent depository and other institutions with accounts at the Federal Reserve.

autoregressive behavior. We also include dummy variables for each day of the maintenance period to control for systematic variation in the variables; Carpenter and Demiralp (forthcoming) document an intra-maintenance-period pattern to the federal funds rate. We include the level of cumulative reserve balances to control for the fact that demand for balances has a maintenance-period-frequency component as well as a daily-frequency component. In an extreme example, on the last day of a maintenance period, one would expect demand to be lighter than usual if banks had already satisfied their balance requirements for the period. We include the error for the daily forecast of balances made by the Federal Reserve. Hamilton (1998) and Carpenter and Demiralp (forthcoming) use this variable to measure the liquidity effect in the funds market. We use it here to capture deviations in price and quantity that are due to unintentional changes in reserve balances. As shown later, our results for the liquidity effect are broadly consistent with previous work.

We also include separate dummy variables for "special pressure days"—specifically, the day after a holiday; quarter end; year end; first of the month; fifteenth of the month; month end; and settlement of Treasury two-, three-, five-, and ten-year notes, including Treasury inflation-protected securities.[2] These are days of increased payment flows through banks' reserve accounts and, as a result, represent days of increased uncertainty. Increased uncertainty should be associated with a greater demand for balances to avoid an overdraft. Finally, for the excess balances equation, we include carryover, broken down by bank size. Everything else remaining the same, a higher level of balances carried over from the previous maintenance period should induce banks to hold lower balances in the current maintenance period.

While the regressions include the control variables as well as the variables of interest, to ease exposition, we present the coefficients on these control variables first in table 1 before presenting the rest of the results from the model. Looking at the dummies for the days

[2]We exclude Treasury bill auctions, as these are regular weekly auctions and are thus captured by our daily dummy variables. The exceptions to this would be the handful of occasions when bill auctions were delayed due to debt limit constraints.

Table 1. Control Variables

Sample Period: January 26, 1994–July 13, 2005*

Variable	$(Deviation\ from\ Target)_t$		$(Daily\ ER)_t$	
	Coeff.	s.e.	Coeff.	s.e.
Lagged Dependent Variable	0.27	0.047	0.27	0.026
$D_{First\ Thursday}$	−0.00082	0.015	0.65	0.28
$D_{First\ Friday}$	−0.058	0.016	0.056	0.26
$D_{First\ Monday}$	0.0033	0.016	1.53	0.22
$D_{First\ Tuesday}$	−0.049	0.015	0.93	0.23
$D_{First\ Wednesday}$	−0.032	0.015	0.98	0.23
$D_{Second\ Thursday}$	0.00030	0.015	1.54	0.23
$D_{Second\ Friday}$	−0.064	0.015	1.66	0.22
$D_{Second\ Monday}$	0.026	0.016	4.13	0.27
$D_{Second\ Tuesday}$	−0.040	0.018	4.22	0.41
$D_{Second\ Wednesday}$	0.12	0.031	9.63	1.23
$Cumulative\ ER \times D_{First\ Friday}$	−0.011	0.0030	−0.082	0.069
$Cumulative\ ER \times D_{First\ Monday}$	−0.0083	0.0048	−0.089	0.069
$Cumulative\ ER \times D_{First\ Tuesday}$	−0.0082	0.0028	−0.35	0.073
$Cumulative\ ER \times D_{First\ Wednesday}$	−0.016	0.0041	−0.37	0.072
$Cumulative\ ER \times D_{Second\ Thursday}$	−0.017	0.0038	−0.70	0.074
$Cumulative\ ER \times D_{Second\ Friday}$	−0.013	0.0049	−1.0039	0.093
$Cumulative\ ER \times D_{Second\ Monday}$	−0.016	0.010	−1.79	0.24
$Cumulative\ ER \times D_{Second\ Tuesday}$	−0.040	0.011	−2.058	0.47
$Cumulative\ ER \times D_{Second\ Wednesday}$	−0.090	0.024	−4.11	1.22
$(Forecast\ Miss)_t$	−0.0095	0.0035	0.79	0.038
$D_{Month\ End}$	0.027	0.034	2.45	0.26
$D_{Month\ Start}$	0.012	0.021	1.60	0.22
$D_{Quarter\ End}$	0.28	0.0764	4.27	0.41
$D_{Quarter\ Start}$	0.17	0.081	2.54	0.42
$D_{Year\ End}$	−0.45	0.17	5.047	1.21
$D_{Year\ Start}$	0.25	0.11	1.94	0.81

(*continued*)

Table 1 (continued). Control Variables

Sample Period: January 26, 1994–July 13, 2005*

Variable	*(Deviation from Target)$_t$* Coeff.	s.e.	*(Daily ER)$_t$* Coeff.	s.e.
$D_{\textit{Mid-Month}}$	0.09	0.012	2.31	0.20
$D_{\textit{Day Before Holiday}}$	−0.02	0.017	0.10	0.19
$D_{\textit{Day After Holiday}}$	−0.06	0.077	1.73	0.21
$D_{\textit{Treasury 2}}$	0.11	0.041	−0.85	0.36
$D_{\textit{Treasury 3}}$	0.065	0.032	−0.51	0.41
$D_{\textit{Treasury 5}}$	0.098	0.045	1.47	0.39
$D_{\textit{Treasury 10}}$	−0.045	0.016	−0.33	0.39
$(\textit{Required Operating Balances})_t$	0.00070	0.00059	−0.042	0.0085
Target	0.0014	0.0012	−0.13	0.023
$(\textit{Carry-in\_Large})_t$	—	—	−0.51	0.43
$(\textit{Carry-in\_Other})_t$	—	—	4.69	1.85
$(\textit{Carry-in\_Large})_t \times \textit{Anticipated } \Delta \times D_{\textit{One Day Before a Tightening}}$	—	—	−5.17	12.0080
$(\textit{Carry-in\_Large})_t \times \textit{Anticipated } \Delta \times D_{\textit{One Day Before an Easing}}$	—	—	−2.931	10.021

Note: Tables 1 and 2 report the results from the same regression but split the variables into two groups for exposition.
*Data for 2001 exclude September 11 through September 19.

of the maintenance period, we note that both Fridays have negative and statistically significant coefficients in the federal funds equation, as shown in the second and third columns. These results suggest that the funds rate consistently trades soft to the target on Fridays and indicate that the Desk typically provides more reserves on Fridays than are demanded at the target. Also of note is that the funds rate systematically trades firm to the target on the last day of the maintenance period. From the excess balances equation, shown in the last two columns, we can see that excess balances tend to start off low early in the period and gradually rise, peaking on settlement Wednesday.

Looking at the coefficients on cumulative excess, although many of the coefficients in the federal funds equation are statistically significant, they are only economically significant on the last two days, where an extra \$1 billion of cumulative excess is associated with 4 and 9 basis points of softness, respectively. The negative coefficients in the excess balances equation suggest that the Desk recognizes the pressure that cumulative excess places on banks' demand for balances and works to offset the effect.

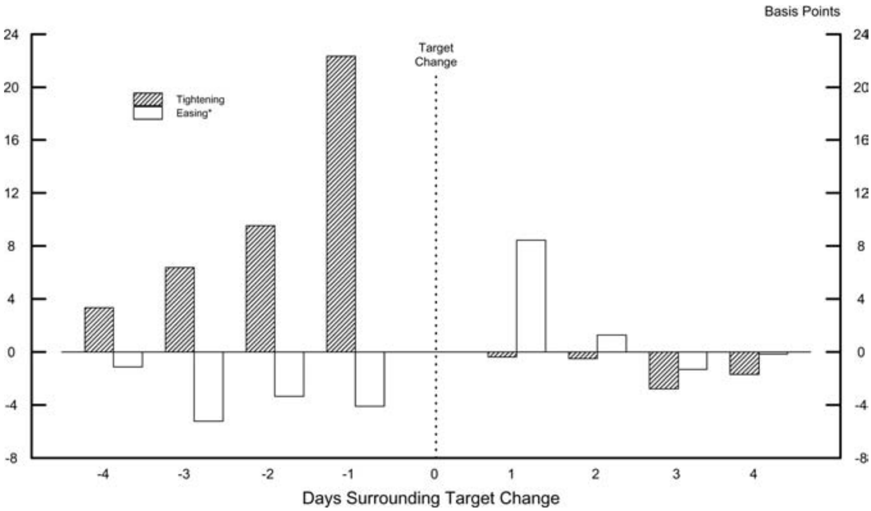
The carryover variable is negative for the large banks, indicating that these institutions act with the motivation to maximize profits and use their reserves efficiently. The coefficient is positive for small banks, confirming our understanding that these institutions do not closely manage their reserve positions. In order to test whether the banks boost their balances in the maintenance period before an anticipated rate hike in order to carry over the surplus, we interact lagged carryover balances with anticipated policy changes on the day before a target change for large banks. The coefficients are insignificant.

The coefficient on the forecast miss is consistent with results in Carpenter and Demiralp (forthcoming) for the funds rate equation. Essentially, this coefficient says that a \$1 billion change in reserve balances changes the federal funds rate about 1 basis point. For the excess balances equation, the coefficient is slightly (but statistically significantly) less than unity. Hamilton (1997) suggests that these exogenous changes in reserve balances are partially offset by borrowing from the discount window, an interpretation consistent with a coefficient below 1. The other variables have similar, logical interpretations. On balance, these control variables should allow us to focus exclusively on the anticipation effect, feeling confident that we have accounted for other systematic variation in the dependent variables.

2.1 Measuring Anticipation

Figure 1 shows the deviation of the effective federal funds rate from the target rate on days leading up to policy changes at FOMC meetings over the period 1994 to 2004. As can be seen, on days prior to increases in the target, the funds rate was on average above the target rate, and on days prior to decreases in the target, the funds rate was below the target. While this evidence is suggestive, it does

Figure 1. Federal Funds Rate Deviations from Target Surrounding a Target Change (1994–2004)



*Data for 2001 exclude September 11 through September 19.

not control for whether or not the change in the target rate was expected—the crux of the anticipation effect.

To measure the degree of anticipation of changes in the target rate, we use a technique that generalizes the methodology proposed by Kuttner (2001) to measure expectations of the Federal Reserve's policy actions based on the price of federal funds futures contracts.[3] The key idea is that the spot-month rate for federal funds futures contracts on a particular day t reflects the expected average funds rate for that month, conditional on the information prevailing up to that date.[4] Based on this fact and knowing that the effective funds

[3]One ironic implication of the present paper is that a systematic anticipation effect should tend to get priced into futures contracts. As a result, the method for inferring anticipated changes is likely biased. Preliminary investigation of the phenomenon suggests that the bias is likely small, but future research should strive to make the estimation precise. In any event, this bias implies that we will understate any anticipation effect we find, so our general results should be unaffected.

[4]Naturally, this measure presumes that market participants are aware of the target and can observe the changes. If the market participants were unaware that the target had changed, expectations would not necessarily reflect the changes in the policy instrument.

rate as a monthly average is very close to the target rate (typically within a few basis points), the spot-month futures rate on any day k prior to a target change that is expected to occur on day t can be expressed as

$$\mathit{Spot\ Rate}_k = \frac{[(N_b \times \rho_{t-1}) + (N_a \times E_k(\rho_t)]}{N} + \mu_k, \quad k < t, \tag{1}$$

where ρ_t is the target funds rate on day t, E_k is the expectations operator based on information as of day k, and μ_k is a term that may represent the risk premium or day-of-month effects in the futures market. In an efficient market with risk-neutral investors, this term would be zero. N_b is the number of days before a target change, N_a is the number of days after a target change, and hence $N = N_b + N_a$ is the total number of days in a given month.

Assuming that the target change occurs on day t, the spot rate on day t is given by

$$\mathit{Spot\ Rate}_t = \frac{[(N_b \times \rho_{t-1}) + (N_a \times \rho_t)]}{N} + \mu_t. \tag{2}$$

The difference between the spot-month rates prior to and after the target change—i.e., equation (2) − equation (1)—gives us the policy surprise as of day k:

$$\begin{aligned}&\mathit{Spot\ Rate}_t - \mathit{Spot\ Rate}_k \\ &\quad = \Phi \underbrace{[\rho_t - E_k(\rho_t)]}_{\textit{Unanticipated target change as of day } k}, \quad \text{where } \Phi = \left(\frac{N_a}{N}\right).\end{aligned} \tag{3}$$

Equation (3) is used to compute the policy surprise on any day k prior to a target change that takes place on day t (i.e., $k < t$), except for two cases:

1. Kuttner (2001) notes that the day-t targeting error and the revisions in the expectation of future targeting errors may be nontrivial at the end of the month. Consequently, if a target change occurs in the last three days of the month, the difference in one-month forward rates is used to derive the

policy surprise, since the one-month rate reflects the expected average funds rate for the next month:

$$(One\ Month\ Rate)_t - (One\ Month\ Rate)_k$$
$$= \Phi \underbrace{[\rho_t - E_k(\rho_t)]}_{Unanticipated\ Policy\ Change\ as\ of\ day\ k},$$
$$\text{where } \Phi = \left(\frac{N}{N}\right) = 1.$$

2. If the number of days in the forecast horizon is equal to (or greater than) the day of the month in which the target is changed, we need to use the one-month forward rate from the *previous* month to assess the market's expectations on day k. For instance, if our goal is to derive the anticipated policy change five days prior to a policy meeting, and if the meeting occurs on the second day of the month, we need to look at the one-month forward rate on day $k = N - 3$ of the previous month and the spot rate on day 2 of the current month to compute the anticipated and unanticipated policy changes. That is,

$$(Spot\ Rate)_t - (One\ Month\ Rate)_k^{\text{Previous Month}}$$
$$= \Phi \underbrace{[\rho_t - E_k(\rho_t)]}_{Unanticipated\ Policy\ Change\ as\ of\ day\ k}, \quad \text{where } \Phi = \frac{N_a}{N}.$$

This methodology allows us to estimate expectations of policy changes k days prior to a target change, which extends Kuttner's method of computing anticipated policy actions one day before the target change (i.e., $k = 1$).[5] This generalization provides us with an essential tool in testing the anticipation effect, because we can investigate how the funds rate responds to expectations as well as how the anticipated changes evolve in the days leading to a policy move.

[5]Following Kuttner (2001), we adjust for one timing mismatch on October 15, 1998, when the target change took place after the futures market had closed. In order to deal with this occurrence, we treat the data as if the target change took place on the next day.

2.2 Estimating the Anticipation Effect

Before we present the regression coefficients associated with the anticipation effect, it is informative to take a look at how the accuracy of policy expectations has evolved in time. Figure 2 displays the components of target changes that are unanticipated by the market for policy tightenings and easings, respectively.[6] Consistent with the improvements in the transparency of monetary policy actions, the component of target changes that surprised market participants declined gradually over time both for policy tightenings and policy easings.

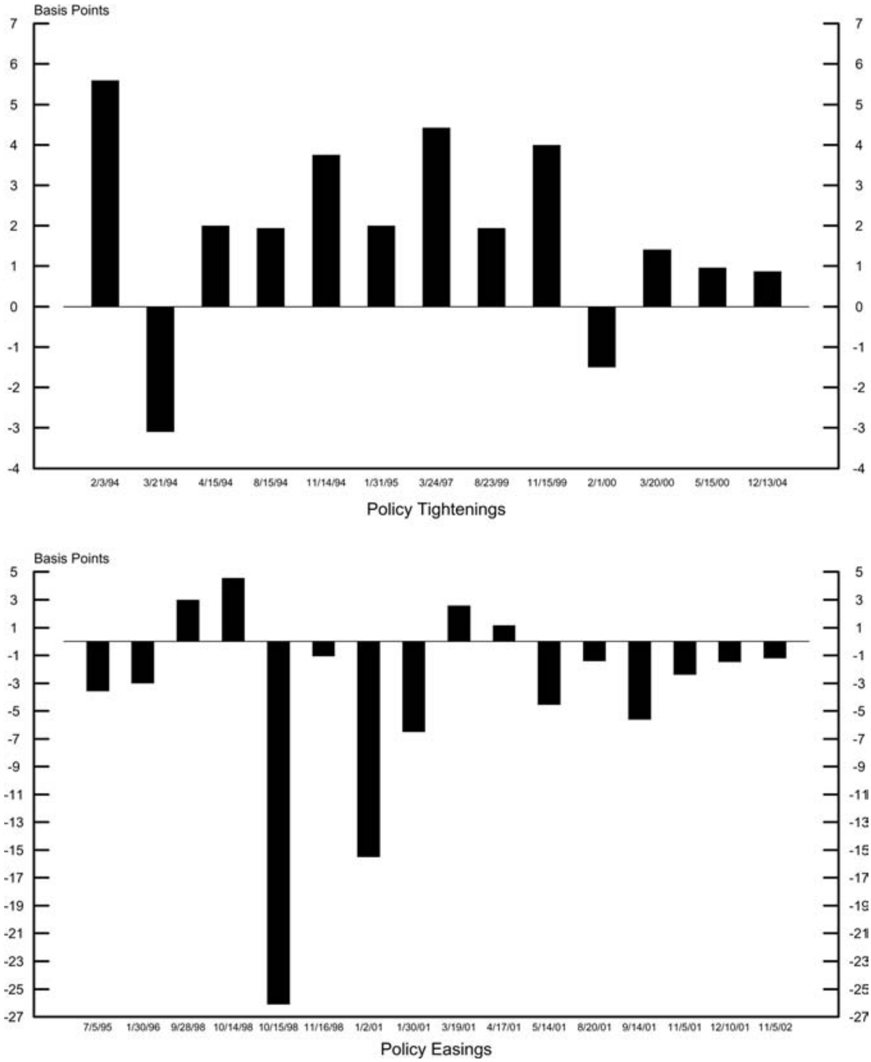
As noted above, we interacted the expected change in the federal funds rate with dummy variables for one through nine days before a policy change. To avoid conditioning our estimation on whether or not there was a policy change, a fact that is only known ex post,[7] we focus exclusively on anticipation of policy changes that took place at FOMC meetings.[8] Of course, during our sample period, there were intermeeting policy changes, but these moves were all surprises, and we do not believe that banks planned in advance for them. We do, however, want to allow for an asymmetry between an expected increase and an expected decrease. We interact the expected change in the funds rate with a dummy variable that denotes an upcoming FOMC meeting. To allow for the asymmetry, we create one dummy for meetings where there was either no change or an increase in the funds rate and another for meetings where there was either no change or a decrease in the funds rate. We assume, therefore, that the sign of an impending change in the target rate change is known by banks—an assumption we view as entirely plausible. Because some

[6] Unanticipated change is computed as the difference between the actual size of a target change and the anticipated change.

[7] We thank Jim Hamilton for pointing out our previous error in conditioning on information only knowable ex post.

[8] Prior to 1998, during the period of contemporaneous reserve accounting, reserve requirements and contractual clearing balances were calculated over a computation period that overlapped with all but the last two days of the maintenance period over which the requirements were to be satisfied. Since 1998, computation periods have ended prior to the beginning of the maintenance period. We interacted dummy variables for the lagged-accounting period with the anticipation variable to test whether or not this structural shift affects our results. We fail to reject that the coefficients are jointly equal to zero.

Figure 2. Unanticipated Target Changes on the Day before a Policy Action



of the observations that are multiple days prior to a policy move are in a previous maintenance period, we include in our estimation only those anticipations that are in the same maintenance period, within which the motivation to clear arbitrage opportunities is dominant.

Table 2. Anticipation Effect

Variable	$(Deviation\ from\ Target)_t$		$(Daily\ ER)_t$	
	Coeff.	**s.e.**	**Coeff.**	**s.e.**
$Anticipated\ \Delta \times D_{Nine\ Days\ Before\ a\ Tightening}$	0.055	0.054	1.33	0.88
$Anticipated\ \Delta \times D_{Eight\ Days\ Before\ a\ Tightening}$	0.056	0.058	0.050	0.57
$Anticipated\ \Delta \times D_{Seven\ Days\ Before\ a\ Tightening}$	0.014	0.044	1.23	0.58
$Anticipated\ \Delta \times D_{Six\ Days\ Before\ a\ Tightening}$	0.057	0.043	0.41	0.47
$Anticipated\ \Delta \times D_{Five\ Days\ Before\ a\ Tightening}$	0.028	0.044	0.31	0.34
$Anticipated\ \Delta \times D_{Four\ Days\ Before\ a\ Tightening}$	0.12	0.055	0.68	0.40
$Anticipated\ \Delta \times D_{Three\ Days\ Before\ a\ Tightening}$	0.29	0.060	1.26	0.34
$Anticipated\ \Delta \times D_{Two\ Days\ Before\ a\ Tightening}$	0.37	0.052	1.87	0.34
$Anticipated\ \Delta \times D_{One\ Day\ Before\ a\ Tightening}$	0.46	0.067	1.17	0.44
$Anticipated\ \Delta \times D_{Nine\ Days\ Before\ an\ Easing}$	0.078	0.083	1.45	1.0089
$Anticipated\ \Delta \times D_{Eight\ Days\ Before\ an\ Easing}$	0.11	0.13	0.38	0.53
$Anticipated\ \Delta \times D_{Seven\ Days\ Before\ an\ Easing}$	−0.066	0.19	−0.37	0.57
$Anticipated\ \Delta \times D_{Six\ Days\ Before\ an\ Easing}$	−0.11	0.11	−0.30	0.48
$Anticipated\ \Delta \times D_{Five\ Days\ Before\ an\ Easing}$	−0.0078	0.049	0.26	0.57
$Anticipated\ \Delta \times D_{Four\ Days\ Before\ an\ Easing}$	0.078	0.058	−0.57	0.46
$Anticipated\ \Delta \times D_{Three\ Days\ Before\ an\ Easing}$	0.017	0.059	−0.20	0.46
$Anticipated\ \Delta \times D_{Two\ Days\ Before\ an\ Easing}$	0.18	0.11	−0.34	0.56
$Anticipated\ \Delta \times D_{One\ Day\ Before\ an\ Easing}$	0.23	0.076	−0.055	0.74
$D_{Day\ of\ a\ Tightening}$	−0.18	0.048	0.42	0.57
$D_{Day\ of\ an\ Easing}$	0.089	0.029	−0.38	0.36
$D_{Day\ of\ a\ Tightening} \times Unanticipated\ \Delta$	−0.50	0.62	−5.40	7.60
$D_{Day\ of\ an\ Easing} \times Unanticipated\ \Delta$	0.43	0.56	5.22	2.97

Notes: Tables 1 and 2 report the results from the same regression but split the variables into two groups. For Daily ER regressions, the anticipated change variable is replaced with a dummy variable where $|Anticipated\ \Delta| > 0.125$.

The results shown are from the regression that had the control variables reported in table 1. As shown in the second and third columns of table 2, the results for the federal funds rate equation indicate a statistically significant anticipation effect in the funds market only for four days prior to a tightening and for two days prior to an easing.[9] The coefficients suggest that the funds rate moves in the direction of the anticipated change, but not fully. Prior to anticipated tightenings, the funds rate moves almost halfway—or about $12^1/_2$ basis points for an anticipated 25-basis-point policy move—to the anticipated new target on the day before the policy change and is elevated as many as three days prior. For anticipated easings, the effect is much more muted, although it is still statistically significant. This asymmetric effect will be confirmed in our theoretical model presented below. Because requirements are satisfied over a two-week period, there is an option value to waiting until the latter part of the period to satisfy these requirements. Given this pattern, which is reflected both in the data and in our model, there is less scope for banks to react to an anticipated easing by lowering balances further to take advantage of lower expected rates later in the period. Doing so would increase the probability of a costly overnight overdraft, and so the anticipation effect in this case is attenuated. For anticipated policy easings, the funds rate appears to move less than one-fourth of the way to the anticipated new target, or about 6 basis points for a 25-basis-point reduction in the target funds rate.

We do find some evidence that the Desk accommodates the increase in demand for reserve balances prior to an anticipated policy tightening—as indicated by the positive, statistically significant coefficients up to four days prior to a tightening, shown in the last two columns. Those results imply that over the four days before a fully anticipated increase in the target federal funds rate, the Desk provides between \$.75 and \$1.75 billion more in excess reserve each day than would be typical, holding all other things constant, for a total of about \$5 billion. Taking the results of the two equations together, however, we can infer that the increase in supply is not sufficient to fully offset the increased demand; the evidence is the funds rate trading firm to the target despite an increased provision of balances. These results imply that the Desk leans against the firmness but does not fully counteract it. Similarly, prior to anticipated policy

[9]For the excess balances equation, we replace the expected change with a dummy variable that equals 1 if the expected change is greater than $12^1/_2$ basis points; that is to say, better than even odds of at least a 25-basis-point change. This substitution is made because banks must decide if they think a change is coming or not, rather than acting on the size of the change, in order to shift balances.

easings, the Desk does not drain sufficient balances to offset fully the softness in the market, likely in an effort to avoid leaving the System with insufficient balances.

The tightening episode that began in June 2004 has been characterized as particularly well anticipated and predictable. As an extension, we test to see if the anticipation effect is different in this recent episode. Tables 3 and 4 present the same regressions but with dummy variables for the 2004 tightening episode interacted with our

Table 3. Control Variables

Sample Period: January 26, 1994–July 13, 2005*

	(Deviation from Target)$_t$		***(Daily ER)$_t$***	
Variable	**Coeff.**	**s.e.**	**Coeff.**	**s.e.**
Lagged Dependent Variable	0.27	0.047	0.27	0.026
$D_{First\ Thursday}$	−0.0033	0.016	0.59	0.28
$D_{First\ Friday}$	−0.061	0.016	0.0040	0.26
$D_{First\ Monday}$	0.0011	0.016	1.46	0.23
$D_{First\ Tuesday}$	−0.051	0.015	0.87	0.24
$D_{First\ Wednesday}$	−0.034	0.015	0.94	0.23
$D_{Second\ Thursday}$	−0.0014	0.015	1.49	0.23
$D_{Second\ Friday}$	−0.066	0.015	1.63	0.23
$D_{Second\ Monday}$	0.024	0.016	4.11	0.27
$D_{Second\ Tuesday}$	−0.041	0.018	4.18	0.41
$D_{Second\ Wednesday}$	0.12	0.031	9.58	1.23
Cumulative ER $\times D_{First\ Friday}$	−0.011	0.0030	−0.084	0.069
Cumulative ER $\times D_{First\ Monday}$	−0.0087	0.0048	−0.10	0.070
Cumulative ER $\times D_{First\ Tuesday}$	−0.0083	0.0028	−0.35	0.073
Cumulative ER $\times D_{First\ Wednesday}$	−0.016	0.0041	−0.37	0.072
Cumulative ER $\times D_{Second\ Thursday}$	−0.018	0.0038	−0.70	0.073
Cumulative ER $\times D_{Second\ Friday}$	−0.013	0.0050	−1.0070	0.093

(*continued*)

Table 3 (continued). Control Variables

Sample Period: January 26, 1994–July 13, 2005*

Variable	$(Deviation\ from\ Target)_t$ Coeff.	s.e.	$(Daily\ ER)_t$ Coeff.	s.e.
$Cumulative\ ER \times D_{Second\ Monday}$	−0.016	0.010	−1.80	0.25
$Cumulative\ ER \times D_{Second\ Tuesday}$	−0.040	0.011	−2.07	0.48
$Cumulative\ ER \times D_{Second\ Wednesday}$	−0.090	0.024	−4.10	1.22
$(Forecast\ Miss)_t$	−0.0094	0.0035	0.79	0.038
$D_{Month\ End}$	0.025	0.035	2.45	0.26
$D_{Month\ Start}$	0.013	0.021	1.58	0.22
$D_{Quarter\ End}$	0.28	0.077	4.27	0.41
$D_{Quarter\ Start}$	0.17	0.081	2.55	0.43
$D_{Year\ End}$	−0.45	0.17	5.051	1.21
$D_{Year\ Start}$	0.25	0.11	2.017	0.76
$D_{Mid\text{-}Month}$	0.091	0.012	2.33	0.20
$D_{Day\ Before\ Holiday}$	−0.020	0.017	0.11	0.19
$D_{Day\ After\ Holiday}$	−0.060	0.077	1.74	0.21
$D_{Treasury\ 2}$	0.11	0.041	−0.89	0.36
$D_{Treasury\ 3}$	0.067	0.032	−.44	0.40
$D_{Treasury\ 5}$	0.098	0.045	1.52	0.39
$D_{Treasury\ 10}$	−0.044	0.016	−.34	0.39
$(Required\ Operating\ Balances)_t$	0.00072	0.00057	−.041	0.0085
$Target$	0.0018	0.0013	−.13	0.024
$(Carry\text{-}in\_Large)_t$	—	—	−.54	0.43
$(Carry\text{-}in\_Other)_t$	—	—	4.67	1.85
$(Carry\text{-}in\_Large)_t \times Anticipated\ \Delta \times D_{One\ Day\ Before\ a\ Tightening}$	—	—	−.58	9.70
$(Carry\text{-}in\_Large)_t \times Anticipated\ \Delta \times D_{One\ Day\ Before\ an\ Easing}$	—	—	−.74	10.070

Note: Tables 3 and 4 report results from the same regression but split the variables into two groups.
*Data for 2001 exclude September 11 through September 19.

Table 4. Anticipation Effect

Variable	$(Deviation\ from\ Target)_t$		$(Daily\ ER)_t$	
	Coeff.	**s.e.**	**Coeff.**	**s.e.**
$Anticipated\ \Delta \times D_{Nine\ Days\ Before\ a\ Tightening}$	0.057	0.068	0.84	0.14
$Anticipated\ \Delta \times D_{Eight\ Days\ Before\ a\ Tightening}$	0.013	0.045	0.18	0.55
$Anticipated\ \Delta \times D_{Seven\ Days\ Before\ a\ Tightening}$	0.037	0.048	0.90	0.69
$Anticipated\ \Delta \times D_{Six\ Days\ Before\ a\ Tightening}$	0.034	0.042	0.80	0.53
$Anticipated\ \Delta \times D_{Five\ Days\ Before\ a\ Tightening}$	−0.026	0.039	0.38	0.46
$Anticipated\ \Delta \times D_{Four\ Days\ Before\ a\ Tightening}$	0.076	0.058	0.15	0.46
$Anticipated\ \Delta \times D_{Three\ Days\ Before\ a\ Tightening}$	0.21	0.067	0.78	0.30
$Anticipated\ \Delta \times D_{Two\ Days\ Before\ a\ Tightening}$	0.31	0.055	1.060	0.46
$Anticipated\ \Delta \times D_{One\ Day\ Before\ a\ Tightening}$	0.42	0.086	0.38	0.44
$Anticipated\ \Delta \times D_{Nine\ Days\ Before\ a\ Tightening} \times D_{2004}$	−0.0035	0.067	1.015	1.66
$Anticipated\ \Delta \times D_{Eight\ Days\ Before\ a\ Tightening} \times D_{2004}$	0.31	0.12	−0.50	1.60
$Anticipated\ \Delta \times D_{Seven\ Days\ Before\ a\ Tightening} \times D_{2004}$	−0.16	0.11	1.43	1.015
$Anticipated\ \Delta \times D_{Six\ Days\ Before\ a\ Tightening} \times D_{2004}$	0.17	0.061	−1.54	0.61
$Anticipated\ \Delta \times D_{Five\ Days\ Before\ a\ Tightening} \times D_{2004}$	0.26	0.048	−0.22	0.61
$Anticipated\ \Delta \times D_{Four\ Days\ Before\ a\ Tightening} \times D_{2004}$	0.18	0.096	1.45	0.65
$Anticipated\ \Delta \times D_{Three\ Days\ Before\ a\ Tightening} \times D_{2004}$	0.27	0.11	1.027	0.64
$Anticipated\ \Delta \times D_{Two\ Days\ Before\ a\ Tightening} \times D_{2004}$	0.19	0.12	1.74	0.53
$Anticipated\ \Delta \times D_{One\ Day\ Before\ a\ Tightening} \times D_{2004}$	0.11	0.11	1.87	0.76
$Anticipated\ \Delta \times D_{Nine\ Days\ Before\ an\ Easing}$	0.07	0.083	1.46	1.0053
$Anticipated\ \Delta \times D_{Eight\ Days\ Before\ an\ Easing}$	0.11	0.13	0.39	0.53
$Anticipated\ \Delta \times D_{Seven\ Days\ Before\ an\ Easing}$	−0.068	0.19	−0.35	0.56
$Anticipated\ \Delta \times D_{Six\ Days\ Before\ an\ Easing}$	−0.11	0.11	−0.28	0.49

(*continued*)

Table 4 (continued). Anticipation Effect

Variable	*(Deviation from Target)$_t$* Coeff.	s.e.	*(Daily ER)$_t$* Coeff.	s.e.
$Anticipated\ \Delta \times D_{Five\ Days\ Before\ an\ Easing}$	−0.0082	0.049	0.26	0.57
$Anticipated\ \Delta \times D_{Four\ Days\ Before\ an\ Easing}$	0.078	0.058	−0.57	0.46
$Anticipated\ \Delta \times D_{Three\ Days\ Before\ an\ Easing}$	0.016	0.060	−0.19	0.46
$Anticipated\ \Delta \times D_{Two\ Days\ Before\ an\ Easing}$	0.18	0.11	−0.34	0.56
$Anticipated\ \Delta \times D_{One\ Day\ Before\ an\ Easing}$	0.23	0.076	−0.060	0.74
$D_{Day\ of\ a\ Tightening}$	−0.18	0.048	0.42	0.57
$D_{Day\ of\ an\ Easing}$	0.089	0.029	−0.38	0.36
$D_{Day\ of\ a\ Tightening} \times Unanticipated\ \Delta$	−0.51	0.62	−5.60	7.63
$D_{Day\ of\ an\ Easing} \times Unanticipated\ \Delta$	0.43	0.57	5.24	2.99

Note: Tables 3 and 4 report results from the same regression but split the variables into two groups.
In ER regressions, the anticipation variable is replaced with a dummy variable where $|Anticipated\ \Delta| > 0.125$.

anticipation-effect variables. These results suggest that the anticipation effect was more pronounced during this tightening cycle. The regression that uses excess reserves as the dependent variable suggests that the Desk also provided somewhat more balances in this cycle as well. We read these results to indicate that the anticipation effect is a systematic phenomenon, but the particularly clearly signaled series of rate hikes beginning in 2004 amplified the effect.

One immediate question is whether or not the Desk could fully offset the increased demand for balances in advance of an anticipated tightening of policy. The answer to this counterfactual question, which we will consider in section 4, must be inferred based on the average deviation of the funds rate from the target and estimates of the liquidity effect. The factors affecting the demand for balances, however, are complicated and reflect both day-specific demand and demand for balances across the fourteen-day maintenance period. The next section describes demand for balances, following which we address the feasibility of completely offsetting the shift in demand and the potential ramifications.

3. The Demand for Balances and the Anticipation of Policy

The demand side of the federal funds market comes from banks' desire to hold balances at the Federal Reserve. Banks exchange their holdings of Federal Reserve balances in the federal funds market. Total demand for balances can be broken down into three components. First, the demand for required reserve balances—that is, funds on deposit at the Federal Reserve to satisfy reserve requirements—is a function of regulatory requirements imposed on banks by the Federal Reserve. The Federal Reserve requires that banks hold reserves, either on deposit at the Federal Reserve or as vault cash, related to the level of their customers' transactions deposits. In addition, banks with low levels of required reserve balances but with significant transactions hitting their Federal Reserve accounts may wish to hold contractual clearing balances with the Federal Reserve to help guard against overdrafts. Lastly, banks may wish to hold balances in addition to the required or contracted level—excess balances—because deficiencies on requirements and overnight overdrafts are penalized, and so holding excess balances serves as a buffer.[10] We will now discuss these components in further detail, which will provide the institutional background for the demand model developed in the appendix.

3.1 Required Reserve Balances

Required reserves are a function of the level of reservable deposits at banks. Over a two-week computation period, the average level of deposits and the reserve requirement are calculated. Over the associated two-week maintenance period, which begins on a Thursday (seventeen days after the end of the computation period) and ends on a Wednesday, a bank must satisfy these requirements by holding reserves on deposit at the Federal Reserve or as vault cash. Balances held on a Friday are automatically also attributed to the following

[10]For a more complete discussion of the demand for reserve balances and the federal funds market, see Carpenter and Demiralp (forthcoming) and the references therein.

Saturday and Sunday. The requirement must be satisfied *on average* over the maintenance period, which means that, for purposes of reserve requirements, balances are perfectly substitutable across days of the maintenance period.

Because of the lag between the computation period and the maintenance period, reserve requirements are known with certainty in advance of the maintenance period.[11] Banks are allowed to carry over small excesses or deficiencies from one maintenance period to the next. Hence, a small deficiency in one period can be made up in the next period, and a small excess can be used in the subsequent period to fulfill requirements. However, banks can only carry over excesses or deficiencies for one maintenance period. Deficiencies in required reserve balances beyond carryover provisions are penalized at a rate of 1 percentage point (annual rate) above the primary credit rate (that is, the discount rate) in effect for borrowing from the Federal Reserve Bank on the first day of the calendar month in which the deficiency occurs.[12]

3.2 Contractual Clearing Balances

Contractual clearing balances facilitate clearing of transactions drawn on banks' Federal Reserve accounts, and their use was expanded with the Monetary Control Act in 1980 to help depository institutions with low required reserve balances limit the risk of overdrafts without having to hold large levels of excess balances. Banks must agree in advance of a maintenance period to hold a given level of contractual clearing balances, and—as with required reserve balances—this level must be met on a period-average basis. Beginning in January 2004, banks were allowed to adjust the level of contractual clearing balances each maintenance period, but the level may not be adjusted within a maintenance period. Contractual clearing balances differ from required reserves in an important way;

[11] In 1984, the Federal Reserve began "contemporaneous reserve accounting" in which the computation and maintenance period overlapped, and banks only knew their reserve requirement with certainty for the final two days of the maintenance period. In 1998, the Federal Reserve returned to "lagged reserve accounting."

[12] Prior to January 2003, reserve deficiency charges were calculated as 2 percentage points above the discount rate.

banks receive implicit interest on their holdings of contractual clearing balances, up to the contracted amount (plus a small allowance), in the form of credits to defray the cost of services—such as check clearing—provided by the Federal Reserve. Contractual clearing balances are subject to a clearing balance band of plus or minus the greater of $25,000 or 2 percent of the contracted level, giving the bank a bit of leeway in satisfying their requirements. Deficiencies beyond the clearing band up to 20 percent of the level of contractual clearing balances are assessed a penalty of 2 percent per annum, and deficiencies greater than 20 percent of contractual clearing balances are assessed a penalty of 4 percent per annum. Balances in a bank's account at the Federal Reserve are first applied to required reserve balances and subsequently used to satisfy contractual clearing balances.

3.3 Excess Balances

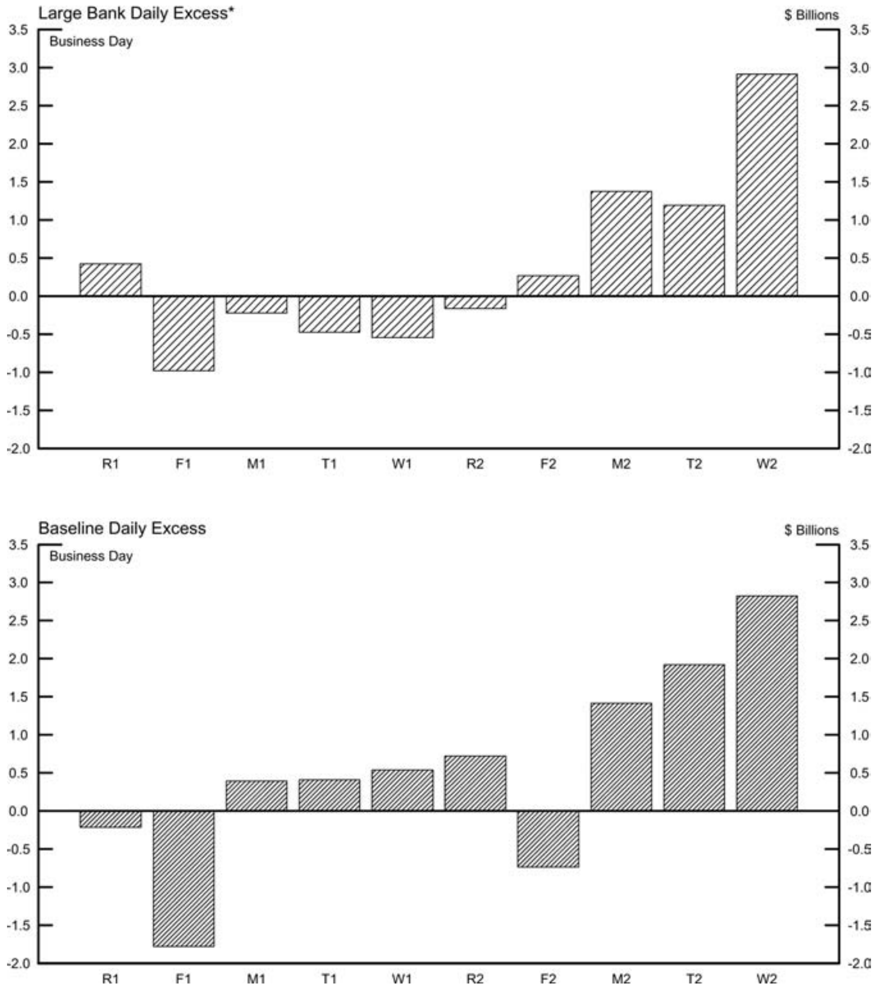
Any balances held in excess of those required to satisfy either of the above requirements are considered to be excess balances. Because these balances earn no return and do not satisfy any regulatory requirement, they have an opportunity cost of the prevailing federal funds rate. Large banks tend to manage their reserve accounts closely and typically end each maintenance period close to zero excess balances. Smaller banks, for which the dollar value of the opportunity cost may be relatively small, sometimes have excess balances, because the transactions cost of closely managing their accounts would be too high. That said, excess balances serve as a buffer against a possible costly overnight overdraft. Transactions that are settled late in the day on a bank's Federal Reserve account could unexpectedly drive the balance below zero; borrowing from the discount window is currently priced 1 percentage point over the target rate, and overnight overdrafts are assessed a fee of 4 percentage points (annual rate) above the target federal funds rate—more than a slap on the wrist. As a result, banks often demand greater levels of excess balances when flows in and out of their accounts are in greater volumes, and thus a greater uncertainty attends their end-of-day balance. From 1994 to 2004, total balances averaged about $20.8 billion, of which $11.7 billion were required reserve balances, $7.3 billion were contractual clearing balances, and $1.5 billion were excess balances. The lowest total balances were around $12 billion for a couple of days in 2000.

3.4 Demand for Balances and Policy Changes

As discussed above, figure 1 displays the average deviation of the federal funds rate from the target in the four days prior to and the four days following changes in the target federal funds rate since 1994. As the figure indicates, there is a clear, consistent pattern of funds rates firm relative to the target on days before increases in the target rate and funds rates soft to the target on days before decreases in the target rate. One of the simplest explanations for this phenomenon is intertemporal arbitrage. If banks expect the funds rate to be higher tomorrow, and funds are perfectly substitutable across days, there is an incentive to bid aggressively for the funds rate today in order to avoid borrowing funds when interest rates are expected to be high. Although Hamilton (1997) shows that there are systematic changes in the funds rate, and thus a strict martingale property does not exist in the federal funds rate, we could expect arbitrage to work at least partially in that direction.

The appendix presents in detail a dynamic-optimization model of daily reserve demand for a representative large bank, akin to that presented in Clouse and Dow (2002). The bank's objective is to minimize the expected cost of maintaining its reserve position subject to fees imposed for overdrafts, reserve deficiencies, and contractual clearing balance deficiencies. The bank must choose a target level for reserve balances each day before a random shock to its level of balances is realized. The top panel of figure 3 plots the pattern of daily excess for large banks averaged over maintenance periods from 1994 to present. The bottom panel plots the level of daily excess implied by the model when the federal funds rate is set equal to 2 percent each day. The intra-maintenance-period pattern is qualitatively similar, lending support to the descriptive power of the model. Of note is the fact that derived demand for excess balances is lower on Fridays but tends to increase through the maintenance period. The intuition is that on a Friday, the bank must pay three days of interest in borrowing reserve balances, but an overdraft on Friday is penalized for only one day's overdraft. As a result, on a relative basis, overdrafts are cheaper on Fridays than on other days,

Figure 3. Daily Excess Balances



*Large bank excess is calculated from 1994 to present.

and banks hold less excess as insurance. For the general uptrend, the intuition is as follows. Because holding excess funds is costly, banks would like to balance reducing excess against the expected cost of an overdraft and a deficiency. Banks want to avoid getting locked in to too large a cumulative reserve position early in the period, because there is limited scope to reduce balances on the last days of the maintenance period without incurring a high expected cost of an overdraft. Hence, they wait until late in the maintenance period to obtain more information about their remaining reserve need and then hold sufficient balances to meet their requirements. Recall that these day-of-the-maintenance-period shifts in demand for balances were incorporated into our empirical models.

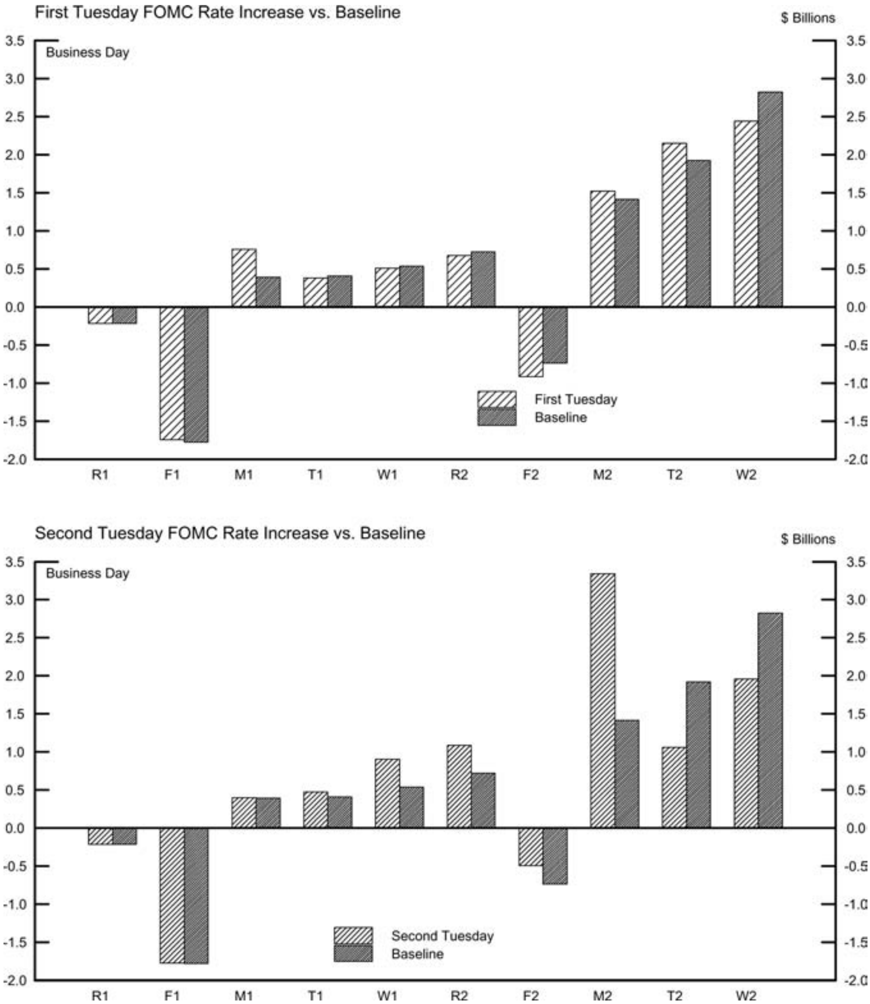
Next, we simulate maintenance periods in which banks correctly anticipate that the federal funds rate will be raised from 2 percent to $2^1/_4$ percent on the first or the second Tuesday of the maintenance period.[13] Figure 4 plots the results. Demand for balances in each case is shifted earlier in time relative to the baseline. Banks want to hold more of their reserve balances when funds are cheap and less when funds are more costly. This result may seem obvious, but it is important to note that demand is not shifted so much that there is zero demand on days after the rate increase. In particular, the same tension exists between holding funds early in the period and the possibility of getting locked in to an overly high level of excess balances.

We also simulate maintenance periods in which the federal funds rate is lowered 25 basis points from $2^1/_4$ percent to 2 percent, again on the first or the second Tuesday of the maintenance period. Figure 5 shows the results, and the pattern is reversed qualitatively. The optimal strategy is for a bank to run leaner balances early in the maintenance period in order to fulfill its requirements after the funds rate is lower. The anticipation effect is not symmetric, however, for increases and decreases in the funds rate. Given that the optimal strategy with no expected change in the funds rate is for banks to carry fewer reserves early in the period, an anticipated decrease in the funds rate reinforces the baseline case, whereas an anticipated increase in the funds rate works against the bank's typical strategy. Indeed, as we have already seen earlier in the empirical results, an anticipated decline in the funds rate creates less of a change from the optimal program under an unchanged funds rate than does an anticipated increase.

As was stated before, this model is only one of demand for reserve balances, and our results in this section suggest that demand should be shifted if the funds rate is expected to change. By combining these results from our empirical findings on both quantity and price

[13]Typically, FOMC meetings and announced changes to the target fall on Tuesdays.

Figure 4. Daily Excess Balances

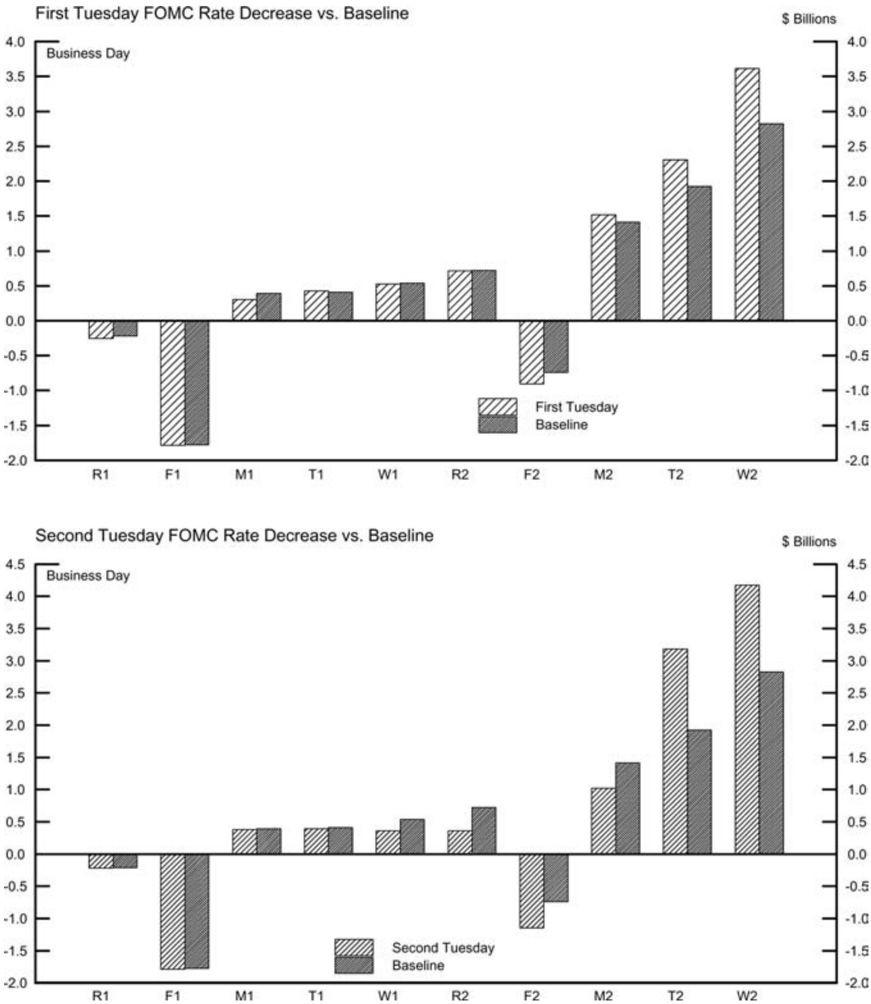


in the previous section, we can make inferences about supply and demand together.

4. Implications of the Anticipation Effect

We now explore the strategy of the Desk of only partially offsetting the anticipation effect. Our theoretical model suggests an interior solution for the portion of demand for balances that is shifted prior

Figure 5. Daily Excess Balances



to the anticipated change; that is to say that a finite quantity of balances should be able to satisfy this demand on the days before the policy tightening. The intuition is fairly simple. Demand for balances comprises day-specific demand to cover payments in and out of a bank's Federal Reserve account and maintenance-period demand to cover reserve requirements and contractual clearing balance requirements. If a large amount of balances are provided before the policy decision, the quantity of balances demanded following the target change would fall, perhaps dramatically. As a result, either the quantity supplied would outstrip the quantity demanded and federal funds would trade far below the target rate, or banks would have extremely lean balances and run a higher risk of overdraft or discount window borrowing, leading to higher volatility in the market.

Our regression results provide a means to analyze this question. Although the results are not immune to the Lucas critique, at face value they do provide support for the Desk's stated intent of only partially accommodating demand prior to changes in order to avoid a substantial drain afterward that might lead to volatility. As first explored by Hamilton (1997) and Carpenter and Demiralp (forthcoming), the coefficient on the error of the forecast of balances used for open market operations is an estimate of the liquidity effect. In our results, an extra \$1 billion results in a 1-basis-point reduction in the federal funds rate. A 25-basis-point increase that is fully anticipated is associated with four days of positive deviations from the target of 3, $7^1/_4$, $9^1/_4$, and $11^1/_2$ basis points, respectively. Using our estimate of the liquidity effect, these four days would require a total of almost \$31 billion of excess reserves in addition to the \$5 billion that we estimate is typically provided and in addition to any excess that would normally be provided, like the pattern shown in figure 3. It is the draining of these extra balances that is the difficulty mentioned in the Desk's annual report. It is possible that a large draining operation would leave balances at such a low level that demand becomes very inelastic. As a result, a minor error in forecasting that causes a deviation of supply from the quantity demand at the target could result in a large movement in the funds rate.

If the FOMC meeting takes place on the first Tuesday of the maintenance period, the bulk of the maintenance-period demand for balances will have been satisfied with the extra provision of balances early in the period. On days following the FOMC meeting, therefore, the primary demand for balances is the day-specific demand. The intertemporal substitutability of maintenance-period demand tends to smooth the funds rate—unfulfilled demand on one day can be met the next, and the funds rate need not move appreciably. Day-specific demand, by definition, cannot be spread across days, and thus the funds rate should be more sensitive to mismatches of supply and demand. Day-specific demand is driven by daily transaction needs and is therefore much more volatile relative to requirement-related demand—the component that can be substituted across the days of a maintenance period. Indeed, Carpenter and Demiralp (forthcoming) show that relatively small changes in the supply of balances have little effect on the funds rate precisely because of the typically intertemporal substitutability. By supplying the majority of the maintenance-period demand for balances early in a maintenance period, on days subsequent to an FOMC meeting, the funds rate would be more sensitive to forecast misses on the days following the meeting.

Moreover, it seems plausible that there may be some rough lower bound on the absolute level of balances needed for the funds market to function smoothly; however, estimating this bound is problematic. For maintenance periods with an FOMC meeting on the first Tuesday, there are six remaining days over which balances could be drained, for an average of almost $5 billion to be drained each day. For maintenance periods with required balances of less than $18 billion, such open market operations would leave the market with a level of total balances at the lower end of the range observed in our sample. Of course, it is impossible to know with certainty if the Desk could overcome the anticipation effect, given the current data and the fact that our results are implicitly conditioned on the current operating environment. Nevertheless, plausible measures of the size of the operations needed to offset the anticipation effect—and therefore a possible need to drain those balances later—suggest that the argument made in the annual report has merit.

Part of that rationale is a desire to avoid undue volatility in the funds market. Table 5 presents some of the coefficients from a regression of the intraday standard deviation of the federal funds rate on a specification identical to that in the federal funds rate equation.[14] None of the coefficients is positive and statistically significant, a fact that suggests that the Desk's current strategy avoids adding intraday volatility given the pressures of anticipation effect. Indeed, the only statistically significant coefficient is negative in sign, suggesting *less* volatility the day before an anticipated policy move.

[14]Intraday standard deviation is a volume-weighted measure of standard deviation, based on total brokered funds rate transactions on a given day.

Table 5. Intraday Volatility

Variable	Coeff.	s.e.
$Anticipated\ \Delta \times D_{Nine\ Days\ Before\ a\ Tightening}$	−0.12	0.12
$Anticipated\ \Delta \times D_{Eight\ Days\ Before\ a\ Tightening}$	−0.059	0.039
$Anticipated\ \Delta \times D_{Seven\ Days\ Before\ a\ Tightening}$	−0.062	0.041
$Anticipated\ \Delta \times D_{Six\ Days\ Before\ a\ Tightening}$	−0.056	0.051
$Anticipated\ \Delta \times D_{Five\ Days\ Before\ a\ Tightening}$	−0.051	0.052
$Anticipated\ \Delta \times D_{Four\ Days\ Before\ a\ Tightening}$	−0.039	0.053
$Anticipated\ \Delta \times D_{Three\ Days\ Before\ a\ Tightening}$	−0.057	0.079
$Anticipated\ \Delta \times D_{Two\ Days\ Before\ a\ Tightening}$	−0.025	0.044
$Anticipated\ \Delta \times D_{One\ Day\ Before\ a\ Tightening}$	0.049	0.086
$Anticipated\ \Delta \times D_{Nine\ Days\ Before\ an\ Easing}$	−0.059	0.074
$Anticipated\ \Delta \times D_{Eight\ Days\ Before\ an\ Easing}$	−0.20	0.20
$Anticipated\ \Delta \times D_{Seven\ Days\ Before\ an\ Easing}$	−0.39	0.31
$Anticipated\ \Delta \times D_{Six\ Days\ Before\ an\ Easing}$	0.029	0.064
$Anticipated\ \Delta \times D_{Five\ Days\ Before\ an\ Easing}$	−0.064	0.058
$Anticipated\ \Delta \times D_{Four\ Days\ Before\ an\ Easing}$	−0.081	0.086
$Anticipated\ \Delta \times D_{Three\ Days\ Before\ an\ Easing}$	−0.097	0.056
$Anticipated\ \Delta \times D_{Two\ Days\ Before\ an\ Easing}$	−0.19	0.12
$Anticipated\ \Delta \times D_{One\ Day\ Before\ an\ Easing}$	−0.13	0.068
$D_{Day\ of\ a\ Tightening}$	−0.014	0.047
$D_{Day\ of\ an\ Easing}$	0.00068	0.046
$D_{Day\ of\ a\ Tightening} \times Unanticipated\ \Delta$	1.10	0.79
$D_{Day\ of\ an\ Easing} \times Unanticipated\ \Delta$	−0.93	0.32

Having established that an anticipation effect exists in the federal funds market, we may ask whether or not this effect spills over to other financial markets. Market rates can be influenced both by current interest rates and expected future rates. Appealing to the expectations hypothesis of the term structure, one might think of long rates as being the average of expected future short rates plus a possible term premium or risk premium. If this assumption is valid, we would expect to see the largest impact (if any) of the anticipation effect on other overnight rates and a diminishing impact for longer-dated yields, because the effect of the anticipation effect on short rates is confined to a few days prior to each target rate change. The rest of the expected path of short rates is unchanged. In particular, if the market assumes a reaction function for the Federal Reserve, news about the economy could signal innovations to expected future policy moves. In fact, Lange, Sack, and Whitesell (2003) do present strong evidence of an improvement in the ability of financial markets to predict future changes in policy by the FOMC. In this section, however, we try to find out whether the existence of an anticipation effect in the funds market per se has any impact on broader financial markets, independent of the effects of policy anticipation on these rates. In order to capture those changes in interest rates that are purely due to the anticipation effect in the federal funds market, we estimate an autoregressive specification for each interest rate, because the lagged dependent variable is expected to capture any movements that are due to other financial market developments. Furthermore, we regress each rate on announcement surprises about the producer price index, the unemployment rate, the consumer price index, and GDP. Market expectations for each release are estimated by the median market forecast as compiled and published by Money Market Services the Friday before each release. The surprise component of each data release is computed as the actual released value less the market expectation. Lastly, we included the fitted value of the anticipation effect from our previous estimation. The general empirical specification is of the following form:

$$
\begin{aligned}
y_t = &\sum_{i=1}^{5} \xi_i y_{t-i} + \sum_{i=1}^{5} \gamma_i PPI_{t-i} + \sum_{i=1}^{5} \delta_i Unemp_{t-i} + \sum_{i=1}^{5} \alpha_i CPI_{t-i} \\
&+ \sum_{i=1}^{5} \beta_i GDP_{t-i} + \sum_{i=1}^{5} \phi_i D^B D_{t+i}^{Tight} Anticipated\ \Delta \\
&+ \sum_{i=1}^{5} \phi_i D^B D_{t+i}^{Ease} Anticipated\ \Delta + \varepsilon_t, \qquad (4)
\end{aligned}
$$

where y_t is the change in the interest rate measure at time t, and *PPI* , *Unemp, CPI,* and *GDP* are the surprise terms associated with these announcements.

Table 6 shows the results of several regressions in which we attempt to quantify the impact of an anticipation effect in the funds market prior to policy tightenings on a selection of other financial market variables. The first row gives the results for the overnight Treasury repurchase agreement (RP) rate—a close substitute for federal funds, because banks can meet balance requirements also by overnight RPs. For the three days prior to an anticipated tightening—the days when the anticipation effect is the strongest—the estimated spillover to the RP market is statistically significant. The point estimate suggests that almost three-quarters of the firmness in the federal funds market shows up in the RP market. Further out the yield curve, however, the effect is much attenuated. We interpret these results as suggesting that the anticipation effect in the funds market has almost no effect on other financial markets. Table 7 presents similar results for anticipated policy easings. There appears to be a bit of evidence that yields on Treasury bills up to three months may be affected by the anticipation effect in the funds market but only for one day. Similarly, for the longer-dated yields, there is some evidence that the anticipation effect triggers a Fisher-type response by flattening out the yield curve on the day before a policy action. In terms of effecting volatility in financial markets, anticipated easings tend to reduce implied volatilities of ten-year and thirty-year bonds in the two days prior to the target cut.

5. Conclusions

The anticipation effect in the federal funds market has been a topic of growing interest over the last decade as the Federal Reserve has become more transparent in its policy decisions. In this paper, we document evidence of the anticipation effect in the funds market since 1994. This effect became more pronounced over time and received particular media attention prior to the policy tightenings starting in the second half of 2004, consistent with the improvements in the Federal Reserve's communications policy and the public's expectations of policy actions.

Table 6. Implications of Anticipation Effect in Other Financial Markets prior to Policy Tightenings

	One Day prior to a Tightening		Two Days prior to a Tightening		Three Days prior to a Tightening		Four Days prior to a Tightening	
Dependent Variable	**Coeff.**	**s.e.**	**Coeff.**	**s.e.**	**Coeff.**	**s.e.**	**Coeff.**	**s.e.**
RP	0.74	0.19	0.76	0.24	0.47	0.19	0.040	0.58
T-Bill (One-month)	0.12	0.12	−0.22	0.28	0.56	0.20	0.18	0.56
T-Bill (Three-month)	0.095	0.089	0.058	0.19	0.068	0.14	0.22	0.41
T-Bill (Six-month)	0.076	0.051	0.22	0.093	0.011	0.087	0.060	0.25
T-Note (One-year)	0.044	0.043	0.18	0.12	−0.00075	0.11	0.014	0.29
T-Note (Two-year)	0.0015	0.048	0.10	0.15	−0.017	0.15	−0.17	0.33
T-Note (Five-year)	−0.086	0.052	0.088	0.15	−0.093	0.15	−0.30	0.29
T-Note (Ten-year)	−0.15	0.053	0.15	0.13	−0.14	0.14	−0.60	0.24
T-Bond (Thirty-year)	−0.12	0.044	0.081	0.11	−0.11	0.16	−0.54	0.24
Implied Volatility (Eurodollar)	−0.15	0.59	−0.38	1.320	−2.22	1.41	−0.31	3.36
Implied Volatility (10-yr T-Note)	−0.49	0.25	0.65	0.36	−0.67	0.37	0.068	0.77
Implied Volatility (30-yr T-Bond)	0.018	0.31	0.61	0.50	−0.76	0.43	−0.13	1.77

Table 7. Implications of Anticipation Effect in Other Financial Markets prior to Policy Easings

	One Day prior to an Easing		Two Days prior to an Easing	
Dependent Variable	**Coeff.**	**s.e.**	**Coeff.**	**s.e.**
RP	0.0025	0.16	−0.085	0.50
T-Bill (One-month)	0.75	0.32	0.74	0.48
T-Bill (Three-month)	0.75	0.32	0.28	0.30
T-Bill (Six-month)	0.14	0.17	0.090	0.19
T-Note (One-year)	0.098	0.18	−0.054	0.21
T-Note (Two-year)	0.12	0.18	−0.24	0.26
T-Note (Five-year)	0.14	0.18	−0.40	0.33
T-Note (Ten-year)	0.16	0.18	−0.42	0.35
T-Bond (Thirty-year)	0.18	0.17	−0.39	0.28
Implied Volatility (Eurodollar)	−0.011	3.55	2.97	4.33
Implied Volatility (10-yr T-Note)	−0.0094	0.49	−2.52	0.88
Implied Volatility (30-yr T-Bond)	−1.35	0.61	−2.27	0.98

The theoretical model developed in this paper confirms the intuition that banks have an incentive to shift their holdings of reserve balances to the days when funding is expected to be cheaper. The results from the econometric equations suggest that demand does indeed shift as predicted in theory, but supply does not shift to the same extent. As a result, the funds rate moves in the direction of the anticipated change. Furthermore, this anticipation effect is significantly larger in the post-2004 period, which gave rise to the media attention mentioned above.

A natural question would be whether or not this effect can be effectively counteracted by the Open Market Trading Desk. Because a change in the target for the federal funds rate requires a decision by the Federal Open Market Committee, a plausible goal for the Desk would be to maintain the old target until the new one is announced. A definitive answer is impossible, given the fact that our results are estimated over a period that is characterized by only partial accommodation of the increased demand. Nevertheless, we find that offsetting the anticipation effect is likely possible but would require extremely large open market operations, potentially leaving the market with a level of balances at which demand is quite inelastic. Indeed, even if the Desk were able to force trading to the target, the rationale stated by the Open Market Trading Desk—only partially accommodating the increased demand to avoid volatility later—remains a plausible characterization of the market. If the supply of balances were increased in advance of an anticipated tightening, it is likely that the only demand for balances in the days following the tightening would be the day-specific demand to clear payments. This demand is much less elastic with respect to price than period-average demand, because it cannot be substituted across days. As a result, the funds rate could become quite sensitive to small errors in supply provision, and the market could become volatile. Our results suggest no such increased volatility, which we interpret as support for the Desk's current strategy.

The existence of an anticipation effect in the funds market also has implications for the traditional view of the monetary transmission mechanism. The conventional view relies on the liquidity effect to explain how open market operations affect the overnight rate; increased supply lowers the funds rate, and decreased supply raises the funds rate. The phenomenon referred to as "open-mouth operations" following Guthrie and Wright (2000) suggests that the Federal Reserve can affect the funds rate merely through statements. Prior to announcing changes in the target rate (i.e., prior to February 1994), changes in the target rate were sometimes signaled to the market by the use of certain types of open market operations. The empirical evidence shown in this paper suggests that the Desk does not need to implement open market operations to signal target changes, and indeed the funds rate moves toward the new target even before the announcement of the policy move and prior to the implementation of open market operations associated with the new target in the post-1994 era. Nevertheless, both the anticipation effect studied here and open-mouth operations rely on the credibility of the Desk to *maintain* the funds rate. That is to say, market participants must believe that supply and demand will subsequently be aligned at the target rate. Hence, while the existence of an anticipation effect implies funds rate movements independent of changes in the balances prior to a policy move, it necessitates a strong liquidity effect on other days, as documented in Carpenter and Demiralp (forthcoming).

The anticipation effect is clearly important in the federal funds market. The evidence presented above, however, suggests that the marginal impact of the anticipation effect in the funds market on broader markets is minimal. To be sure, with increased transparency of monetary policy, markets have begun to price in changes that are well anticipated. We test to see whether, over and above this effect, the anticipation of policy changes in the funds market spills over to other markets. We conclude that, in line with the expectations hypothesis of the term structure, the effect is minimal outside of overnight markets.

Appendix. Theoretical Model of the Demand for Balances

Specifically, consider the following objective function at the business-day frequency:[15]

$$\min_{x_t^*} E\left\{\left(\sum_{t=1}^{10}(od_t + x_t f\!f_t\right) + rd + ccbd - cbe\right\}, \tag{5}$$

where E is the expectations operator. The bank is attempting to minimize the expected cost of its reserve account, which comprises overdraft fees, od_t; the cost of borrowing funds in the market,[16] $x_t f\!f_t$ (where x_t is the bank's closing balances and $f\!f_t$ is the prevailing federal funds rate); deficiency fees for required reserves, rd; and deficiency fees for contractual clearing balances, $ccbd$; but is reduced by earnings on contractual clearing balances, cbe. The bank is assumed to choose a target closing balance x_t^* that is subject to a stochastic shock, so that

$$x_t = x_t^* + \varepsilon_t$$
$$\varepsilon_t : N(0, \sigma_\varepsilon^2).$$

[15] As noted in Stigum (1990), the bulk of the transactions in the federal funds market are overnight.

[16] Without loss of generality, the cost of funds could also be considered the opportunity cost of not lending out funds the bank has into the market.

The cost of overdrafts is defined as

$$od_t = \min[x_t, 0] * \phi_{od}, \tag{6}$$

where ϕ_{od} is the overdraft fee. The cost of reserve requirement deficiencies is computed on a period-average basis as a function of required reserve balances (RR), so we write

$$rd = \max\left[RR - \sum_{1}^{10} x_t^* \omega, 0\right] * \phi_{rd} \tag{7}$$

$$\omega = \begin{cases} 3 & \textit{if } t = 2, 7 \\ 1 & \textit{otherwise} \end{cases},$$

which says that Fridays count three times and ϕ_{rd} is the reserve deficiency fee. The cost of deficiencies for contractual clearing balances can be written as

$$ccbd = \begin{cases} 0 \\ \quad \textit{if } CCB - \left(\sum_1^{10} x_t^* \omega - RR\right) \le 0 \\ CCB - \left(RR - \sum_1^{10} x_t^* \omega\right) * \phi_{cbd}^1 \\ \quad \textit{if } 0 < CCB - \left(\sum_1^{10} x_t^* \omega - RR\right) \le .2CCB \\ CCB - \left(RR - \sum_1^{10} x_t^* \omega\right) * \phi_{cbd}^2 \\ \quad \textit{if } -.2 * CCB < CCB - \left(\sum_1^{10} x_t^* \omega - RR\right) \end{cases} \tag{8}$$

where ϕ_{cbd}^1 and ϕ_{cbd}^2 are contractual clearing balance deficiency fees.

The above expression combines the maintenance-period-average nature of contractual clearing balances with the nonlinear fee structure attached to deficiencies. Finally, earnings credits reduce the cost of the reserve position by

$$cbe = \left(RR - \sum_{t=1}^{10} x_t\right) * ecr, \tag{9}$$

where ecr is the earnings credit rate.

Taken together, these equations define a stochastic, nonlinear, finite dynamic programming problem with ten periods where the choice variable is the target closing balance on each of the ten business days of the maintenance period. The model abstracts from uncertainty about the federal funds rate, carryover provisions, and the clearing balance allowance. Funds rate determination is overlooked for now, as this is only a model of demand; supply of balances will be discussed below. Although the carryover provisions can be important (see Clouse and Dow 2002), the fundamental story is unchanged, and including carryover would introduce a significant increase in computational complexity.[17] The clearing balance allowance is a minor omission that is of little relevance.

Solving the model allows us to examine the implied demand for excess balances on a daily basis throughout the maintenance period. Although excess balances are strictly defined only for a maintenance period as a whole, the concept of daily excess is useful. Daily excess can be defined as the level of balances on a day less one-fourteenth the level of required balances—that is, what excess would be if requirements were defined daily instead of biweekly. We simulate our model using 2 percent as the target (and therefore expected) federal funds rate. Based on the actual rules for Federal Reserve balances, overdraft fees are 4 percent; reserve deficiencies are penalized at 1 percentage point over the primary credit rate, which is 1 percentage point over the target rate, for a deficiency fee of 4 percent. Contractual clearing balance deficiencies up to 20 percent of the clearing balance are penalized at 2 percent, and deficiencies over 20 percent of the clearing balances are penalized at 4 percent. We chose reserve requirements to be \$10 billion and contractual clearing balances to be \$10 billion to roughly replicate the aggregate funds market. We chose the variance of the stochastic shock so that the level of excess balances for a two-week reserve maintenance period was \$1.5 billion, essentially calibrating the model to the actual data.

The model is solved as follows. The state variable is defined as the cumulative position to date; that is, the sum of end-of-day balances. This variable is used in the final period to calculate whether or not period-average balance requirements are fulfilled. Accordingly, a grid for the state variable is constructed. The model is solved recursively,

[17] Our results in the empirical section suggest that the abstraction from carryover does not have a significant impact on the implications derived from the model.

beginning with the last day of the maintenance period. For each value of the state variable—here equal to the position-to-date at the end of the ninth day—an optimal choice for the tenth day's target closing balance is chosen. This value is selected by evaluating a grid for the choice variable at each possible value. The stochastic shock to end-of-day balances is simulated by a ten-point discrete approximation to a normal distribution. The maintenance-period cost of each value of the choice variable can thus be computed in expected value for each value of the state variable. Thus, we find a mapping between the state variable coming into the last day and the optimal choice *conditional on the state variable.*

We can assign an expected cost to each value of the state variable at the end of day 9. Assuming that an optimal choice will be made, we can step back to the optimal choice for day 9. For each grid value of the state variable at the end of day 8, we can search to find the optimal choice for day 9. Each possible value of the choice variable will imply, in expected value, a particular value of the state variable at the end of day 9 and, thus, from our previous computation, an expected cost for the maintenance period as a whole. That is to say, the optimal choice on day 9 is conditional on both the value of the state variable at the end of day 8 and the expected cost associated with the expected value of the state variable at the end of day 9 that is determined by the choice on day 9. This logic is recursed back to the first day. For each day, then, we have an optimal choice of a target end-of-day balance that is assigned to each grid value of the state variable. To simulate a maintenance period, we begin on day 1, assume the state variable is equal to 0, take the optimal choice of target end-of-day balance for a state variable of 0, and add a draw from a random normal variable. We then compute the end-of-day position for day 1 (that is, the realized balance) and proceed to day 2, taking this end-of-day balance as our new value for the state variable. We select the optimal target balance in day 2 and proceed forward to the end of the maintenance period.

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Credit Cycles, Credit Risk, and Prudential Regulation*

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This paper finds strong empirical support of a positive, although quite lagged, relationship between rapid credit growth and loan losses. Moreover, it contains empirical evidence of more lenient credit standards during boom periods, both in terms of screening of borrowers and in collateral requirements. We find robust evidence that during upturns, riskier borrowers get bank loans, while collateralized loans decrease. We develop a regulatory prudential tool, based on a countercyclical, or forward-looking, loan loss provision that takes into account the credit risk profile of banks' loan portfolios along the business cycle. Such a provision might contribute to reinforce the soundness and the stability of banking systems.

JEL Codes: E32, G18, G21.

*This paper is the sole responsibility of its authors, and the views represented here do not necessarily reflect those of the Banco de España. We thank R. Repullo and J. M. Roldán for very fruitful and lively discussions about prudential banking supervisory devices. We are also grateful for the detailed comments provided by V. Salas; H. Shin, the editor; J. Segura; an anonymous referee; and participants at the BCBS/Oesterreichische Nationalbank Workshop; the Bank of England workshop on the relationship between financial and monetary stability; X Reunión de la Red de Investigadores de Bancos Centrales Iberoamericanos in Perú; XX Jornadas Anuales de Economía in Uruguay; Foro de Finanzas in Madrid; and FUNCAS Workshop Basilea II y cajas de ahorros in Alicante. In particular, we would like to express our gratitude for the comments of S. Carbó, X. Freixas, M. Gordy, A. Haldane, P. Hartman, N. Kiyotaki, M. Kwast, M. Larraín, J. A. Licandro, I. van Lelyveld, P. Lowe, L. A. Medrano, J. Moore, C. Tsatsaronis, and B. Vale. Any errors that remain are entirely the authors' own. Corresponding author: Saurina: C/Alcalá 48, 28014 Madrid, Spain; Tel +34-91-338-5080; e-mail: jsaurina@bde.es.

1. Introduction

Banking supervisors, after many painful experiences, are quite convinced that banks' lending mistakes are more prevalent during upturns than in the midst of a recession.[1] In good times both borrowers and lenders are overconfident about investment projects and their ability to repay and to recoup their loans and the corresponding fees and interest rates. Banks' overoptimism about borrowers' future prospects, coupled with strong balance sheets (i.e., capital well above minimum requirements) and increasing competition, brings about more liberal credit policies with lower credit standards.[2] Thus, banks sometimes finance negative net present value (NPV) projects only to find later that the loan becomes impaired or the borrower defaults. On the other hand, during recessions—when banks are flooded with nonperforming loans, high specific provisions, and tighter capital buffers—banks suddenly turn very conservative and tighten credit standards well beyond positive net present values. Only their best borrowers get new funds; thus, lending during downturns is safer and credit policy mistakes much lower. Across many jurisdictions and at different points in time, bank managers seem to overweight concerns regarding type 1 lending policy errors (i.e., good borrowers not getting a loan) during economic booms and underweight type 2 errors (i.e., bad borrowers getting financed). The opposite happens during recessions.

Several explanations have appeared in the literature to rationalize fluctuations in credit policies. First of all, the classic principal-agency problem between bank shareholders and managers can feed excessive volatility into loan growth rates. Once managers obtain a reasonable return on equity for their shareholders, they may engage in other activities that depart from the firm's value maximization and focus more on their own rewards. One of these activities might be excessive credit growth in order to increase the social presence of the bank (and its managers) or the power of managers in a continuously enlarging organization (Williamson 1963). If managers are

[1] See, for instance, Caruana (2002), Ferguson (2004), and the numerous joint announcements by U.S. bank regulators in the late nineties warning U.S. banks to tighten credit standards.

[2] A loose monetary policy can also contribute to overoptimism through excess liquidity provision.

rewarded more in terms of growth objectives instead of profitability targets, incentives to rapid growth may result. This has been documented previously by the expense preference literature and, more recently, by the literature that relates risk and managers' incentives.[3]

Strong competition among banks or between banks and other financial intermediaries erodes margins as both loan and deposit interest rates get closer to the interbank rate. To compensate for the fall in profitability, bank managers might increase loan growth at the expense of the (future) quality of their loan portfolios. Excess capacity in the banking industry is being built up. Nevertheless, that will not impact immediately on problem loans, so it might encourage further loan growth.

In a more formalized framework, Van den Heuvel (2002) shows that the combination of risk-based capital requirements, an imperfect market for bank equity, and a maturity mismatch in banks' balance sheets gives rise to a bank capital channel of monetary policy. In boom periods, when banks show strong balance sheets and capital buffers, they overlend. However, as the expansion heads to its end, the surge in loan portfolios has eroded much of the capital buffer; at that point, a monetary shock may trigger a decline in bank profits, stringent capital ratios, and a tightening of lending standards and, subsequently, of loans available to firms and households.[4]

Herd behavior (Rajan 1994) might also help to explain why bank managers finance negative NPV projects during expansions. Credit mistakes are judged more leniently if they are common to the whole industry. Moreover, a manager whose bank systematically loses market share and underperforms its competitors in terms of earnings growth increases his or her probability of being fired. Thus, managers have a strong incentive to behave as their peers, which, at an aggregate level, enhances lending booms and recessions. Short-term objectives are prevalent and might explain why banks finance projects during expansions that, later on, will become nonperforming loans.

Berger and Udell (2004) have developed the so-called institutional memory hypothesis in order to explain the markedly cyclical

[3]For the former, see (among others) Edwards (1977), Hannan and Mavinga (1980), Akella and Greenbaum (1988), and Mester (1989). For the latter, see Saunders, Strock, and Travlos (1990), Gorton and Rosen (1995), and Esty (1997).

[4]Ayuso, Pérez, and Saurina (2004) find evidence of this cyclical behavior of capital buffers.

profile of loans and nonperforming loan losses. It states that as time passes since the last loan bust, loan officers become less and less skilled to grant loans to high-risk borrowers. That might be the result of two complementary forces. First, the proportion of loan officers that experienced the last bust decreases as the bank hires new, younger employees and the former ones retire. Thus, there is a loss of learning experience. Second, some of the experienced officers may forget the lessons of the past, especially as more years go by and the former recession becomes a more distant memory.[5]

Finally, collateral might also play a role in fueling credit cycles. Usually, loan booms are intertwined with asset booms.[6] Rapid increases in land, house, or share prices increase the availability of funds for those who can pledge such assets as collateral. At the same time, the bank is more willing to lend since it has an (increasingly worthier) asset to back the loan in case of trouble. On the other hand, it could be possible that the widespread confidence among bankers results in a decline in credit standards, including the need to pledge collateral. Collateral, as risk premium, can be thought to be a signal of the degree of tightening of individual bank loan policies.[7]

Despite the theoretical developments and the banking supervisors' experiences, the empirical literature providing evidence of the link between rapid credit growth and loan losses is scant.[8] In this paper we produce clear evidence of a direct, although lagged, relationship between credit cycle and credit risk.[9] A rapid increase in loan portfolios is positively associated with an increase in nonperforming loan ratios later on. Moreover, those loans granted during

[5]Kindleberger (1978) contains the idea of fading bad experiences among economic agents.

[6]See Borio and Lowe (2002), Davis and Zhu (2004), and Goodhart, Hofmann, and Segoviano (2005).

[7]The Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices shows the cyclical nature of bank lending standards, loan demand, and loan spreads. Asea and Blomberg (1998) find, with bank-level variables, that the probability of collateralization increases during contractions and decreases during expansions in the United States.

[8]Clair (1992), Keeton (1999), and Salas and Saurina (2002) are a few exceptions.

[9]Goodhart, Hofmann, and Segoviano (2005) document that credit over GDP is a good predictor of future defaults. Dell'Ariccia and Marquez (forthcoming) predict that episodes of financial distress are more likely in the aftermath of periods of strong credit expansion.

boom periods have a higher probability of default than those granted during periods of slow credit growth. To our knowledge, this is the first time that such an empirical study, based on loan-by-loan information, relating credit-cycle phase and future problem loans is being carried out. Finally, we show that in boom periods collateral requirements are relaxed, while the opposite happens in recessions, which we take as evidence of looser credit standards during expansions.

The three empirical avenues provide similar results: In boom periods, when lending accelerates, the seeds for problem loans are being sown. During recession periods, when banks curtail credit growth, they become much more cautious, both in terms of the quality of the borrowers and the loan conditions. Therefore, banking supervisors' concerns are well rooted both in theoretical and empirical grounds and deserve careful scrutiny and a proper answer by regulators. We call the former findings procyclicality of ex ante credit risk, as opposed to the behavior of ex post credit risk (i.e., nonperforming loans), which increases during recessions and declines in good periods.[10] The issue here is to realize that lending policy mistakes occur in good times; thus, a prudential response from the supervisor might be needed at those times.

We develop a new regulatory devise specifically designed to cope with procyclicality of ex ante credit risk. It is a countercyclical, or forward-looking, loan loss provision that takes into account the former empirical results. Spain already had a dynamic provision (the so-called statistical provision) with a clear prudential bias (Fernández de Lis, Martínez Pagés, and Saurina 2000). The main criticism to that provision (coming from accountants, not from banking supervisors) was that resulting total loan loss provisions were excessively "flat" through an entire economic cycle. Although it shares the prudential concern of the statistical provision, the new proposal does not achieve, by construction, a flat loan loss provision through the cycle. Instead, total loan loss provisions are still higher in recessions, but they are also significant when credit policies are the most lax and therefore credit risk (according to supervisors' experiences and our empirical findings) is entering at a high speed on bank loan portfolios. By making a concrete proposal, we would like

[10] A thorough discussion of banking regulatory tools to cope with procyclicality of the financial system is in Borio, Furfine, and Lowe (2001).

to open a debate on banking regulatory tools that can contribute to dampen business-cycle fluctuations and, thus, to enhance financial stability.

The rest of the paper is organized as follows. Section 2 provides the empirical evidence on credit cycles and credit risk. Section 3 explains the rationale and workings of the new regulatory tool through a simulation exercise. Section 4 contains a policy discussion, and section 5 concludes.

2. Empirical Evidence on Lending Cycles and Credit Risk

2.1 Problem Loan Ratios and Credit Growth

Salas and Saurina (2002) model problem loan ratios as a function of both macro- and microvariables (i.e., bank balance sheet variables). They find that lagged credit growth has a positive and significant impact on ex post credit risk measures. Here, we follow that paper in order to disentangle the relationship between past credit growth and current problem loans. Although in spirit the methodology is similar, there are some important differences worth pointing out. First of all, we use a longer period, which allows us to consider two lending cycles of the Spanish economy. Secondly, we focus more on loan portfolio characteristics (industry and regional concentration and importance of collateralized loans) of the bank rather than on balance sheet variables, which are much more general and difficult to interpret. For that, we take advantage of the information contained in the Central Credit Register (CCR) database run by Banco de España.[11] The equation we estimate is the following:

$$\begin{aligned} NPL_{it} = {} & \alpha NPL_{it-1} + \beta_1 GDPG_t + \beta_2 GDPG_{t-1} + \beta_3 RIR_t \\ & + \beta_4 RIR_{t-1} + \delta_1 LOANG_{it-2} + \delta_2 LOANG_{it-3} \\ & + \delta_4 LOANG_{it-4} + \chi_1 HERFR_{it} + \chi_2 HERFI_{it} \\ & + \phi_1 COLIND_{it} + \phi_2 COLFIR_{it} + \omega SIZE_{it} + \eta_i + \varepsilon_{it}, \end{aligned} \quad (1)$$

[11] Any loan above €6,000 granted by any bank operating in Spain must be reported to the CCR. A detailed description of the CCR content can be found in Jiménez and Saurina (2004) and Jiménez, Salas, and Saurina (forthcoming).

where NPL_{it} is the ratio of nonperforming loans over total loans for bank i in year t. In fact, we estimate the logarithmic transformation of that ratio (i.e., $\ln(NPL_{it}/(100 - NPL_{it}))$) in order to not curtail the range of variation of the endogenous variable. Since problem loans present a lot of persistence, we include the left-hand-side variable in the right-hand side lagged one year. We control for the macroeconomic determinants of credit risk (i.e., common shocks to all banks) through the real rate of growth of the gross domestic product ($GDPG$) and the real interest rate (RIR), proxied as the interbank interest rate less the inflation of the period. Both variables are included contemporaneously as well as lagged one year since some of the impacts might take some time to appear.

Our variable of interest is the loan growth rate, lagged two, three, and four years. A positive and significant parameter for those variables will be empirical evidence supporting the prudential concerns of banking regulators since the swifter the loan growth, the higher the problem loans in the future.

Moreover, we control for risk-diversification strategies of each bank through the inclusion of two Herfindahl indexes (one for region, $HERFR$, and the other for industry, $HERFI$). We also include as a control variable the size of the bank ($SIZE$)—that is, the market share of the bank in each period of time. Equation (1) also takes into account the specialization of the bank in collateralized loans, distinguishing between those of firms ($COLFIR$) and those of households ($COLIND$).

Finally, η_i is a bank fixed effect to control for idiosyncratic characteristics of each bank, constant along time. It might reflect the risk profile of the bank, the way of doing business, etc. ε_{it} is a random error. We estimate model 1 in first differences in order to prevent from biasing the results due to a possible correlation between unobservable bank characteristics and some of the right-hand-side variables. Given that some of the explanatory variables might be determined at the same time as the left-hand-side variable, we use a GMM estimator (Arellano and Bond 1991).

All the information from each individual bank comes from the CCR. Table 1 contains the descriptive statistics of the variables. The period analyzed covers two credit cycles of the Spanish banking sector (from 1984 to 2002), with an aggregate maximum for NPL around 1985 and, again, in 1993. We focus on commercial

Table 1. Descriptive Statistics

Variable	Mean	St. Dev.	Min.	Max.
NPL_{it}	3.94	5.70	0.00	99.90
$GDPG_t$	2.90	1.51	−1.03	4.83
RIR_t	4.14	2.90	−0.67	8.12
$LOANG_{i,t-2}$	17.36	14.37	−17.29	71.97
$LOANG_{i,t-3}$	17.37	13.93	−13.80	67.82
$LOANG_{i,t-4}$	17.54	14.09	−11.10	64.68
$HERFR_{it}$	52.68	24.86	11.26	98.87
$HERFI_{it}$	18.47	9.82	7.45	70.26
$COLIND_{it}$	19.25	16.28	0.00	69.91
$COLFIR_{it}$	20.47	12.89	0.00	70.35
$SIZE_{it}$	0.59	1.05	0.00	8.79

Note: NPL_{it} is the nonperforming loan ratio—that is, the quotient between nonperforming loans and total loans. $GDPG_t$ is the real rate of growth of gross domestic product. RIR_t is the real interest rate, calculated as the interbank interest rate less the inflation of the period. $LOANG_{it}$ is the rate of the growth of loans for bank i. $HERFR_{it}$ is the Herfindahl index of bank i in terms of the amount lent to each region. $HERFI_{it}$ is the Herfindahl index of bank i in terms of the amount lent to each industry. $COLIND_{it}$ is the percentage of fully collateralized loans to households over total loans for bank i. $COLFIR_{it}$ is the percentage of fully collateralized loans to firms over total loans for bank i. $SIZE_{it}$ is the market share of bank i. All variables are shown in percentage points. i denotes the bank and t denotes the year.

and savings banks, which represent more than 95 percent of total assets among credit institutions (only small credit cooperatives and specialized financial firms are left aside). Some outliers have been eliminated in order to avoid the possibility that a small number of observations, with a very low relative weight over the total sample, could bias the results. Thus, we have eliminated those extreme loan growth rates (i.e., banks with a loan growth rate lower or higher than the 5th and 95th percentile, respectively).

Results appear in the first column of table 2 (labeled "Model 1"). As expected, since we take first differences of equation (1) and ε_{it} is white noise, there is first-order residual autocorrelation and

Table 2. GMM Estimation Results of Equation (1) Using DPD (Arellano and Bond 1991)

	Model 1		**Model 2**		**Model 3**		**Model 4**	
Variables	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
$NPL_{i,t-1}$	0.5524	0.0887***	0.5520	0.0889***	0.5499	0.0841***	0.5447	0.0833***
Macroeconomic Characteristics								
$GDPD_t$	−0.0631	0.0135***	−0.0654	0.0137***	−0.0709	0.0131***	−0.0716	0.0134***
$GDPG_{t-1}$	−0.0771	0.0217***	−0.0770	0.0220***	−0.0750	0.0212***	−0.0777	0.0209***
RIR_t	0.0710	0.0194***	0.0703	0.0193***	0.0704	0.0195***	0.0711	0.0192***
RIR_{t-1}	0.0295	0.0103***	0.0292	0.0103***	0.0262	0.0098***	0.0263	0.0101***
Bank Characteristics								
$LOANG_{i,t-2}$	−0.0008	0.0013	−0.0008	0.0013				
$LOANG_{i,t-3}$	0.0018	0.0012	0.0018	0.0012				
$LOANG_{i,t-4}$ (α)	0.0034	0.0012***	0.0029	0.0012**				
$\lvert LOANG_{i,t-2} - AVERAGE\ LOANG_i \rvert$			0.0004	0.0017				
$\lvert LOANG_{i,t-3} - AVERAGE\ LOANG_i \rvert$			−0.0005	0.0016				
$\lvert LOANG_{i,t-4} - AVERAGE\ LOANG_i \rvert$ (β)			0.0025	0.0019				
$LOANG_{i,t-2} - AVERAGE\ LOANG_t$					0.0007	0.0012	0.0011	0.0013
$LOANG_{i,t-3} - AVERAGE\ LOANG_t$					0.0015	0.0013	0.0014	0.0014
$LOANG_{i,t-4} - AVERAGE\ LOANG_t$ (α)					0.0025	0.0013**	0.0020	0.0013

(continued)

Table 2 (continued). GMM Estimation Results of Equation (1) Using DPD (Arellano and Bond 1991)

	Model 1		Model 2		Model 3		Model 4	
Variables	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**	**Coefficient**	**SE**
Bank Characteristics (continued)								
$\lvert LOANG_{i,t-2} - AVERAGE\ LOANG_t \rvert$							−0.0026	0.0018
$\lvert LOANG_{i,t-3} - AVERAGE\ LOANG_t \rvert$							0.0017	0.0017
$\lvert LOANG_{i,t-4} - AVERAGE\ LOANG_t \rvert$ (β)							0.0029	0.0018
$HERFR_{it}$	0.0212	0.0096**	0.0209	0.0097**	0.0207	0.0098**	0.0218	0.0099**
$HERFI_{it}$	−0.0032	0.0094	−0.0025	0.0095	−0.0038	0.0098	−0.0026	0.0097
$COLFIR_{it}$	0.0034	0.0063	0.0034	0.0063	0.0034	0.0065	0.0046	0.0065
$COLIND_{it}$	−0.0125	0.0072*	−0.0125	0.0072*	−0.0141	0.0073*	−0.0141	0.0074*
$SIZE_{it}$	0.0199	0.0482	0.0153	0.0486	0.0213	0.0475	0.0261	0.0484
Time Dummies	No		No		No		No	
No. Observations	868		868		868		868	
Time Period	1984–2002		1984–2002		1984–2002		1984–2002	
Sargan Test $[\chi(2)_{138}]$/p-value	124.76	0.78	125.56	0.77	123.85	0.80	122.86	0.82
First-Order Autocorrelation (m_1)	−5.43		−5.37		−5.36		−5.28	
Second-Order Autocorrelation (m_2)	−1.27		−1.4		−1.34		−1.24	
Test Asymmetric Impact (p-value)								
$\alpha + \beta = 0$	—		0.01		—		0.01	
$\alpha - \beta = 0$	—		0.84		—		0.73	

Note: See note in table 1 for a description of the variables. NPL_{it}, $HERFR_{it}$, $HERFI_{it}$, $COLFIR_{it}$, and $COLIND_{it}$ are treated as endogenous using three lags for NPL_{it} and two for the others. Robust SE reported. *, **, and *** are significant at the 10 percent, 5 percent, and 1 percent levels, respectively.

not second order. A Sargan test of validity of instruments is also fully satisfactory. The results of the estimation are robust to heteroskedasticity.

Regarding the explanatory variables, there is persistence in the *NPL* variable. The macroeconomic control variables are both significant and have the expected signs. Thus, the acceleration of GDP, as well as a decline in real interest rates, brings about a decline in problem loans. The impact of interest rates is much more rapid than that of economic activity. The more concentrated the credit portfolio in a region, the higher the problem loan ratio, while industry concentration is not significant. Collateralized loans to households are less risky (10 percent level of significance), mainly because these are mortgages that, in Spain, have the lowest credit risk. The parameter of the collateralized loans to firms, although positive, is not significant. The size of the bank does not have a significant impact on the problem loan ratio.

Finally, regarding the variables that are the focus of our paper, the rate of loan growth lagged four years is positive and significant (at the 1 percent level). The loan growth rate lagged three years is also positive, although not significant. Therefore, rapid credit growth today results in lower credit standards that, eventually, bring about higher problem loans.

The economic impact of the explanatory variables is significant. The long-run elasticity of GDP growth rate, evaluated at the mean of the variables, is -1.19; that is, an increase of 1 percentage point in the rate of GDP growth (i.e., GDP grows at 3 percent instead of at 2 percent) decreases the *NPL* ratio by 30.1 percent (i.e., it declines from 3.94 percent to 2.75 percent). For interest rates, a 100-basis-point increase brings about a rise in the *NPL* ratio of 21.6 percent. Regarding loan growth rates, an acceleration of 1 percent in the growth rate has a long-term impact of a 0.7 percent higher problem loan ratio.

We have performed numerous robustness tests. Model 2 (the second column of table 2) tests for the asymmetric impact of loan expansions and contractions. We augment model 1 with the absolute value of the difference between the loan credit growth of bank i in year t and its average over time. All model 1 results hold, but it can be seen that there is some asymmetry: rapid credit growth of a bank (i.e., above its own average loan growth) increases nonperforming loans, while slow growth (i.e., below average) has no significant impact on problem loans.[12] If instead of focusing on credit growth of bank i (either alone or compared to its average growth rate over time), we look at the relative position of bank i in respect to the rest of the banks at a point in time (i.e., at each year t), we find that the relative loan growth rate lagged four years still has a positive and significant impact on bank i's *NPL* ratio (model 3, third column of table 2). The parameter of relative credit growth lagged three years is positive but not significant. The rest of the variables keep their sign and significance. Model 4 (the last column of table 2) shows that there is asymmetry in the response of nonperforming loans to credit growth. When banks expand their loan portfolios at a speed above the average of the banking sector, future nonperforming loans increase, while there is no significant effect if the loan growth is below the average.[13] Finally, the former results are robust to changes in the macroeconomic control variables (not shown). If we substitute time dummies for the change in the GDP growth rate and for the real interest rate, the loan growth rate is still positive and significant in lag 4 (although at the 10 percent level) and, again, positive (although not significant) in lag 3.

All in all, we find a robust statistical relationship between rapid credit growth at each bank portfolio and problem loans later on. The lag is around four years, so bank managers and short-term investors (including shareholders) might have incentives to foster credit growth today in order to reap short-term benefits to the expense of long-term bank stakeholders, including depositors, the deposit guarantee fund, and banking supervisors.

2.2 Probability of Default and Credit Growth

Instead of focusing on bank-aggregated-level credit risk measures, in this section we analyze the probability of default at an individual

[12]Note that in model 1, regression results are the same for the variable rate of growth of loans in bank i at year t as they are for the difference between the former variable and the average rate of growth of loans of bank i along time. That is because the latter term is constant over time for each bank and disappears when we take first differences in equation (1).

[13]Note that the relevant test here is to test if $\alpha + \beta$ (and $\alpha - \beta$) is significant, not each of them alone.

loan level and its relation to the cyclical position of the bank credit policy. The hypothesis is that, for the reasons explained in section 1 above, those loans granted during credit booms are riskier than those granted when the bank is reining in loan growth. That would provide a rigorous empirical microfoundation for prudential regulatory devises aimed at covering the losses embedded in policies regarding rapid credit growth.

In order to test the former hypothesis, we use individual loan data from the CCR. We focus on new loans granted to nonfinancial firms with a maturity larger than one year and keep track of them the following years. We study only financial loans (i.e., excluding receivables, leasing, etc.), which are 60 percent of the total loans to nonfinancial firms in the CCR, granted by commercial and savings banks. The equation estimated is

$$\begin{aligned}\Pr(DEFAULT_{ijt+k} = 1) &= F(\theta + \alpha(LOANG_{it} - averageLOANG_i)\\ &\quad + \beta\left|LOANG_{it} - averageLOANG_i\right|\chi LOANCHAR_{iit}\\ &\quad + \delta_1 DREG_i + \delta_2 DIND_i + \delta_3 BANKCHAR_{it} + \varphi_t + \eta_i),\end{aligned} \tag{2}$$

where we model the probability of default of loan j, in bank i, some k years after being granted (i.e., at $t+2$, $t+3$, and $t+4$)[14] as a logistic function $[F(x) = 1/(1 + exp(-x))]$ of the characteristics of that loan ($LOANCHAR$), such as its size, maturity (i.e., between one and three years and more than three years), and collateral (fully collateralized or no collateral); a set of control variables (i.e., the region where the firm operates, $DREG$, and the industry to which the borrower pertains, $DIND$); and the characteristics of the bank that grants the loan ($BANKCHAR$), such as its size and type (i.e., commercial or savings bank). We also control for macroeconomic characteristics, including time dummies (φ_t).

We do not consider default immediately after the loan is granted (i.e., in $t + 1$) because it takes time for a bad borrower to reveal as

[14]We consider that a loan is in default when its doubtful part is larger than the 5 percent of its total amount. Thus, we exclude from default small arrears, mainly technical, that are sorted out by borrowers in a few days and that, usually, never reach the following month. The level and the evolution of the probability of default (PD) across time and firm size in Spain can be seen in Saurina and Trucharte (2004). On average, large firms (i.e., those with annual sales above €50 million) have a PD between four and five times lower than that of small and medium-sized enterprises (i.e., firms with annual turnover below €50 million).

such. When granted a loan, a borrower takes the money from the bank and invests it into the project. As the project develops, the borrower is either able to repay the loan and the due interest payments or is not able to pay and defaults. Therefore, it takes time for the default to occur.

Once we have controlled for loan, bank, and time characteristics, we add the relative loan growth rate of bank i at time t with respect to financial loans granted to nonfinancial firms ($LOANG_{it} - averageLOANG_i$)—that is, the current lending position of each bank in comparison to its average loan growth. If α is positive and significant, we interpret this as a signal of more credit risk in boom periods when, probably, credit standards are low. On the contrary, when credit growth slows, banks become much more careful in scrutinizing loan applications; as a result, next-year defaults decrease significantly. To our knowledge, this is the first time that such a direct test has been run. Additionally, we test for asymmetries in that relationship, as in the previous section. We have considered only those banks with a loan growth rate within the 5th and 95th percentile, to eliminate outliers.

It is very important to control for the great heterogeneity due to firm effects, even more because our database does not contain firm-related variables (i.e., balance sheet and profit and loss variables). For this reason, we have controlled for firm (loan) characteristics using a random effects model, which allows us to take into account the unobserved heterogeneity (without limiting the sample as the conditional model does) assuming a zero correlation between the firm effects and the rest of the characteristics of the firm.[15]

Table 3 shows the estimation results for the pool of all loans granted. We observe that the faster the growth rate of the bank, the higher the likelihood to default in the following years. We observe that α is positive and significant when we consider defaults three and four years later, and α is positive, although not significant, for defaults two years after the loan was granted (table 3, columns 1, 3, and 5). As mentioned before, although not reported in table 3, we control for macroeconomic characteristics, region and industry

[15]We have also estimated a logit model with fixed effects, and the results are quite similar.

Table 3. GMM Estimation Results of Equation (2) Using a Random Effect Logit Model (Results for Pool of All Loans Granted)

Variables	(1) Coeff.	(1) SE	(2) Coeff.	(2) SE
Dependent Variable	$DEFAULT_{ijt+2}$ (0/1)		$DEFAULT_{ijt+2}$ (0/1)	
Bank Characteristics				
$LOANG_{it} - AVERAGE$ $LOANG_i$ (α)	0.001	0.001	−0.001	0.001*
$\|LOANG_{it} - AVERAGE$ $LOANG_i$ (β)	—	—	0.005	0.001***
Province Dummies	Yes		Yes	
Industry Dummies	Yes		Yes	
No. Observations	1,823,656		1,823,656	
Time Period	1985–2004		1985–2004	
Wald Test [$\chi(2)$]/p-value	8,959	0.00	9,121	0.00
Test Asymmetric Impact (p-value)				
$\alpha + \beta = 0$	—		0.00	
$\alpha - \beta = 0$	—		0.00	

Variables	(3) Coeff.	(3) SE	(4) Coeff.	(4) SE
Dependent Variable	$DEFAULT_{ijt+3}$ (0/1)		$DEFAULT_{ijt+3}$ (0/1)	
Bank Characteristics				
$LOANG_{it} - AVERAGE$ $LOANG_i$ (α)	0.002	0.001***	0.001	0.001
$\|LOANG_{it} - AVERAGE$ $LOANG_i\|$ (β)	—	—	0.001	0.001
Province Dummies	Yes		Yes	
Industry Dummies	Yes		Yes	
No. Observations	1,643,708		1,643,708	
Time Period	1985–2004		1985–2004	
Wald Test [$\chi(2)$]/p-value	4,800	0.00	4,874	0.00
Test Asymmetric Impact (p-value)				
$\alpha + \beta = 0$	—		0.00	
$\alpha - \beta = 0$	—		0.93	

(*continued*)

Table 3 (continued). GMM Estimation Results of Equation (2) Using a Random Effect Logit Model (Results for Pool of All Loans Granted)

	(5)		(6)	
Variables	**Coeff.**	**SE**	**Coeff.**	**SE**
Dependent Variable	$DEFAULT_{ijt+4}$ (0/1)		$DEFAULT_{ijt+4}$ (0/1)	
Bank Characteristics				
$LOANG_{it} - AVERAGE\ LOANG_i$ (α)	0.002	0.001**	0.002	0.002
$\lvert LOANG_{it} - AVERAGE\ LOANG_i \rvert$ (β)	—	—	0.000	0.002
Province Dummies	Yes		Yes	
Industry Dummies	Yes		Yes	
No. Observations	1,433,074		1,433,074	
Time Period	1985–2004		1985–2004	
Wald Test [$\chi(2)$]/p-value	2,992	0.00	3,054	
Test Asymmetric Impact (p-value)				
$\alpha + \beta = 0$	—		0.04	
$\alpha - \beta = 0$	—		0.55	

Note: *DEFAULT* is a dummy variable that takes 1 if the loan is doubtful and 0 otherwise. $LOANG_{it}$ is the growth rate of all financial credits granted to firms for bank i. We also control for bank size and type (i.e., commercial or savings) and for loan characteristics (i.e., size, maturity, and collateral). Region, industry, and time dummies have been included. *, **, and *** are significant at the 10 percent, 5 percent, and 1 percent levels, respectively.

of the borrowing firm, size and type of the bank lender, and, finally, for size, maturity, and collateral of the loan granted.

We have also investigated if there is an asymmetric impact of loan growth over defaults (columns 2, 4, and 6 in table 3). In good times, when loan growth of each bank is above its average, we find a positive and significant impact on future defaults (two, three, and four years later). However, in bad times, with loan growth below the bank's average, there is no impact on defaults. Thus, this asymmetric effect reinforces the conclusions about too-lax lending policies during booms.

To test the robustness of the former results, table 4 shows the estimation of the model when the loan growth rate of the bank is introduced without any comparison to its average value. The results obtained are exactly the same: there is no effect on the probability of

Table 4. GMM Estimation Results of Equation (2) Using a Random Effect Logit Model (Loan Growth Rate of Bank Introduced without Comparison to Its Average Value)

Variables	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
Dependent Variable	$DEFAULT_{ijt+2}$ (0/1)		$DEFAULT_{ijt+3}$ (0/1)		$DEFAULT_{ijt+4}$ (0/1)	
Bank Characteristics						
$LOANG_{it}$	0.001	0.001	0.002	0.001***	0.002	0.001***
Province Dummies	Yes		Yes		Yes	
Industry Dummies	Yes		Yes		Yes	
No. Observations	1,823,656		1,643,708		1,433,074	
Time Period	1985–2004		1985–2004		1985–2004	
Wald Test $[\chi(2)]$/p-value	8,966	0.00	4,802	0.00	2,987	0.00

Note: *DEFAULT* is a dummy variable that takes 1 if the loan is doubtful and 0 otherwise. $LOANG_{it}$ is the growth rate of all financial credits granted to firms for bank i. We also control for bank size and type (i.e., commercial or savings) and for loan characteristics (i.e., size, maturity, and collateral). Region, industry, and time dummies have been included. *, ** and *** are significant at the 10 percent, 5 percent, and 1 percent levels, respectively.

default in $t+2$ and a positive and significant one on the likelihood of default in $t+3$ and $t+4$.

In terms of the economic impact, the semi-elasticity of the credit growth is 0.13 percent for default in $t+3$ (0.13 percent in $t+4$),[16] which means that if a bank grows 1 percentage point, then the likelihood of default in $t+3$ is increased by 0.13 percent (0.13 percent in $t+4$). If a bank was expanding its loan portfolio at one standard deviation above the average rate of growth, the impact would be 1.9 percent (1.9 percent). Thus, the economic impact estimated is low for the period analyzed and the sample considered, despite the significance of the variables.

All in all, the previous results show that in good times, when credit is growing rapidly, credit risk in bank loan portfolios is also increasing.

2.3 Collateral and Credit Growth

This section provides evidence of the behavior of banks in terms of their credit policies along the business cycle. The argument so far has been that too-rapid credit growth comes with lower credit standards and, later on, manifests in a higher number of problem loans. Here, we provide some complementary evidence based on the tight relationship between credit cycles and business cycles. We argue that banks adjust their credit policies depending on the business-cycle position. For instance, in good times, banks relax credit standards and are prepared to be more lenient in collateral requirements. On the other hand, when a recession arrives, banks toughen credit conditions and, in particular, collateral requirements.

If the hypothesis presented in the former paragraph is true, we would have complementary evidence to support prudential regulatory policies. If it is true that, during boom times, loan portfolios are increasingly loaded with higher expected defaults, then it should also be true that other protective devises for banks, such as collateral, are eroded.[17] The following equation allows us to test the relationship between collateral and economic cycle.

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[16]The marginal effect of the k-variable is computed as $ME_k = \frac{d[\Pr ob(y=1|\bar{x})]}{dx_k} = \Lambda(\hat{\beta}\bar{x})[1-\Lambda(\hat{\beta}\bar{x})]\hat{\beta}_k$. Then, the semi-elasticity is given by $ME_k / Average\ Default$.

[17]It might also be the case that, during good times, banks decrease credit risk spreads in their granted loans partially as a result of overoptimism and tight

$$\Pr(\mathit{Collateral}_{ijklt} = 1) = F(\theta + \alpha \mathit{GDPG}_{t-1} + \beta|\mathit{GDPG}_{t-1} - \mathit{Average\ GDP}| + \mathit{Control\ Variables}_{ijklt}) \quad (3)$$

A full description of model 3 and its control variables is in Jiménez, Salas, and Saurina (forthcoming). Here we only focus on the impact of GDP growth on collateral, controlling for the other determinants of collateral. The variable on the left-hand side takes the value of 1 if the loan is collateralized and 0 otherwise. j refers to the loan, i refers to the bank, k refers to the market, l refers to the firm (borrower), and t refers to the time period (year). We estimate equation (3) using a probit model. As control variables, we use borrower characteristics (i.e., if they were in default the year before or the year after the loan was granted, their indebtedness level, and their age as a borrower), bank characteristics (size, type of bank, and its specialization in lending to firms), characteristics of the borrower-lender relationship (duration and scope), and other control variables (such as the level of competition in the loan market, the size of the loan, and the industry and region of the borrower).[18]

The database used is the CCR. We focus on all new financial loans above €6,000 with a maturity of one year or more, granted by any Spanish commercial or savings bank to nonfinancial firms every year during the time period between December 1984 and December 2002. We exclude commercial loans, leasing, factoring operations, and off-balance-sheet commitments for homogeneity reasons.

The first column in table 5 shows the results of estimating model 3 for the pool of loans, nearly two million loans. There is a negative and significant relationship between GDP growth rates and collateral; that is, in good times banks lower collateral requirements, and they increase them in bad times. In terms of the impact, the semi-elasticity of *GDPG* is −3.1 percent, which means that an

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competition among banks. The opposite would happen in bad times, when bank managers would tighten credit spreads. Unfortunately, our database does not allow us to test this hypothesis.

[18] Jiménez, Salas, and Saurina (forthcoming) contains a similar analysis on a different sample of loans and using a different estimation procedure (i.e., fixed effects).

Table 5. GMM Results of Equation (3) Using a Probit Model

	All Borrowers			
	(1) All Terms		(2) All Terms	
Variables	**Coeff.**	**SE**	**Coeff.**	**SE**
Dependent Variable				
$COLLATERAL_t$ (1/0)				
Macroeconomic Characteristics				
$GDPG_{t-1}$ (α)	−0.045	0.001***	−0.047	0.001***
$\|GDPG_{t-1} - Average\ GDPG_{t-1}\|$ (β)	—	—	−0.011	0.002***
Regional Dummies	Yes		Yes	
Industry Dummies	Yes		Yes	
No. Observations	1,972,336		1,972,336	
Time Period	1985–2002		1985–2002	
χ^2 Covariates/p-value	279,056	0.00	279,007	0.00
Test Asymmetric Impact (p-value)				
$\alpha + \beta = 0$	—		0.00	
$\alpha - \beta = 0$	—		0.00	

(*continued*)

Table 5 (continued). GMM Estimation Results of Equation (3) Using a Probit Model

	Old Borrowers				**New Borrowers**			
	(3) Long Term		**(4) Short Term**		**(5) Long Term**		**(6) Short Term**	
Variables	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
Dependent Variable								
$COLLATERAL_t$ (1/0)								
Macroeconomic Characteristics								
$GDPG_{t-1}$ (α)	−0.067	0.001***	−0.021	0.002***	−0.054	0.002***	−0.019	0.004***
$\lvert GDPG_{t-1} - Average\ GDPG_{t-1}\rvert$ (β)	−0.004	0.002**	−0.026	0.004***	0.002	0.004	−0.027	0.007***
Regional Dummies	Yes		Yes		Yes		Yes	
Industry Dummies	Yes		Yes		Yes		Yes	
No. Observations	823,340		723,924		254,755		170,317	
Time Period	1985–2002		1985–2002		1985–2002		1985–2002	
χ^2 Covariates/p-value	147,630	0.00	39,368	0.00	41,708	0.00	13,668	0.00
Test Asymmetric Impact (p-value)								
$\alpha + \beta = 0$	0.00		0.00		0.00		0.00	
$\alpha - \beta = 0$	0.00		0.14		0.00		0.26	

Note: *COLLATERAL* is a dummy variable that takes 1 if the loan granted to a firm is collateralized and 0 otherwise. *GDPG* is the real growth rate of gross domestic product. We also control for bank size, type (i.e., commercial, savings, or cooperative), and lending specialization; for borrower characteristics (i.e., if they were in default the year before or the year after the loan was granted, their indebtedness level, and their age as a borrower); for characteristics of the borrower-lender relationship (duration and scope); and for the level of competition in the loan market, the size of the loan, and the industry and region of the borrower. ** and *** are significant at the 5 percent and 1 percent levels, respectively.

increase of 1 percentage point in *GDPG* reduces the likelihood of collateral by 3.1 percent. In the bond market, Altman, Resti, and Sironi (2002) find evidence of a positive and significant correlation between the probability of default (PD) and the loss given default (LGD). Focusing on the loan market, our results show that the positive correlation between PD and LGD need not hold since—as the recession approaches (and the PD increases)—banks take more collateral on their loans, which might decrease the LGD.[19]

The cyclical behavior of banks regarding collateral is not symmetric. Column 2 in table 5 shows that the likelihood to pledge collateral decreases proportionally more in upturns than it increases in downturns, as the negative and significant value of the parameter of the absolute value of the difference between GDP rate of growth and its average across the period studied points out (i.e., −0.092 in upturns versus −0.058 in downturns). Despite the asymmetry, the negative relationship between loan PD and LGD still might hold. Moreover, from a prudential point of view, there are even more concerns regarding the too-lax credit policies maintained by banks during upturns.

Credit markets are segmented across borrowers and across maturities. Therefore, it might be possible that the former aggregated results do not hold for particular market segments. To carry out this robustness exercise, the database is split into two groups: short term (maturing at one to three years) and long term (maturing at more than three years). A second classification of the loans relates to the experience of the borrower. One group of loans, labeled "old," contains those loans from borrowers about whom, at the time the loan is granted, there is already past information in the database (for instance, if they were in default the previous year). The other group of loans, which we call "new," is from borrowers obtaining a loan for the first time. Table 5 (columns 3–6) shows that, although there are some differences across the maturity of borrowers and across old and new borrowers, the main results hold. For old borrowers, the impact of the business cycle on collateral policy is larger for long-term loans than for short-term ones. We find the same result across new borrowers, but the magnitude of the decline in collateral as the

[19] We thank M. Gordy for pointing out this implication.

economy improves is lower. For short-term loans—both old and new borrowers—collateral requirements decline during upturns but do not increase during downturns, either because the firm has no collateral to pledge or because banks put in place other strategies to recover their short-term loans.

3. A New Prudential Tool

The former section has shown clear evidence of a relationship between rapid credit growth and a deterioration in credit standards that eventually leads to a significant increase in credit losses. Banking regulators, aware of this behavior and concerned about long-term solvency of individual banks as well as the stability of the whole banking system, might wish to implement some devices in order to alleviate the market imperfection.

Borio, Furfine, and Lowe (2001) contains a detailed discussion of procyclicality and banking regulator responses. There has been a lot of discussion about the impact of capital requirements on the cyclical behavior of banks.[20] Here, we want to focus on loan loss provisions since we think that they are the proper instrument to deal with expected losses. Thus, we propose a new prudential provision that addresses the fact that credit risk builds up during credit boom periods. This new provision is in addition to the already existing specific and general provisions. The general provision can be interpreted as a provision for the inherent or latent risk in the portfolio—that is, an average provision across the cycle. The new loan loss provision (or the third component of the total loan loss provision) is based on the credit-cycle position of the bank in such a way that the higher the credit growth of the individual bank, the more it has to provision. On the contrary, the lower the credit growth, the more provisions the bank can liberate from the previously built reserve. Analytically, we can write

$$LLP_{total} = \textit{specif.} + g\Delta C + \alpha(\Delta C - \gamma C_{t-1}), \tag{4}$$

[20]The issue of procyclicality of capital requirements has drawn a lot of attention (Daníelsson et al. 2001, Kashyap and Stein 2004, and Gordy and Howells 2004, to name a few).

where the total loan loss provision (LLP_{total}) has three components: (i) the specific provision (*specif.*), (ii) the latent provision (applied on each new loan granted to cover the average credit risk, g), and (iii) the countercyclical, or forward-looking, provision, where C_{t-1} is the stock of loans for the previous period, γ is the average loan growth rate across banks and across a lending cycle, and ΔC is the absolute growth in total loans. Thus, when the loan portfolio grows above the average historical growth rate, the provision is positive, and it is negative otherwise.

Note that the provision is positive in boom periods and negative during recessions. The more distant the bank behavior is from the total system, the larger the provisioning impact. The underlying idea is quite simple: the more rapid the credit growth, the higher the increase in market share and, presumably, following our empirical results, the higher the credit risk assumed by the bank and, therefore, the higher the provision. The asymmetry found in some of the results of the former section (see table 2) points toward an increase in loan loss provisions in good times, when credit risk increases and there is rapid credit growth, and allowing the previously built loan loss reserves to be depleted in downturns, when the former rapid credit growth materializes as loan losses.

Our proposal is a very simple and intuitive prudential tool to cope with credit risk linked to cyclical lending policies. The provision is not expected to replace the existing provisions but rather to reinforce them. Therefore, we would have specific provisions for impaired assets already individually identified, plus provisions to cover inherent losses in homogeneous groups of loans (i.e., losses incurred but not yet identified in individual loans), as well as provisions that take into account the position of the bank in the credit cycle and, thus, its credit risk profile.

The third component of LLP_{total}, the countercyclical one, has been considered in our proposal as an additional loan loss provision. Alternatively, it could be included in capital requirements (for instance, asked through pillar 2 of the Basel II framework).[21] Banking supervisors, according to their experiences regarding lending cycles and credit risk, might ask banks to hold higher capital levels

[21]See Basel Committee on Banking Supervision (2004).

during booms in order to take into account future problem loan developments. Note that this proposal might contribute to alleviate potential concerns, if any, about increased capital procyclicality within the Basel II framework.

3.1 Simulations

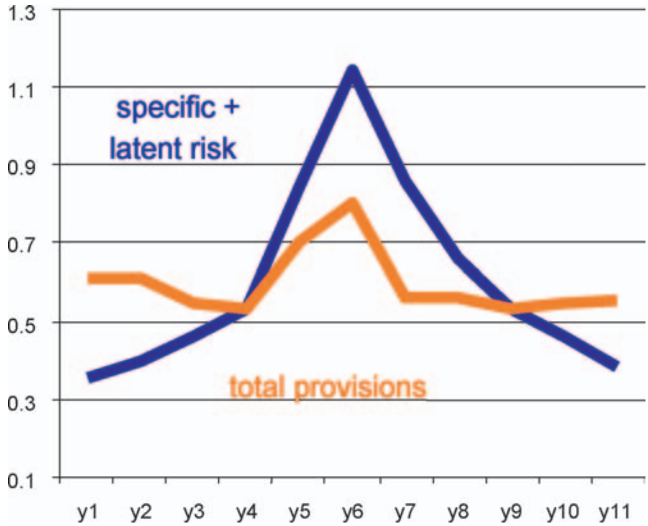
One way to understand the workings of the provision put forward is through a simulation exercise. We simulate a full economic and lending cycle in eleven years. During the first two years, the economy is expanding at full steam, which means rapid credit growth and very low specific loan loss provisions (as a result of low problem loan ratios). From year 3 onward credit growth decreases and problem loans increase with a subsequent increase in specific provisioning requirements. In year 6 the trough is reached with a maximum in provisioning requirements and a minimum in lending growth. From year 7 onward the credit and the economy recover and specific provisions decline. Figure 1 shows the evolution of loan loss provisions over total loans during the eleven years. The evolution of the specific provision plus the general (latent risk) provision (i.e., the first two parts of our provisioning formula (4)) is quite cyclical, with a significant rise around the trough period.

Regarding the third component of the total loan loss provision, when loan growth rates are above the average loan growth rate (i.e., the first three years in our simulation), its amount is positive, charged in the profit and loss account (P&L), and accrued in a provision fund or reserve account. When loan growth starts to dip below the average (between years 4 and 9), the amount is negative and is accrued in the P&L from the previously built fund.[22] From year 10 onward the provision resumes a positive value (as a result of a new expansionary credit cycle), and the fund is being built up again.

What is the final impact of the new provision over a framework that already has a specific and a general provision? The total loan loss provision is smoother than the sum of the specific and

[22]Of course, it is understood that the fund cannot be negative; that is, the bank is not allowed to write as income in the P&L something that has not been previously built up.

Figure 1. Simulation Exercise: Loan Loss Provisions as a Percentage of Total Loans



general provisions (figure 1). But the smoothing is far from total. There is still quite a significant variation of total loan loss provisions across the credit cycle. Of course, during recessions provisions reach the maximum amount, as the specific one dominates the landscape. However, in true boom periods (i.e., years 1 and 2) when loan growth is extremely high, provisioning requirements through the third component of the provision are significant. The new provision is countercyclical, but it does not have a significant impact on total loan loss provisions unless the variability in credit growth rates is extreme, which—for most of the banks—is not the case. At the same time, the volatility of profits is somewhat lower through the cycle.

4. Policy Discussion

The empirical results of the former section provide a rationale for countercyclical loan loss provisions, apart from those covering impaired assets or the latent risk in the loan portfolio. However, accounting frameworks do not fully recognize such a coverage. For instance, although from a prudential point of view there is a rationale for setting aside provisions since the loan is granted, accountants are reluctant to allow it.[23]

Since January 2005, all European Union firms (either banks or nonfinancial firms) with quoted securities in any EU organized market have to comply with International Financial Reporting Standards (IFRS, formerly called International Accounting Standards, or IAS). That means a change in the provisioning system based on specific and general provisions. From 2005 onward, banks have to set aside provisions to cover individually identified impaired assets; for homogeneous loan portfolios, they will be required to cover losses incurred but not yet identified in individual loans. IAS 39 does not allow banks to set aside provisions for future losses when a loan is granted. Therefore, the new standards do not perfectly match the prudential concerns of banking regulators. Borio and Tsatsaronis (2004) show a way to sort out this problem through a decoupling of objectives (i.e., one is to provide unbiased information; the other is to instill a degree of prudence). We believe a more fundamental question is, what purpose should the accounting framework serve and, more importantly, at what price? Financial stability concerns and, therefore, prudent accounting should probably be higher on the list of priorities, especially since there is overwhelming evidence of earnings management. The incentives to alter the accounting numbers will not disappear with IAS.[24] If investors might not, in any case, get the unbiased figures, there might be room for instilling prudent behavior through the accounting rules.

Alternatively, if accounting principles are written in a way that does not allow for sheltering prudential concerns, banking regulators might try other devices in order to counterbalance the negative impact of excessive decreases in credit standards during boom periods. For instance, pillar 2 of the new capital framework put forward by supervisors in Basel II might include a stress test of capital requirements that might be based along the lines developed here for

[23] That is not the case with insurance companies, where the technical provision to cover the risk incurred appears just after the insurance policy has been sold to the customer.

[24] For a theoretical rationale of income smoothing, see (among others) Fudenberg and Tirole (1995) and Goel and Thakor (2003).

the new provision. In a sense, if the accounting framework does not provide enough flexibility to banking supervisors, they should find it through the allowed supervisory discretion of pillar 2.

Either as an additional provision or as a capital requirement, the third component of total loan loss provisions will help to counter the cyclical behavior of own funds in Basel II. Basel I was not properly tracking banks' risks. Basel II is meant to tie capital requirements more closely to risk. Capital requirements will increase during recessions as the probability of default increases. However, the evidence provided in this paper argues that (ex ante) credit risk increases during boom periods. Therefore, without interfering with Basel II pillar 1 capital requirements, pillar 2 adjustment might help to take into account those increases in ex ante credit risk and, somehow, soften the procyclicality of capital requirements.[25]

Rajan (1994) discusses possible regulatory interventions that would reduce the expansionary bias in lending policies—among them, decreasing the amount of loanable funds or imposing credit controls. However, both proposals do not seem very feasible since they might have other negative, unintended consequences, as the author recognizes. Alternatively, close monitoring of bank portfolios by supervisors, and the corresponding penalties, might be the answer. However, that will increase the cost of supervision substantially. Our loan loss provision proposal is inexpensively monitored and easily available for bank supervisors. Moreover, it is not designed to curtail credit growth but to account for the negative impact of too-lax lending policies. It is up to each bank manager to decide its lending policy, but if the lending policy is reckless, loan loss provisions should be proportionally higher to account for future higher credit losses.

This paper also has some implications in terms of financial information disclosure and transparency. It is argued that more disclosure of information by banks will help investors to discipline bank managers and, therefore, to help banking supervisors as well. In fact, that is the main rationale for pillar 3 of Basel II. However, some recent research (Morris and Shin 2002) points toward a more-nuanced position regarding the welfare achievements of more transparency and

[25]The loan loss provision we propose here might work as the "second instrument" proposed by Goodhart (2005) to maintain financial stability.

disclosure and the above-mentioned widespread existence of earnings management. In fact, Rajan (1994) finds what he calls a counterintuitive comparative statics: "Allowing banks to fudge their accounting numbers and to maintain secret (sic) reserves can improve the quality of their lending decisions."

The new provision is fully transparent. Investors and, more generally, any bank stakeholder could "undo" its effects since they only need to look at the lending growth rate of the bank and the average of the system. Of course, transparency could improve even more if regulators make it compulsory to release the amount of the stress provision in the annual report of each bank. Here, we are not trying to manage earnings or, more precisely, to smooth banks' income through that provision. Instead, we are just trying to cope with latent risks in bank loan portfolios in a way that is fully transparent and not properly addressed by IAS or even Basel II capital requirements. In fact, it might be possible that our proposal could contribute to a decline in income-smoothing practices across banks since (at least partially) some of their causes would be covered by the new provision. Thus, contrary to Rajan, banking regulators would have no need to allow banks more discretion to "fudge" their accounts since the regulatory framework would allow for an appropriate coverage of latent risks in good times and a lower impact on the P&L in bad periods that would result in a less volatile pattern for profits through the cycle.

Banco de España has applied the so-called statistical provision from mid-July 2000 onward. It is a countercyclical provision. When the three currently existing loan loss provisions (i.e., specific, general, and statistical) are added up through an economic cycle, the quotient between total loan loss provisions and total loans remains almost constant along time. Accountants did not ever like this total smoothing effect along the credit cycle. The new provision that we have developed in this paper does not have those drawbacks. First of all, the quotient between total loan loss provisions and total loans shows a cyclical pattern (i.e., increases in bad times), but that pattern is much less pronounced than before (figure 1). From a prudential point of view, it is very important that total loan loss provisions are relatively high in the peak of the lending boom. Secondly, although total loan loss provisions are high in boom periods, the maximum is reached around the recession, when impaired assets are also at their maximum. Thus, loan loss provisions are not completely smooth along the business cycle.

5. Conclusions

Increasing banking competition—coupled with agency problems, strong balance sheets, and some other characteristics of banking markets (such as risk-related capital requirements, imperfections in the equity market, and maturity mismatches)—may bring about lower credit standards that translate into too-expansionary credit policies and, eventually, higher loan losses. Therefore, a bank regulator concerned about the negative effects of too-rapid credit growth on individual banks' solvency and on the whole stability of the banking system might use some prudential tools in order to curtail excessive lending during boom periods and, by the same token (although in the opposite direction), too-conservative credit policies during recessions.

The empirical literature on the relationship between excessive loan growth and credit risk is scant. The first contribution of this paper is to provide more precise and robust evidence of a positive, although quite lagged, relationship between rapid credit growth and future nonperforming loans of banks. Moreover, we also find a direct relation between the phase of the lending cycle and the quality and standards of the loans granted. During lending booms, riskier borrowers obtain funds, and collateral requirements are significantly decreased. Lower credit standards and a substantial lag between decisions made on loan portfolios and the final appearance of loan losses point toward credit risk significantly increasing during good times. Therefore, credit risk increases in boom periods, although it only pops up as loan losses during bad times.

The second contribution of this paper is to develop a loan loss provision (i.e., a prudential tool) that takes into account the former developments. The idea is that banks should provision during good times for the increasing risk that is entering their portfolios and that will only reveal as such with a lag. On the other hand, in bad times banks could use the reserves accumulated during boom periods in order to cover the loan losses that appear but that entered the portfolio in the past. Thus, we develop a countercyclical provision that is a direct answer to the robust empirical finding of credit risk increasing in good times.

Accounting frameworks usually do not allow for countercyclical provisioning—that is, for the coverage today of latent credit risk in banks' portfolios. Therefore, given the interest of supervisors in a prudent coverage of risks, it might be possible to transform the former countercyclical provision into a capital requirement based on a stress test included in pillar 2 of Basel II, the new regulatory capital framework for banks. In doing that, those that have shown concerns about increased procyclicality of Basel II might find some help.

All in all, the paper combines theoretical arguments with robust empirical findings to provide the rationale for a countercyclical loan loss provision. The paper is a contribution to the intense debate among supervisors and academics on the proper tools to enhance financial stability.

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Interbank Contagion in the Dutch Banking Sector: A Sensitivity Analysis*

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We investigate interlinkages and contagion risks in the Dutch interbank market. Based on several data sources, including survey data, we estimate the exposures in the interbank market at bank level. Next, we perform a scenario analysis to measure contagion risks. We find that the bankruptcy of one of the large banks will put a considerable burden on the other banks but will not lead to a complete collapse of the interbank market. The exposures to foreign counterparties are large and warrant further research. An important contribution of this paper is that we show, using survey data, that the entropy estimation using large exposures data as applied in many previous papers gives an adequate approximation of the actual linkages between banks. Hence, this methodology does not seem to introduce a bias.

JEL Codes: G15, G20.

1. Introduction

The interbank market is an important market in managing a bank's liquid funds. It is a market with largely unsecured exposures of

*The views expressed in this paper are the authors' only and do not necessarily represent those of De Nederlandsche Bank (DNB). The authors would like to thank many colleagues at DNB, Martin Summer, Christian Upper, workshop participants of the CCBS Expert forum at the Bank of England on May 17–19, 2004, and two anonymous referees for useful comments. All remaining errors are our own. Author contact: De Nederlandsche Bank, Supervisory Policy Division, P.O. Box 98, 1000 AB Amsterdam, The Netherlands. Tel: +31 (0)20 524 2024, e-mail: i.p.p.van.lelyveld@dnb.nl or tel. +31 (0)20 524 2385, e-mail: f.r.liedorp@dnb.nl. Alternate address for van Lelyveld: P.O. Box 9108, 6500 HK, Nijmegen, The Netherlands.

significant size. Furthermore, the banking sector is consolidating more and more in many countries, leading to an evermore interlinked market. Such a closely linked market might be prone to contagion. These developments have led researchers and policymakers alike to take an interest in this subject, resulting in a number of valuable studies. These studies, which we will discuss in more detail shortly, generally rely on proxies of actual bank-to-bank exposures. An important finding is that the fragility of the interbank market is highly dependent on the characteristics of the market: both the market structure and the magnitude of interbank linkages determine the contagion path.

The present study adds to the literature in two ways. First, we are able to shed light on the validity of the proxy for exposures used in previous studies. In addition to information on large exposures for nearly the entire market, we have direct information about bank-to-bank exposures from a selected number of banks, covering about 80 percent of the market. Comparing the results based on the large exposure proxy and the survey exposures provides evidence that the proxy used in previous studies seems to be an adequate one. Second, the process of consolidation has gone further in the Netherlands than in most countries; loans and deposits of the five largest banks, as a percentage of the total, were at 79 percent and 88 percent, respectively, in 2004. Furthermore, the Netherlands is a small open economy. The Dutch case can thus serve as a natural experiment, showing what the effects of contagion are in a closely linked market.

The structure of the paper is as follows. Section 2 discusses existing research, while section 3 explains the methodology and describes the data sources and data characteristics. Then we present an analysis of the results in section 4. We pay particular attention to the comparison between the results based on the two separate data sources. Section 5 presents our conclusions and the policy implications implied by the analysis.

2. Previous Research into the Interbank Market

Only recently a strand of literature has begun to analyze the structure of the interbank market as a source of financial sector contagion. Theory discerns both direct and indirect contagion (de Bandt and Hartmann 2000). Direct contagion results from direct (financial) linkages between banks, such as credit exposures. Indirect contagion is the result of expectations about a bank's health and about the resilience of the sector. In contrast, the exposure of banks to similar events (such as asset price fluctuations) cannot, by definition, result in direct contagion.[1] Obviously, although these two contagion channels can work separately, direct contagion and indirect contagion are not mutually exclusive and may even reinforce each other. For instance, a bank failure may lead to further bank failures through direct linkages and may induce further bankruptcies even if depositors only assume the existence of linkages between banks (regardless of whether these assumptions are true or not). In our paper, we focus on direct linkages between banks and thus on the risk of direct contagion.

In the literature, it has become clear that the structure of the interbank market is of crucial importance for contagion, as it determines the impact of a shock to an individual bank on the complete system. Allen and Gale (2000) distinguish three types of interbank market structures. First, they define a complete structure as one where banks are symmetrically linked to all other banks in the system. Second, an incomplete market structure exists when banks are only linked to neighboring banks. A special case of this structure—the money-center structure—is introduced by Freixas, Parigi, and Rochet (2000). In this structure, the money-center bank is linked symmetrically to the other banks, while the latter have no links among themselves. Third, a disconnected incomplete market structure is defined as one where two separate (but internally connected) markets exist simultaneously. A complete market structure may give the highest level of insurance against unexpected liquidity shocks hitting an individual bank because of diversification effects. However, such a structure might also spread shocks more easily through the system, as shocks will not remain isolated at one bank or at a cluster of banks. In a model based on that of Diamond and Dybvig (1983), Dasgupta (2004) investigates the effect of a signal about a bank's health on customers' expectations and shows that contagion mainly runs from debtor banks to creditor banks.

[1] However, *assumed* similarities in banks' risk structure may lead to indirect contagion.

Empirical studies that try to model the structure of the interbank market and the following contagion risks have been carried out for several countries (Elsinger, Lehar, and Summer, forthcoming; Degryse and Nguyen 2004; Upper and Worms 2004; Mistrulli 2005; Blåvarg and Nimander 2002; Sheldon and Maurer 1998; and Wells 2004). See table 1. Most of these studies use balance sheet data or large exposures data as proxies to determine the interbank market structure. Blåvarg and Nimander (2002) and Mistrulli (2005) use bilateral observed data to model contagion risk. Mistrulli concludes that in the Italian case, the estimation based on aggregate data may underestimate contagion risk. However, this conclusion is based on a comparison of the results using, on the one hand, the maximum entropy and, on the other hand, the observed bilateral exposure data. Given the emergence of a money-center-bank structure in the Italian interbank market, it is clear that the assumption of maximum entropy becomes less appropriate. Müller (2003) explores the Swiss interbank market using new data from the Swiss National Bank. Applying network analysis,[2] she discerns systemically important banks and possible contagion paths. Furfine (1999) estimates contagion risk in the U.S. interbank market but uses bilateral data from the Fedwire payment system to build the interbank market structure. The majority of these studies find that contagion effects are small, especially since high loss rates are rare. This paper is related to these studies in several ways. For one, we base our analysis on balance sheet data and large exposures data as well. Furthermore, we use different loss rates to test the strength of the system under different shocks. However, we add a second model variant in which we incorporate the answers of banks with respect to their bilateral exposures. This provides the opportunity to test the usefulness of the large exposures data for estimating the interbank market structure.

Nevertheless, all these models focus on the credit or solvency risk of a bank failure and usually do not incorporate the effects of liquidity risk, such as the drying up of credit lines or falling asset prices. Müller (2003) introduces liquidity risk in the Swiss

[2]Müller (2003) measures, for example, the number and size of interbank interlinkages, the distance from other banks, the importance of counterparties, and the position in the network.

Table 1. Overview of Existing Literature

	Data Period	Methodology	Notes	Results
Austria Elsinger, Lehar, and Summer (forthcoming)	2001	• Network model of interbank exposures combined with macroeconomic shock		• Most failures are caused by macroeconomic shock • Recovery rates, determined by model, are high
Belgium Degryse and Nguyen (2004)	1993–2002	• Cross-entropy minimization using large exposures data	• Different loss ratios • Failure if loss > tier 1	• Failure of domestic bank cannot trigger Belgian bank failure; Belgian banks exposed to French, Dutch, and British banks • Change in market structure (from complete structure to multiple money centers) decreases contagion effects • "International risk of contagion deserves more attention than domestic contagion risk"
Germany Upper and Worms (2004)	1998	• Maximum entropy • Cross-entropy minimization using large exposures data	• With/without safety net • Different loss ratios • Failure if loss > tier 1	• Two-tier structure in interbank market • Contagion is serious possibility • Losses increase sharply if loss rate > 40 percent • Safety nets reduce contagion effects

(*continued*)

Table 1 (continued). Overview of Existing Literature

	Data Period	Methodology	Notes	Results
Italy Mistrulli (2005)	1990–2003	• Maximum entropy • Bilateral exposures	• Different loss ratios • Completeness vs. interconnectedness	• Estimation methodology underestimates contagion risk (with regard to observed Italian bilateral exposures) • Domestic risk of contagion more important than foreign contagion risk, but still small • Change in market structure (from complete structure to multiple money centers) increases contagion effects
Sweden Blåvarg and Nimander (2002)	1999	• Bilateral exposures	• Assumption: full principle credit risk (uncollateralized) • FX settlement exposures separately measured • Different loss ratios • Failure if tier $1 < 4\%$ ratio (BIS)	• In most cases contagion will not lead to a failure of the largest banks • Foreign contagion risks stem mainly from FX settlement exposures

(*continued*)

Table 1 (continued). Overview of Existing Literature

	Data Period	Methodology	Notes	Results
Switzerland Sheldon and Maurer (1998)	1987–1995		• A bank failure depends on accounting data as ROA, E(ROA), CAR, overhead • Maximum loan portfolio diversification • One shock, complete loss • Cross-border market not taken into account (though important)	• Contagion effects are small • Domestic interbank market relatively unimportant compared to cross-border market
United Kingdom Wells (2004)	2000	• Maximum entropy • Cross-entropy minimization using large exposures data	• Model 1: lending as dispersed as possible • Model 2: concentration reflected in large exposures data • Model 3: money-center structure • Different loss ratios	• Only limited contagion effects • Spillover effects may occur, but depend heavily on loss rate • In model 2, contagion is higher, but asset losses lower • Losses are highest in model 3

interbank market through the existence of credit lines but finds that such contagion effects are smaller compared with the risk of credit exposures. In a theoretical paper, Cifuentes, Ferrucci, and Shin (2005) model the impact of asset sales of distressed banks on asset prices and the liquidity and solvency position of other banks. They conclude that liquidity requirements can be as effective as capital requirements to prevent contagion effects. Allen and Gale (2004) also analyze liquidity effects and the impact on asset prices and financial fragility. Cocco, Gomes, and Martins (2003) model lending relationships in the interbank market and the behavior of market participants, suggesting that such relationships are important. Obviously, this kind of research merits further attention.

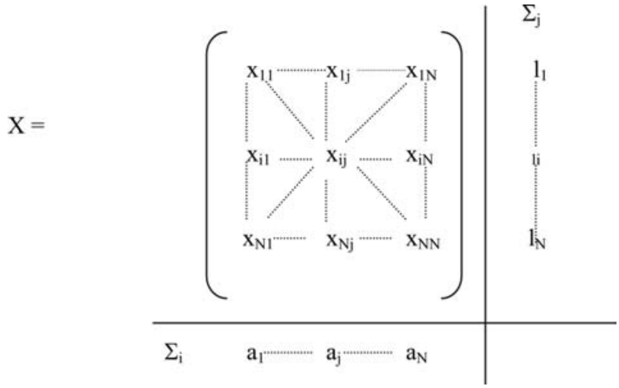
3. Methodology and Data

3.1 Interbank-Lending Matrix

To model the structure of interbank linkages between N banks, we use a matrix like X (figure 1). In this matrix, the columns represent banks' lending, while the rows represent banks' borrowing. Hence, x_{ij} gives the liabilities of bank i toward bank j. Clearly, not all banks need to be a lender and a borrower at the same time. In fact, a bank need not be active in the interbank market at all. In such a case, we would fill the corresponding cell(s) with a zero. Moreover, a bank does not lend to itself: the cells on the main diagonal from upper left to bottom right would all be zeros.

The information problem can then be identified as follows: the sum of each bank's interbank lending and borrowing, a_j and l_i, is known. These data can be obtained from the monthly balance sheet report. What is not known is the distribution of these exposures over the system, i.e., the elements of the matrix X itself. The lack of information cannot be solved easily, as the problem contains more unknowns than equations. Thus, the problem is underidentified, which implies that several solutions may lead to the same outcome (Upper and Worms 2004). There is no unique solution to this problem.

Figure 1. Interbank-Lending Matrix



Source: Upper and Worms (2004).

One solution would be to divide the aggregate exposure proportionally over all N banks. This is called *entropy maximization*.[3] A difficulty with this solution is that it assumes that all lending and borrowing is as dispersed as possible, i.e., interbank activities are completely diversified. This rules out the possibility of relationship banking.[4]

Another way of solving the problem is to *add additional information*. The large exposures data might be suitable to this end but require some additional assumptions. In using the large exposures data, we assume that the distribution obtained from these data is representative of the real distribution of exposures. This is not necessarily true, of course. However, it does improve the picture of the concentration of interbank lending and borrowing. Wells (2004) explains that, given the estimate of the interbank structure (for instance, the

[3]This problem can be compared to the outcome of rolling a pair of dice. Unless one has information that the dice are loaded in some way, the distribution that places equal weight on each outcome should be selected. But this distribution also maximizes the uncertainty, or entropy, about the outcome. Therefore, in the absence of information about concentrations in the interbank market, the maximum entropy distribution is chosen.

[4]As Cocco, Gomes, and Martins (2003) show, however, banks might want to establish relationships with banks whose liquidity shocks are less correlated with their own.

large exposures data), a minimization problem needs to be solved to find a matrix that gets as close to the estimate as possible, given the interbank lending and borrowing totals. This matrix is calculated by use of the RAS algorithm (see also the appendix).

A last approach would be to ask all banks to *report their bilateral exposures*, including the names of the counterparties and the actual amount of the exposure. Owing to the reporting cost, this is deemed impossible for the Dutch banking system as a whole, although we did obtain information from the most important banks.

In this paper we apply the first two approaches (maximum entropy and cross-entropy minimization), although we focus on the approach that adds additional information, as this seems the more relevant one. We add additional information in two different ways: first using only large exposure reporting and then adding ad hoc survey information as described in the next section. This also allows us to compare the outcomes and make an inference about the appropriateness of large exposures data for estimating the interbank market structure and contagion effects.

3.2 Data Sources

It is rather difficult to determine the precise structure of the interbank market. No information is publicly available about the size of the interlinkages in the interbank market. On a confidential basis De Nederlandsche Bank (DNB), as prudential supervisor, regularly receives balance sheet data and large exposures reports. For the analysis, three main data sources have been used, which we will discuss in turn: the monthly balance sheet report, the large exposures data report, and an ad hoc survey obtained from the largest ten banks. The *monthly report* reflects the aggregate interbank assets and liabilities of a bank and is comparable to the U.S. Call Report. Balance sheet data have been collected for December 2002 from all banks under supervision, including foreign subsidiaries and branches. These data concern consolidated data about interbank assets and liabilities, tier 1 capital, and total assets. Interbank exposures are influenced by the end-of-year effect. This implies that reported exposures at this date are lower compared with the rest of the year. However, foreign branches with a parent company within the European Union are exempted from reporting tier 1 capital, since DNB plays no role in solvency supervision of these banks.[5]

In the *large exposures data report,* banks must specify the names and amounts of bank counterparties to which they have an exposure larger than 3 percent of their actual own funds; they must also specify the names and amounts of nonbank counterparties for exposures larger than 10 percent of their actual own funds. The report is subject to many exceptions, and some banks are exempted from reporting.[6] Moreover, most banks only report risk limits and not the actual outstanding amounts, and not all exposures (such as off-balance-sheet positions) are accounted for. From the large exposures data reports, exposures on home (Dutch) and foreign (non-Dutch) bank counterparties have been selected.

To obtain complete information on the larger part of the interbank exposures, the top ten banks with respect to interbank assets were asked to fill in a *survey* on bilateral exposures. Names and amounts—based on interbank deposits, derivatives, and securities—together with an indication as to whether these amounts concern limits or outstandings, were requested for all Dutch bank counterparties for December 2002. In addition, the same data were required for the fifteen largest foreign bank counterparties. However, we only use the information about interbank deposits in this analysis, since derivatives (off balance sheet) and securities are not included in the monthly balance sheet reporting. In general, both the limits and outstandings of the interbank derivatives portfolio are larger than those for the deposit portfolio. This becomes especially clear from the outstanding interbank derivatives, which are on average about 2.5 times larger than interbank deposits, while limits on the derivatives portfolio are on average 1.6 times larger. In contrast, the reported outstanding securities as well as the limits are on average smaller than

[5]In the 1992 Law on Supervision of Credit Institutions, the aspect of "home-country control" was introduced as a consequence of the "EU license." With home-country control, branches of banks located in the EU only need a license from the country of origin and are subject to solvency supervision of this country. The host country does play a role in liquidity supervision.

[6]Not all certified banks are required to report their large exposures data. Branches with a parent company located inside the EU are exempted from reporting. Intraconcern exposures are exempted as well.

those on the interbank deposit portfolio, although this outcome may be related to the data quality.

3.3 Data Description

The Dutch interbank market, based on reporting of all Dutch banks for December 2002, covers about €93 billion of interbank assets and €364 billion of interbank liabilities. This is, respectively, 10 percent and 20 percent of the total balance sheet value of the banks and 210 percent and 397 percent of actual own funds. These exposures are largely not collateralized. The Dutch banks hence borrow on the international interbank market and have a net debit position relative to the rest of the world. This may render the Dutch banking system more likely to be the source of contagion rather than the "victim." The market is dominated by a few large banks, which cover 77 percent (€149 billion) of interbank assets and 85 percent (€309 billion) of interbank liabilities. This dominance restricts the number of possible counterparties in the market and therefore increases contagion risks.

In tables 2 and 3, we present descriptive statistics for the different types of firms active in the Dutch market. Standard deviations are shown in parentheses. Naturally, there are more observations per bank in the large exposures data report compared with the monthly report, as banks are, in most cases, exposed to several counterparties. Additionally, table 3 is divided into risk limits and risk outstandings.

These descriptives show, unsurprisingly, that the large banks are the largest party in the market. The remaining types seem to play only a limited role in the interbank market. Remarkably, for all types, interbank liabilities are larger than interbank assets. All Dutch banks, even the smaller ones, are hence net borrowers on the international interbank market. For the foreign subsidiaries and branches, this might be attributed to the link with the parent company.

Table 4 shows descriptive statistics for the survey data. The ten largest banks that were requested to report these data are of the first three types discerned in the previous tables. We use interbank outstandings from the survey data instead of interbank limits, except for one bank, which only reports risk limits. Zero-risk exposures have been excluded.

Table 2. Descriptives by Type: Monthly Report (x Million Euro), December 2002

Type	Range of Obs.	Interbank Assets Mean (St. Dev.)	Interbank Liabilities Mean (St. Dev.)	Tier 1 Mean (St. Dev.)	Total Assets Mean (St. Dev.)
Large Bank	4	37,220 (15,203)	77,233 (33,778)	14,217 (6,823)	368,560 (210,418)
Other Dutch	19–22	740 (1,094)	932 (1,281)	446 (631)	9,761 (17,077)
Foreign Subsidiary	27–29	338 (305)	628 (923)	105 (93)	1,508 (1,852)
Foreign Branch	9–27	682 (1,810)	748 (1,668)	16 (10)	1,045 (2,161)
Investment Firm	5–6	51 (35)	131 (158)	14 (6)	268 (237)
All Banks	69–88	2,201 (8,269)	4,444 (17,857)	1,012 (3,619)	20,029 (86,397)

Note: Of the foreign branches, the tier 1 capital report is in many cases missing, as the foreign branches are generally exempted from reporting under the "home-country control" principle.

Table 3. Descriptives by Type: Large Exposures Data (x Million Euro), November/December 2002

Type	Limit		Outstanding	
	Number of Observations	Mean (St. Dev.)	Number of Observations	Mean (St. Dev.)
Large Bank	255	2,131 (2,076)	22	409 (380)
Other Dutch	188	85 (121)	153	45 (72)
Foreign Subsidiary	125	48 (62)	216	33 (48)
Foreign Branch	37	12 (24)	74	6 (5)
Investment Firm	–	– –	26	8 (7)
All Banks	605	935 (1,692)	491	48 (123)

Note: Based on bank counterparties, zero-risk exposures are excluded.

Table 4. Descriptives by Type: Survey Data (x Million Euro), December 2002

Type	Limit		Outstanding	
	Number of Observations	Mean (St. Dev.)	Number of Observations	Mean (St. Dev.)
Large Bank	33	1,206 (1,272)	56	705 (2,550)
Other Dutch	0	– –	161	60 (320)
Foreign Subsidiary	0	– –	11	32 (32)
All Banks	33	1,206 (1,272)	228	217 (1,314)

Note: Based on bank counterparties, zero-risk exposures are excluded.

An analysis of the number and relative size of the exposures on the counterparties (Dutch banks, foreign banks) in the survey data shows that a high number of exposures does not necessarily coincide with a high exposure. This holds especially for the exposures on Dutch counterparties, on which the highest number of exposures is reported, whereas the relative exposure (the exposure as a percentage of total exposure) per Dutch bank counterparty is lowest. This decreases the impact of an individual failure, because the loss is relatively small; however, it increases contagion risk, as many banks are linked.

3.4 Scenario Analysis

To measure the risk of contagion in the Dutch banking system, we perform a scenario analysis, using the obtained interbank-lending matrix. To do this, all banks are assumed to fail in turn owing to some exogenous shock. A bankruptcy does not imply that the counterparties of the failed bank lose the total amount of their exposure, as the sale of (some part of) the failed bank's assets may offer compensation.

The possibilities for compensation depend, though, on the bankruptcy legislation in a country. However, little information is available about the level of recovery (i.e., the loss rate).[7] Therefore, we use several loss rates (25 percent, 50 percent, 75 percent, and 100 percent) in this analysis to assess the resilience of the banks. Note that losses, even temporary ones, can have direct and immediate consequences for the liquidity position of a bank and hence for its solvency.[8]

We assume that a bank fails if its exposure to a failed bank (i.e., its loss) is larger than its tier 1 capital:

$$\theta * x_{ij} > c_j, \tag{1}$$

[7] James (1991) finds a mean loss rate of 30 percent of the assets of the failed bank and another 10 percent as direct bankruptcy costs. Furfine (1999) uses a loss rate of only 5 percent.

[8] An interesting theoretical paper in this respect is Cifuentes, Ferrucci, and Shin (2005), where the authors show that if the recovery rate becomes endogenous (and capital requirements or exposure limits are binding), a small shock might already have a large impact.

where θ denotes the loss rate, x_{ij} is the exposure of bank j toward bank i (alternatively, x_{ij} represents bank i's liabilities to bank j), and c_j is the tier 1 capital of bank j. If more than one bank fails, a third bank fails if its exposure to these two banks is larger than its tier 1 capital:

$$\theta * (x_{ij} + x_{kj}) > c_j. \tag{2}$$

In the analysis, we assume that the time span between a perceived increase in credit risk of a bank and the actual failure of the bank is too short for other banks to decrease their exposure to the bank in question. In addition, we do not model increased risk awareness following the initial default, and we thus assume that the loss rate is constant over time. In assessing the scenarios, we report the results prenetting because we are interested in a truly severe scenario. Obviously, having liabilities to a failed bank reduces the net exposure and thus the possible loss. Such a robustness check shows us that, compared with the results discussed in the next section, the effects in the netted case are much smaller, but the overall picture remains the same.

Completely idiosyncratic shocks are rare, and thus our assumption that at first only a single bank fails due to some exogenous shock might be a relatively strong one. It seems more likely that several banks will be simultaneously affected in the case of a shock. Moreover, a bankruptcy is often preceded by a period of distress, and thus other banks are able to take measures in time. Nevertheless, operational risk events are a different matter, as exemplified by the Barings Bank case. There, activities of a single trader led to the demise of the entire bank. In this case, the factor that triggered the failure was idiosyncratic to Barings Bank, so that other banks were not influenced by this shock. Therefore, it has to be kept in mind that although such scenarios may be rather rare events, such shocks do occur. Next to that, such a severe scenario analysis may be useful in determining the sequence and path of contagion. Still, modeling the probability of default, conditional on the state of the economy and/or crisis, would also be a possible future improvement (cf. Elsinger, Lehar, and Summer, forthcoming).

4. Results

4.1 Interbank-Lending Matrices

In this section, we first present the interbank-lending matrix based on the large exposures data and then discuss the matrix estimated with the survey data.[9]

4.1.1 Large Exposures Data

We constructed the largest possible data set of both interbank assets and liabilities and large exposures data, resulting in a data set of 88 banks.[10] The exposures on foreign banks have been divided into five geographical areas: Europe, North America, Turkey, Asia, and RoW (rest of world). Hence each bank has 92 ($88+5-1$) possible counterparties. The interbank assets and liabilities are then divided over the matrix, following the structure of the large exposures data reports.[11] A problem with this approach is that some banks report limits, while other banks report outstandings. This would result in a bias in the estimation toward limit-reporting banks, because the limit amounts are much larger than the outstanding amounts. In our estimation we would then assign a too-high exposure to limit-reporting banks. To circumvent this problem, we express the large exposures data as a percentage of each bank's "total exposure." Here, the "total exposure" can be either total outstandings or the total of all limits. Then the percentage exposures are multiplied with the monthly report asset totals, giving exposure amounts. In the few cases where the large exposures data are missing (not all banks have to report), we use the distribution of interbank liabilities. In addition, because we do not want to allow a bank to have exposures on itself, we set the main diagonal to zero. For estimation purposes, all zeros in the matrix (i.e., a bank pair without a reported linkage) are replaced by a very small number (except for the main diagonal). This reflects

[9]We also estimated a maximum-entropy matrix without any prior information, but as these results are less informative, we do not present them here.

[10]For the foreign branches that do not report tier 1 capital, we use the mean tier 1 capital of a peer group.

[11]A formal explanation can be found in the appendix.

the many small linkages that banks may have but which fall below the reporting threshold and thus do not show up in the large exposures data. Because of this last assumption, banks have linkages with almost all other banks in the interbank-lending matrix, although the estimated exposures resulting from this assumption are small, as expected.

The percentage exposures on all foreign regions together vary between 0 percent and 100 percent of total exposures, where only a few foreign subsidiaries or branches show a 100 percent exposure. The exposure is particularly risky for such banks because the exposure is almost completely on a single foreign region (i.e., the home country, sometimes only the parent company). The average bank is exposed for about one-third (32.0 percent) of its interbank assets to foreign regions. The large banks are exposed to foreign regions by more than three-quarters (ranging between 72.6 percent and 84.6 percent) of their total exposure. The explanation for this higher average may lie in the fact that these banks do not consider the other Dutch banks as interesting counterparties. Of all regions, Europe accounts for most exposures, followed by North America.

Generally, large banks have significant relations with a smaller number of banks than do other banks.[12] The average exposure of a smaller bank to a large bank is about 28 percent of its total exposures, which we consider small in comparison with the market size of the larger banks. Strikingly, we find that foreign branches are mainly exposed to other Dutch banks (69.5 percent), while foreign subsidiaries show a higher dependency on foreign countries (table 5). From this estimated structure of interlinkages, we might deduce the existence of a two-tiered structure in the Dutch interbank market: the first tier consists of the large banks, which transact mainly with each other and with foreign (same-sized) counterparties, while the second tier consists of the remaining banks, which mainly transact with each other and to a certain extent with foreign counterparties. The two tiers are connected, but to a lesser extent than we would expect taking into account the dominance of the large banks in the interbank market.

[12]Since all banks are interlinked (because all zeros in the matrix are replaced by a small number), a threshold value is set to measure the relative number of exposures.

Table 5. Estimated Interbank-Lending Matrix: Large Exposures Data

% exposure of → *on*↓	**Large Bank**	**Other Dutch**	**Foreign Subsidiary**	**Foreign Branch**	**Investment Firm**	**Mean**
Foreign	78.8	20.5	47.2	20.3	22.1	32.0
Other Dutch	6.8	42.3	26.5	69.5	41.2	43.8
G4	14.4	37.3	26.5	10.1	36.6	24.3

Table 6. Estimated Interbank-Lending Matrix: Survey Data

% exposure of → *on*↓	**Large Bank**	**Other Dutch**	**Foreign Subsidiary**	**Foreign Branch**	**Investment Firm**	**Mean**
Foreign	90.3	19.1	45.5	15.6	18.7	29.9
Other Dutch	4.2	58.3	37.1	78.7	51.5	54.7
G4	5.5	22.7	17.4	5.6	29.8	15.4

The percentages shown in table 5 are the average exposures per type. Note that although the large banks are exposed only for 6.8 percent of their total exposures to other Dutch banks, the exposure in absolute amounts may well exceed the absolute amount of, for instance, the 42.3 percent of the exposure of "Other Dutch" to other Dutch banks.

4.1.2 Survey Data

In the second variant, the survey data obtained from the ten banks are used and substituted in the interbank-lending matrix. For the remaining banks, we continue to use the large exposures data. The percentage exposures of individual banks on the foreign regions vary between 0 percent and 100 percent of total exposures, where on average the exposure on foreign regions decreases slightly to 29.9 percent. For the large banks, however, the exposures on foreign regions have increased for all four banks (now ranging between 76.3 percent and 99.8 percent). In general, the exposures of the large banks are less dispersed over the Dutch system and are concentrated on foreign exposures (table 6). Europe remains the largest "single" exposure for Dutch banks, followed by North America. The remaining banks show a somewhat higher exposure to each other, which explains the decrease in the mean exposure on foreign regions and on the large banks. We again find a high exposure of foreign branches to other Dutch banks (78.7 percent). These figures also support our inference about the existence of a two-tiered structure in the Dutch interbank market. Moreover, the use of different data sources leads to only slightly different outcomes with respect to the characteristics of the Dutch interbank market.

4.2 Scenario Analyses

After estimating the interbank-lending matrix, we run a scenario analysis to reveal any possible contagion effects. In this analysis we let each bank (and region[13]) fail in turn and then check whether any of the other banks has an exposure on the failed bank that results in a loss larger than its tier 1 capital. A practical issue is that we do not have adequate information about the buffer capital of foreign counterparties or, in the aggregate, of regional financial systems. We assume that the foreign regions never fail as a result of the bankruptcy of other banks (or regions). This is plausible because these categories represent large regions, and it seems highly unlikely that a complete region will fail due to the failure of a (number of) Dutch bank(s). However, this assumption might underestimate the fragility of the Dutch system, as domestic defaults could trigger defaults abroad, which could in turn weaken institutions in the Netherlands. Second-round effects occur when other banks, following the failure of the first failed bank, also fail. It is assumed that if more than one bank fails in any given round, they all fail simultaneously.

Conclusions based on our scenario analyses have to be drawn with care. For example, the scenario analysis presented here does not allow for dynamic effects. The large exposures data reports are not complete and make use of risk limits, which in practice are drawn upon to a varying degree. Banks will draw more of their credit line

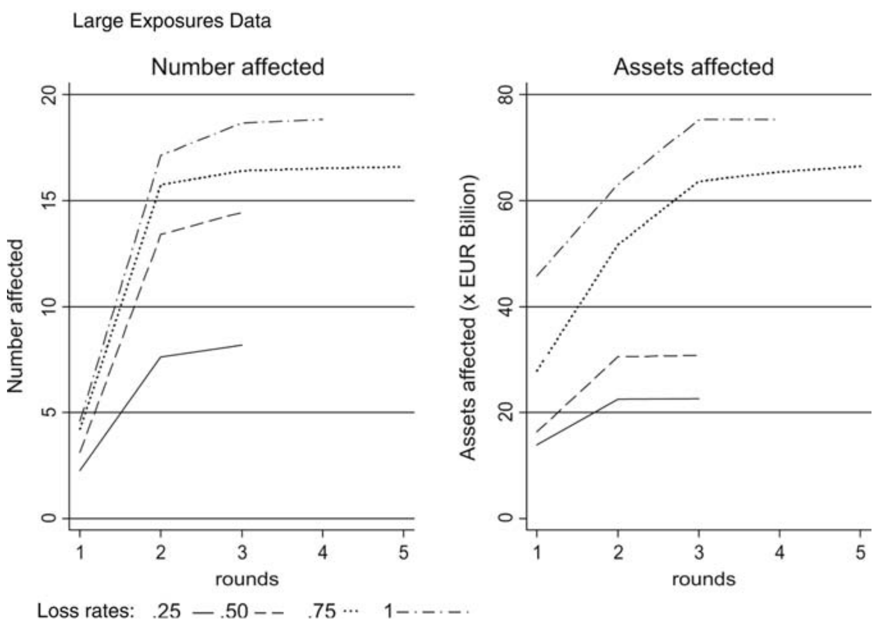
[13]This scenario can be described as an entire country running into trouble due to a domestic crisis, exchange rate crisis, excessive debts, etc.

in the interbank market if they experience problems; the risk limits thus give the upper bound to contagion risks in the interbank market. In addition, the use of outstandings might underestimate risks, since credit lines will be drawn in case of distress. The use of end-of-year data might underestimate risks as well, because interbank assets and liabilities tend to decrease in December every year. The lack of data on tier 1 capital for foreign branches forces further assumptions. Furthermore, the role of collateral has not been included in this analysis. The same remarks hold for the survey data analysis. In addition, the data reported by the ten banks in the survey data had to be standardized. Since the ten banks use different internal systems and definitions, their reports differ in their precision and may show some inconsistencies.

4.2.1 Large Exposures Data

The scenario analysis provides important insights into the contagion risks in the Dutch banking sector. Figure 2 gives an overview

Figure 2. Cumulative Effects of Simulated Failures



of the cumulative effects of a bank failure (including the failure of a region) for each loss rate by round. The left panel shows the mean of the cumulative number of failed banks per round and per loss rate, while the right panel shows the mean of the cumulative assets of these failed banks per round and per loss rate. The first, initiating bank is excluded in these measures. Note that "assets affected" is defined as the total assets of failed banks. This implies that although a bank may suffer losses following a bankruptcy, these losses are not included in the measure of assets affected if the bank does not fail consequently. However, such a small loss makes the bank in question more vulnerable for any other losses it may incur in future rounds. For both graphs it holds that the cumulative effects increase when the loss rate is increased. For a 75 percent loss rate, however, there are more rounds (i.e., five). The explanation for this result is that for the higher loss rate (100 percent), all banks that *can* be affected *are* already affected in previous rounds. Hence, no banks are left to be affected.

The steep rise in the second round in the left panel indicates that a large number of banks fail in this round. The rise in the right panel is much less pronounced. From this, the picture emerges that a small number of sometimes large banks topple in the first round, followed by a larger number of small banks.[14] Then defaults taper off.

Table 7 confirms these results. It shows the maximum number of failed banks and affected assets per loss rate. For comparison purposes, we include the results of estimation without any prior information (labeled "Maximum Entropy"). The maximum-entropy estimation shows that only with a loss rate of 100 percent are sizable losses incurred. Moreover, the maximum-entropy estimation results underestimate contagion effects, in line with Mistrulli (2005), as both the number of banks and the percentages of total assets are lower for each of the loss rates shown. The only exception is the 100 percent loss rate: it is clear that the maximum-entropy method does not function for the highly concentrated and internationalized Dutch market.

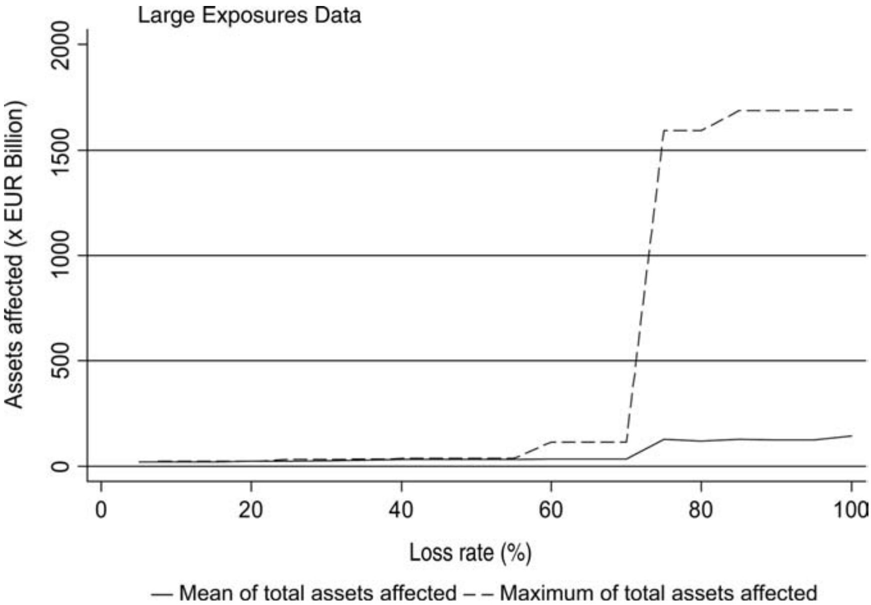
[14] Although it is tempting to think of these rounds as indicating something about time, this is not appropriate. Rather, it reflects how "close" two banks are.

Table 7. Effects of Simulated Failures: Large Exposures Data

	Maximum Entropy			Large Exposures Data					
	Max. Number of Failed Banks	**Max. Amount of Affected Assets**		**Max. Number of Failed Banks**	**Max. Amount of Affected Assets**		**Max. Number of Failed Banks (excl. foreign regions)**	**Max. Amount of Affected Assets (excl. foreign regions)**	
Loss Rate		billions of euro	% total assets		billions of euro	% total assets		billions of euro	% total assets
0.25	10	24	1%	11	30	2%	11	24	1%
0.50	18	33	2%	20	37	2%	17	34	2%
0.75	30	46	3%	47	1,590	90%	21	43	2%
1.00	66	1,340	76%	56	1,690	96%	24	44	3%

Note: For the maximum-entropy estimations, the results are the same whether foreign regions are included or not.

Figure 3. Effects of the Loss Rate on Total Assets Affected



Note: In this graph, the effects of and on foreign regions have been excluded.

Strikingly, for the large exposures data, the asset losses increase sharply for a 75 percent loss rate. In this case, the total assets lost as a percentage of total assets increases from 2 percent to 90 percent. However, this only holds if foreign regions are included in the analysis. The large banks do not fail if the foreign regions are excluded, meaning that the results are driven by the failure of the large banks. Consequently, we might find a turning point at which (one of) the large banks fail(s). This is shown in figure 3. In this figure we graph the mean and maximum amount of total affected assets relative to the loss rate. We clearly see a rise in the mean and a sharp increase in the maximum of total affected assets for a 75 percent loss rate. At this rate, three large banks fail for the first time. The fourth large bank already failed at a 60 percent loss rate. This is also visible in the maximum amount of affected total assets in the figure. From this figure, we might conclude that for a loss rate below 75 percent, no systemic risk emerges.

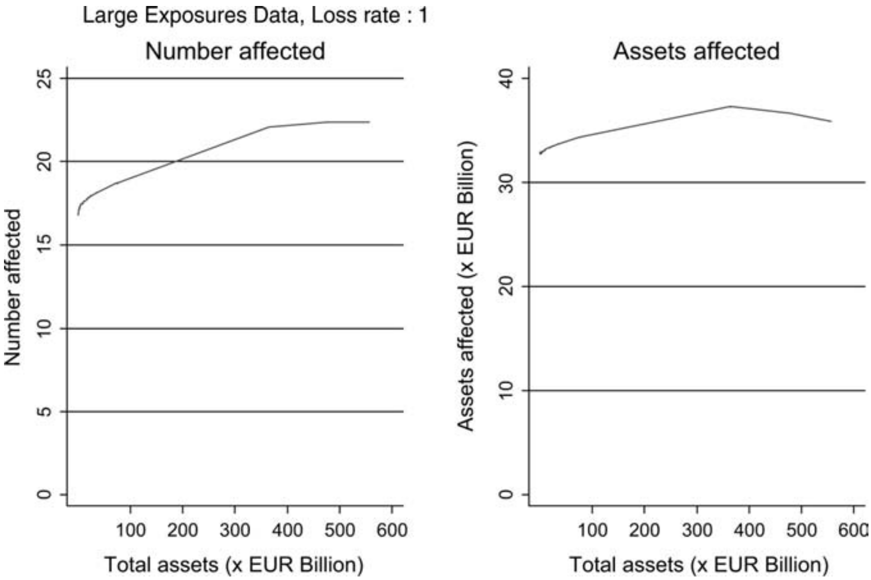
The large banks only affect a relatively small number of banks (at most, twenty-four), with low asset losses. Although the failure of a large bank may result in the bankruptcy of at least one bank of all other types, the failure of a large bank does not affect any of the other large banks. The large banks themselves only fail if either the region Europe or North America fails. In contrast to our expectations, foreign subsidiaries and branches show no explicit vulnerability to the failure of other foreign subsidiaries, branches, or foreign regions but are equally exposed to all types.[15] Investment firms are exposed to all banks.

The region Europe turns out to be the largest risk for the Dutch banking sector, resulting in the highest number of fallen banks and the highest losses in terms of assets. This is intuitive, given the interbank-lending matrix, which showed that many banks have large exposures to Europe. The failure of North America or Asia affects the sector during four rounds, while the effects of a failure of Turkey and RoW only last three rounds. Asset losses are largest for Europe (€1,690 billion) when, at most, fifty-six banks fail. All large banks fail if Europe goes bankrupt with a 75 percent and 100 percent loss rate. If the region North America fails, thirty-four banks fail, and asset losses amount to €680 billion. Fewer and smaller banks fail following the simulated failure of Turkey (twenty-four banks, €40 billion), Asia (twenty-six banks, €40 billion), or RoW (eighteen banks, €35 billion).

In figure 4, the effects of a failure on the domestic number and assets affected are graphed relative to the size of the bank that first bankrupted, for a loss rate of 100 percent. The largest amount of assets lost (€44 billion) is larger than the mean total assets of the other Dutch banks (€10 billion) but many times smaller than the mean total assets of the large banks (€370 billion). Note that the assets of the first bankrupted bank are not included in this measure. Except for the foreign regions, the failure of one of the large banks or a foreign subsidiary has the largest impact on the domestic banking system. There is, however, no substantial evidence that larger banks have higher contagion effects on the domestic system.

[15]The parent company may guarantee its foreign subsidiary or branch, for which counterparties consequently will not experience credit losses. This is not taken into account here.

Figure 4. Effects of Size on Number and Total Assets Affected



Note: In these graphs, the effects of and on foreign regions have been excluded.

Although the failure of a large bank leads to the highest *number* of bank failures if foreign regions are excluded from our analysis, the failure of a relatively small bank, a foreign subsidiary, leads to the highest domestic *asset losses*. Furthermore, the failure of a type 2 bank ("Other Dutch") also has a large effect on the number of failed banks and on the amount of assets lost. An explanation for this result might be that the large banks are especially linked to foreign regions and, to a much lesser extent, to the other banks in the Dutch banking system. Because of this, the effects of a failure of a large bank are mainly absorbed by the foreign regions and can affect the Dutch banks only to a lesser extent. However, since we have no information on foreign banks' assets or capital, the effects of a domestic failure on foreign regions are not shown in figure 4. Given the fact that the large banks are strongly connected to foreign regions, the effects of a domestic failure on foreign regions could be substantial, which, in turn, may have repercussions on the Dutch sector.

Although the results from the first scenario analysis generally confirm expectations, they do show some surprises. The large banks affect a considerable, but still limited, number of banks. Shocks resulting from the failure of a large bank are for a large (but not complete) part absorbed by the foreign regions. This is logical in light of the large foreign exposures held by the large banks, as shown by the interbank-lending matrix. Surprisingly, the bankruptcy of one of the foreign banks in the Dutch banking system results in a high(er) level of lost assets. On the other hand, all these risks are run at a loss rate of 100 percent, whereas losses are many times smaller for lower loss rates. The 100 percent loss rate seems rather high.[16] Europe as a whole does represent a systemic risk, however.

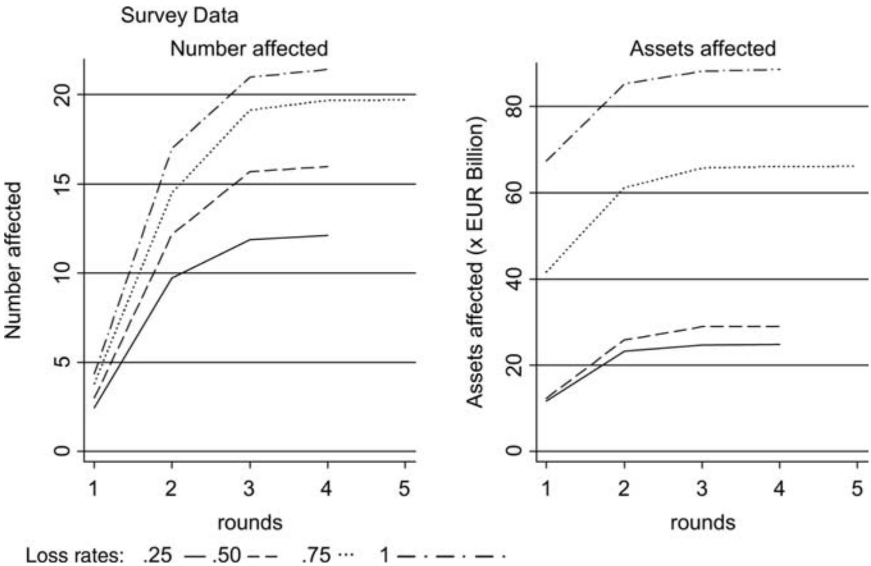
4.2.2 Survey Data

In this section we discuss the scenario using the interbank-lending matrix incorporating the survey data. Similarly to the previous analysis, this scenario analysis shows that a higher loss rate results in higher cumulative losses in terms of the number of fallen banks and assets lost (figure 5). On average, though, the effects are larger for all loss rates. In this analysis we find that a simulated failure with a 75 percent loss rate again has longer-lasting effects than for the 100 percent loss rate. First-round effects are, only with respect to the assets lost, largest for all loss rates. This does not hold for the number of failed banks, however, where the number of failed banks increases in the second round. From this we come to the same conclusion as before: a limited number of sometimes large(r) banks fail in the first round, while many smaller banks follow in later rounds.

Table 8 shows, again, that losses increase sharply for a loss rate of 75 percent. However, these losses are lower than in the previous analysis. The percentage of assets lost now amounts to 45 percent for a 75 percent loss rate and to "only" 73 percent for a complete loss. Again, this can be explained by the interbank-lending matrix used for this analysis and shown in table 6. It showed that only the large banks increased their exposure on foreign regions, while all other banks decreased their interbank positions to foreign regions.

[16] See footnote 4.

Figure 5. Cumulative Effects of Simulated Failures



Note: In these graphs, the effects of and on foreign regions have been excluded.

Therefore, the total amount of assets that can possibly be affected if one of these regions fails is lower. If the foreign regions are excluded, losses are limited but higher than before. In this scenario analysis, a turning point exists at which the large banks fail as well.

If Europe, North America, and RoW are excluded, a failure of one of the large banks affects the highest number of banks and results in the highest asset losses. Strikingly, only a few other Dutch banks (type "Other Dutch") fail following the bankruptcy of one of the large banks (at most, five per large bank). The large banks themselves only fail following the failure of Europe or North America at a 75 percent or 100 percent loss rate or following the failure of RoW at a 100 percent loss rate. The risks that many subsidiaries with Turkish parents run on their home country is reflected by the fact that only Turkish subsidiaries fail if the region Turkey goes bankrupt.

Again, Europe and North America influence the results the most. The influence of the large banks seems to be somewhat larger,

Table 8. Effects of Simulated Failures: Survey Data

Loss Rate	**Maximum Number of Failed Banks**	**Maximum Amount of Affected Assets**		**Maximum Number of Failed Banks (excluding foreign regions)**	**Maximum Amount of Affected Assets (excluding foreign regions)**	
		billions of euro	% total assets		billions of euro	% total assets
0.25	17	35	2%	17	35	2%
0.50	21	47	3%	21	47	3%
0.75	36	794	45%	24	111	6%
1.00	45	1,290	73%	29	125	7%

though, than in the previous analysis. The effects of a failure of the other types—i.e., other Dutch banks, foreign subsidiaries, branches, and investment firms—have also increased. Foreign subsidiaries have larger effects on the assets affected than do other Dutch banks.

If the effects of the different foreign regions are analyzed, it becomes clear that Europe, North America, and RoW are the main risks for the Dutch banking sector. If Europe fails, the highest number of banks fails (forty-five) and the largest amount of assets is lost (€1,290 billion). A simulated failure of the North American region results in thirty failed banks, with asset losses of €480 billion. If Asia fails, a maximum of twenty-eight banks fail, with asset losses of €41 billion. In total, thirty banks fail if RoW goes bankrupt, with asset losses of €516 billion. A failure of Turkey does not lead to large contagion risks: a maximum of six banks fail, and only first-round effects result. Furthermore, all of the failed banks in this case are foreign subsidiaries with the parent company in this particular region.

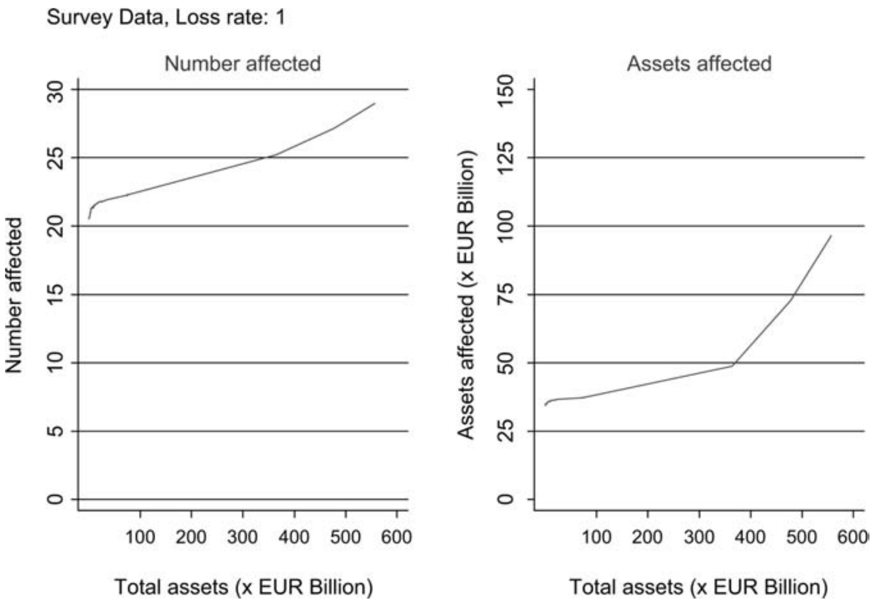
The asset size of the first failed bank still seems unrelated to the number of failed banks and the total assets lost in the domestic banking system in the scenario analysis. Although figure 6 shows an upward-sloping line, this result is triggered by a single data point. Total asset losses (€125 billion) in this scenario analysis are many times larger, though, than in the previous analysis and are a significant part of the mean total assets of the large banks. The effects of a failure on foreign banks are, again, not included in figure 6.

Similarly to the previous analysis, the main threat for the Dutch banking sector stems from abroad. The foreign regions, especially Europe, represent the riskiest counterparties in the case of failure. The large banks only affect a limited number of banks, though, resulting in higher asset losses this time. Again, there are some surprises in the form of smaller banks that affect a large number of banks with high asset losses.

4.3 Large Exposures Data versus Survey Data

In the discussion of the outcomes using either the large exposures data or survey data, it was already apparent that the results are qualitatively similar: large, systemically important banks have a sizable impact but do not infect the entire system. Looking at the

Figure 6. Effects of Size on Number and Total Assets Affected



Note: In these graphs, the effects of and on foreign regions have been excluded.

regions, we see that especially the region Europe is important as a possible source of contagion.

In addition to this qualitative assessment, we inspected the underlying estimated exposure matrices. For each individual bank the range, mean, and median are all very similar. We also looked at the distribution of percentage differences between the large exposures data and the survey data, but interpretation is difficult because (i) it is not clear which of the matrices is the true matrix, and (ii) the tails of the distributions are mainly driven by percentage changes in bank exposure pairs that are very small.

Summarizing, we find that the commonly used large exposures data seem to provide a similar picture of the interbank market characteristics and of contagion effects compared to the survey data we obtained. This can be interpreted as a validation of the approach used in previous studies.

5. Conclusions

The most important risks in the Dutch interbank market stem from exposures on foreign counterparties—in particular, European and North American counterparties. This result holds regardless of the information source used. The national interbank market only seems to carry systemic risks if a large bank fails, although even in this extreme and unlikely event, not all of the remaining banks are affected. In fact, none of the large bank failures trigger the failure of another large bank. The Dutch banking system hence cannot be pictured as one *single* line of dominoes, and the amounts outstanding per counterparty are small (losses are limited). The linkages between the large banks and the foreign regions seem to prevent large(r) negative effects from spreading further into the Dutch market.

This conclusion points to the largest risk for Dutch banks: the foreign regions. Many banks have exposures on the foreign regions. Therefore, if problems arise in one of these regions, then all types of banks will be severely hit. In particular, foreign subsidiaries and/or branches are vulnerable to shocks originating in the parent-company region. However, the indirect effects the failure of a foreign bank may have on the Dutch banking sector are not included in this analysis. Furthermore, it has to be borne in mind, on the one hand, that the foreign regions are aggregated accounts. Each foreign region is formed by summing all exposures to counterparties in that particular region. It is hard to imagine that a region (i.e., all the counterparties within it) could go bankrupt as a whole. On the other hand, examples such as the Asia crisis or the recession following September 11, 2001, point out that we cannot exclude such a scenario. Overall, interbank exposures across countries may form an important link between banks, resulting in considerable possible systemic risks. This will also hold for other small open economies.

Our analysis also shows that maximum entropy is not appropriate for estimating bilateral exposures in a concentrated market, such as the Dutch, the Belgian, or the Swiss market. In addition, for an accurate assessment of the risks in the interbank market, there is not a clear advantage in using either the large exposures data report or survey data. Both data sources give an adequate and similar overview of the risks in the interbank market. At the individual bank level, however, there are important differences. Working from the premise that the survey data are a more reliable source of information, since they have been specially requested, this implies that the large exposures data reports are not well suited for monitoring the interbank exposures of a particular bank. However, for estimates of contagion effects at the macro level, the large exposures data form an appropriate (and easier) data source.

The most important conclusion, based on the research presented, is that in order to improve the informativeness of the analyses, information about foreign exposures is necessary. Other studies in this area suffer from the same issue. In an increasingly integrated market like the interbank market, it might therefore be fruitful to merge the various analyses.

Appendix. Cross-Entropy Minimization

The minimization problem can be formally written as

$$\min \sum_{i=l}^{N} \sum_{j=l}^{N} x_{ij} \ln \left(\frac{x_{ij}}{x_{ij}^{0}} \right) \tag{3}$$

subject to

$$\sum_{j=l}^{N} x_{ij} = a_i \tag{4}$$

$$\sum_{i=l}^{N} x_{ij} = l_j \tag{5}$$

$$x_{ij} \geq 0, \tag{6}$$

with the conventions that $x_{ij} = 0$ if and only if $x_{ij}^{0} = 0$ and $\ln(0/0) = 0$. The RAS algorithm solves this type of problem (Wells 2004).[17]

Using the large exposures data, this becomes

$$x_{ij}^{0,I} = \begin{cases} 0 & \text{if } i = j \\ \frac{E_{ij}}{\sum_{J=l}^{N} E_{ij}} a_i & \text{if bank } i \text{ reports an exposure to bank } j \text{ in the large exposures data,} \end{cases} \tag{7}$$

[17]See Blien and Graef (1997) for an extended explanation of the RAS algorithm or refer to Censor and Zenios (1997) for more information.

where E_{ij} represents the exposure of bank i to bank j as reported in the large exposures data.

Using the survey data together with the large exposures data in the second part of the research, this becomes

$$x_{ij}^{0,II} = \begin{cases} 0 & \text{if } i = j \\ \frac{R_{ij}}{\sum_{J=l}^{N} R_{ij}} a_i & \text{if bank } i \text{ reports an exposure to bank } j \text{ in the survey data} \\ \frac{E_{ij}}{\sum_{J=l}^{N} E_{ij}} a_i & \text{otherwise,} \end{cases} \tag{8}$$

where R_{ij} reflects the exposure of bank i to bank j as reported in the survey data.

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Clustering or Competition? The Foreign Investment Behavior of German Banks*

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Banks often concentrate their foreign direct investment (FDI) in certain countries. This clustering of activities could reflect either the attractiveness of a particular country or agglomeration effects. To find out which of the two phenomena dominates, we need to control for country-specific factors. We use new bank-level data on German banks' FDI for the 1996–2003 period. We test whether the presence of other banks has a positive impact on the entry of new banks. Once we control for the attractiveness of a country through fixed effects, the negative impact of competition dominates. Hence, pure clustering effects are rather unimportant.

JEL Codes: F0, F21.

1. Motivation

International banking has grown rapidly in the past few decades. Merger and acquisition activity in the banking sector and cross-border lending have been on the rise. However, regional patterns of entry into foreign markets vary. Spanish banks, for instance, have made significant inroads into the banking markets of Latin America. Austrian and German banks are quite active in the transition

*This paper represents the authors' personal opinions and does not necessarily reflect the views of the Deutsche Bundesbank. The authors would like to thank Joerg Breitung, Joerg Doepke, Heinz Herrmann, Robert Lipsey, Fred Ramb, Dietmar Scholz, Harald Stahl, participants of seminars held at the Deutsche Bundesbank and the Western Economic Association's Annual Meeting in Denver (2003), and two anonymous referees for most helpful discussions. All errors and inaccuracies are solely our own responsibility. Corresponding author: Buch: University of Tübingen, Economics Department, Mohlstrasse 36, 72076 Tübingen, Germany; e-mail: Claudia.buch@uni-tuebingen.de; Tel: +49 7071 2972962.

economies of central and eastern Europe. And, despite advances in technology, banks' activities abroad tend to remain concentrated on countries hosting financial centers.

These regional concentration patterns suggest that the presence of other banks in a given market matters for entry. In assessing the value of the presence of other banks in their locational choice, though, banks face a trade-off. While a larger presence of other banks implies more competition and thus lower profits for new entrants, positive spillover between the activities of new and old entrants could increase profits. This could create clustering effects. Empirically, it is important to distinguish such spillover effects from general factors that affect the attractiveness of a country.

This paper studies how German banks decide to expand their operations abroad. We focus on the following questions: What characteristics of the local market attract German banks? Do other banks' activities influence new entrants' investment decisions? Is this impact positive or negative, i.e., does the competition or the clustering effect dominate?[1] Are there differences between small and large banks?

It is important for bank regulators to understand whether the observed concentration of international banking activities reflects the attractiveness of a particular country or clustering effects. If clustering effects dominate, regulators could stimulate the emergence of financial centers by attracting some major players to a particular market. Our research thus helps to answer the question of whether financial centers attract banks because they provide a favorable regulatory framework or because banks enjoy positive spillovers from other banks' activities.

In the theoretical literature, different reasons for clustering effects are discussed. These reasons include knowledge spillover between firms, access to labor markets in specialized factors, the scope for backward and forward linkages, and signaling effects that lower information costs (Barry, Görg, and Strobl 2001).

[1]Note that we cannot study clustering *within* host countries. However, in most of the countries in our study, international banking activity is concentrated in a few cities or only one large city. We can, therefore, take country-level clustering effects as proxies for regional clustering.

To the best of our knowledge, this paper is the first to test the role of clustering in banks' foreign direct investment (FDI) decisions. For nonfinancial firms, there is a large body of empirical evidence demonstrating the importance of agglomeration effects. Empirical work finds evidence in favor of clustering effects for British and U.S. investment in Ireland (Barry, Görg, and Strobl 2001), foreign direct investment in France (Crozet, Mayer, and Mucchielli 2003), Japanese investment in Europe (Head and Mayer 2004), or Japanese firms in the United States (Head, Ries, and Swenson 1995). Crozet, Mayer, and Mucchielli (2003) is one of the few studies to find evidence of competition effects.

In the banking literature, a formal theory of financial centers is largely absent. Kindleberger (1978) identifies economies of scale, location, transportation costs, the presence of headquarters of multinational firms, and cultural and regulatory factors as variables contributing to the emergence of (international) financial centers. Information costs might play a role as well. Barron and Valev (2000) have formalized the idea that high costs of acquiring information might induce small banks to follow large banks into foreign markets. If investing abroad requires a (fixed) investment in information, small banks (being more wealth constrained than larger banks) may not be able to pay this fixed cost. Hence, they have an incentive to follow the behavior of larger, better-informed banks. The empirical results on cross-border lending reached by Barron and Valev (2000) confirm this hypothesis.

Our research differs because we use firm-level data on banks' foreign direct investment rather than data on cross-border lending. We use a new and unique data set on FDI and on the balance sheets and income statements of German banks (Deutsche Bundesbank 2005), which enables us to analyze whether and where banks invest abroad and how such decisions are influenced by bank-specific factors. Studying the German banking sector is interesting because of a significant dichotomy between some large internationally active banks and a number of small local and regional banks. For the large banks, foreign borrowing or lending accounted for about half of their balance sheet total in 2001; the corresponding number for the (comparatively small) savings banks was less then 5 percent (OECD 2005). We therefore test whether internationalization patterns differ for small and large banks. We also shed more light on the channels through which clustering might arise by decomposing other banks' activities into the number of competitors and the volume of investment. Moreover, we use a set of explanatory variables that captures the factors identified by Kindleberger (1978).

In section 2, we review earlier empirical evidence on clustering and FDI. In section 3, we describe our data as well as differences in the international activities of small and large banks. Section 4 presents our regression results. We start by explaining the FDI of banks for the full sample and for banks of different sizes. We then test whether banks cluster in specific markets and whether clustering effects are more important for smaller banks. Once we take into account omitted country factors by including a full set of country fixed effects, the impact of other banks' activities on the activities of new banks is insignificant or even negative, which contradicts the hypothesis that German banks seek agglomeration benefits by moving into foreign markets.

2. Earlier Empirical Evidence on Clustering

The clustering of investors in foreign markets and herding behavior have been important areas of research in the finance literature.[2] Yet there is hardly any evidence on clustering in the FDI decisions of banks. Barron and Valev (2000) study banks' foreign activities but focus on cross-border lending. They use data on U.S. banks' short-term foreign assets for the 1982–94 period to test whether small banks follow large banks abroad. Granger noncausality tests show that lending by large banks tends to lead lending by small banks but not vice versa.

Chang, Chaudhuri, and Jayaratne (1997) test whether banks cluster at the national level.[3] Using data for bank branches in

[2]See Bikhchandani and Sharma (2001) for a review of the literature on herding in financial markets. This literature shares similarities to our work, since it addresses the interdependence of the actions of different investors. However, the literature differs in its focus on information costs as a reason for herding and in its empirical focus on time-series evidence for stock markets and markets for securitized financial assets.

[3]De Juan (2003) likewise studies the clustering of bank branches at a national level. Using detailed data on branches of every bank in all Spanish towns, she identifies the optimal size of banking markets.

New York City opened between 1990 and 1995, they find that banks are more likely to open branches in areas where other banks are already active. Applying a similar reasoning to FDI, their empirical analysis is based on a profit function for (foreign) affiliates that takes the following form:

$$\pi_{ijt} = \alpha_0 + \alpha_1 X_{it} + \alpha_2 X_{jt} + \alpha_3 FDI_{jt} + \varepsilon_{ijt}, \tag{1}$$

where π_{ijt} are the profits for bank i from operating a branch in country j, X_{it} is a vector of bank-specific factors for bank i, X_{jt} is a vector of country-specific factors, FDI_{jt} is a proxy for the activities of other banks in country j, and ε_{ijt} is an error term. Rather than estimating the above profit equation directly, Chang, Chaudhuri, and Jayaratne (1997) use the investment of bank i in a given region (FDI_{ijt}) as the dependent variable. The underlying assumption is that higher profits translate to more investment:

$$FDI_{ijt} = \beta_0 + \beta_1 X_{it} + \beta_2 X_{jt} + \beta_3 FDI_{jt} + \varepsilon_{ijt}. \tag{2}$$

The expected coefficient on the activities of other banks (β_3) depends on the relative strength of the clustering and the competition effect. If the competition effect dominates, β_3 is negative. If agglomeration effects lead to the clustering of banks, β_3 is positive. This would be the case if, for instance, the presence of other home-country banks creates some externality in the form of lower information costs or a greater pool of skilled labor (see also Crozet, Mayer, and Mucchielli 2003).

Our empirical setup is also closely related to work by Chang, Chaudhuri, and Jayaratne (1997), who study clustering in FDI decisions made by nonfinancial firms. One key insight of this literature is that country fixed effects must be included in order to control for possible unobserved factors at the country level.[4] Head and Mayer (2004) use FDI by *other* Japanese firms to explain the FDI by Japanese firms in Europe. The number of Japanese affiliates in Europe has a positive and significant impact on FDI, even if a full set of country dummies is included. Studying the locational choice

[4]A similar problem occurs in the literature on herding in financial markets in isolating “spurious” herding, which is driven by market fundamentals, from “intentional” herding (Bikhchandani and Sharma 2001).

of British and U.S. investors in Ireland, Barry, Görg, and Strobl (2001) find evidence of information spillover, a so-called demonstration effect, for investment by British and U.S. firms. A clustering effect, in turn, is found only for U.S. firms.

Finally, Crozet, Mayer, and Mucchielli (2003) study the locational choices of foreign investors in France. They show that firms cluster with their competitors. At the same time, there is heterogeneity in these effects among investors from different countries. For some investors, they even find a negative competition effect of proximity to other firms on the probability of entry.

3. The Data

In this paper, we test whether clustering is important for German banks' foreign investment activity. Since the empirical analysis in this paper is based on a new bank-level data set, we describe the data in this section.

3.1 Construction of the Bank-Level Data Set

We use balance sheet statistics, income statements, and FDI statistics for German banks. The combined data set contains data for eight years (1996–2003). However, due to missing observations for some of the explanatory variables, most of our regressions are based on a reduced data set for the years 1998–2002. Furthermore, OECD countries account for 92 percent of German banks' FDI. For this reason, and because of better data availability than for the non-OECD countries, we restrict our analysis to the OECD region.

We use the monthly balance sheet statistics for German banks to construct a data set containing *all* German banks in existence throughout the period under review. For each of these banks, year-end information on equity capital, total assets, yields from operational business (taken from the income statements), and the claims against and liabilities to resident and nonresident banks and nonbanks is retrieved. The latter are used to calculate the ratio of aggregated cross-border claims and liabilities to total assets as a measure of the internationalization of the individual bank.

The FDI data set contains data from annual full-sample surveys of FDI stocks. (For details see Lipponer 2002, 2003.) The data set starts in 1989 but includes time series for individual banks only from 1996 to 2003. The data mainly contain information from affiliates' balance sheets that is needed to calculate banks' primary and secondary FDI stocks. From this data set, we add the consolidated amounts of primary and secondary outward FDI per foreign affiliate. Some banks have several affiliates in a given host country. However, since we do not have information on the exact location of these affiliates, we aggregate FDI stocks by the country of the foreign affiliate.

We include only banks that report at least one foreign affiliate in at least one year. Hence, we exclude those banks that have domestic affiliates only. Overall, some 5,500 reports by 110 German banks are included in the data set. In 2003, these banks returned reports on some 800 foreign affiliates residing in twenty-eight OECD countries, resulting in around 245 country-level FDI reports.

3.2 Stylized Facts

Our aim in this paper is to explore the determinants of German banks' foreign direct investments, the importance of the presence of other banks, and differences in the behavior of small and large banks. Before turning to regression-based empirical evidence, this section provides descriptive statistics. Unless otherwise stated, all data are for 2003. Table 3, shown in the appendix, provides summary statistics. We define small banks as those with total assets below €31.4 billion (eighty-three banks) and large banks as those with assets exceeding €31.4 billion (twenty-seven banks). These cut-off points roughly correspond to the 75 percent quantile of the asset values of the banks in the sample.

Comparing the internationalization patterns of German banks and nonfinancial firms shows that banks' FDI tends to be more concentrated (this information is not shown in the table). There is, for instance, a large discrepancy between the number of countries in which all German firms maintain foreign affiliates (142) and the corresponding number for banks (65). As already mentioned, German banks' FDI is concentrated in the OECD countries. Moreover, the six OECD host countries with the largest amount of German banks' FDI account for around 91 percent of German banks' FDI stocks in the OECD. The share of the three largest destination countries is still 79 percent. These numbers show that clustering is potentially important for the FDI decisions of German banks.

Some differences also exist between small and large banks. One is that large banks account for 98 percent of FDI and for 88 percent of the number of foreign affiliates. Hence, the average size of foreign affiliates is much smaller for small banks. The average FDI per affiliate of small banks is only around 15 percent of the amount invested per affiliate by large banks.

Another difference concerns the average number of countries in which small and large banks are active and the average number of affiliates per country. (Again, this information is not shown in the table.) While small banks are active—on average—in only 1.7 countries, the corresponding number for the large banks is 6.7 countries. In terms of the number of affiliates per country that banks maintain, the difference is less pronounced (1.3 and 2.3 for the small and large banks, respectively).

A third difference is that FDI is less important for the small German banks than for the large German banks, relative to their balance sheet total (see table 3, panel B).

Hence, measured in terms of total volumes, FDI by small banks makes up only a fraction of all FDI. However, the small banks account for a quite significant percentage of the number of foreign affiliates of German banks. In fact, about 12 percent of all foreign affiliates are affiliates of small banks. Hence, despite its small overall volume, FDI of small banks is important in terms of the number of foreign investments undertaken by German banks abroad.

In summary, the low average volume of activities and the small number of countries in which small banks are present suggest that entry costs are important. Larger banks seem to find it easier to shoulder these costs. However, borders do not prohibit small banks from going abroad altogether. Hence, in the following sections, we will analyze whether foreign activities of small and large banks have different determinants and whether clustering and agglomeration effects are more important for the smaller banks.

4. Empirical Results

This section analyzes the determinants of FDI by German banks. We apply a two-step approach. In a first step, we estimate baseline regressions for the determinants of FDI by banks. We also estimate these regressions separately for small and large banks. In a second step, we test whether banks invest more in countries where other German banks are already present.

4.1 Empirical Model

The empirical analysis is based on an extended gravity equation. Gravity equations relate the magnitude of bilateral economic activities between countries to geographical distance and the size of the economies. The standard gravity model, designed to explain bilateral linkages between a large number of source and host countries, has also been used frequently to explain one source country's FDI in a large set of host countries (see, e.g., Feenstra, Markusen, and Rose 2001 or Egger 2002). When applied to FDI, gravity equations are enriched by a number of variables that capture barriers to the integration of markets, such as regulations and proxies for information costs (i.e., by variables that affect the profitability of investing abroad).

We essentially estimate equation (2) above. In addition to a vector of bank-specific control variables and a vector of country-specific control variables, we also include time fixed effects to capture possible time trends.

We also include a variable that captures the activities of other German banks in a particular host country to test for clustering effects. Interpreting the signs of this variable, however, also requires the inclusion of a full set of country fixed effects. Otherwise, we might falsely attribute a positive effect of the activities of other banks to a clustering effect even though this variable, in fact, proxies omitted country factors.

Since we have bank-level data for *all* German banks, we can model not only the determinants of FDI by banks but also the characteristics of banks that go abroad relative to banks that stay national. Hence, we can distinguish the entry decision (the extensive margin) from the volume of FDI (the intensive margin). The natural candidate for studying this choice is a tobit model (see, e.g., McDonald and Moffit 1980). This model allows us to separate banks' decisions on whether to expand internationally from their decisions on how much to invest in a given market. Hence, the marginal effects of each coefficient indicate the change in the probability of being uncensored (i.e., having a positive value) and the change in the amount invested. In qualitative terms, we obtain the same results for the two marginal effects, i.e., for the probability of being uncensored and for the expected value of the dependent variable conditional upon being uncensored. Therefore, and in order to save space, we report the two marginal effects only for the baseline regression results and restrict ourselves to the tobit coefficients thereafter. We also check the robustness of our results by using a panel probit model, which essentially replicates the first stage of the tobit model. The results are largely the same for the probit and the tobit model.

4.2 Baseline Regression Results

Before testing for clustering effects, we run a set of baseline regressions for banks of different sizes. We regress the amount of FDI on bank-specific and country-specific variables as well as on variables capturing the structure of the domestic banking system.

4.2.1 Bank-Level Explanatory Variables

Table 1 summarizes our first set of regression results. We use the *size* of banks (*assets*), their *profitability*, and their degree of *internationalization* as bank-specific determinants of FDI.[5] Additionally, we include dummy variables for the *bank type* (commercial, savings, and cooperative banks). Foreign banks (i.e., dependent German branches of banks headquartered outside Germany), building and loan associations, and the Bundesbank, its affiliates, and branches are excluded. Special-purpose banks owned by the federal government, also known as "promotional banks," are included. Omitting them does not significantly affect any of the results.

Our findings confirm earlier work on the determinants of international banking activities (see, e.g., Berger et al. 2004). Larger banks maintain larger affiliates abroad (Focarelli and Pozzolo 2001). We also control for the profitability of the reporting bank by including banks' yields from operational business, scaled by total assets.

[5] Table 4 in the appendix provides more detailed definitions and data sources.

Table 1. Regression Results: Baseline Specification

	All Banks		Small Banks		Large Banks	
	M.E. 1	**M.E. 2**	**M.E. 1**	**M.E. 2**	**M.E. 1**	**M.E. 2**
Time Fixed Effects	YES	YES	YES	YES	YES	YES
Dummies for Bank Types	YES	YES	YES	YES	YES	YES
Internationalization	6.65e−04*** (5.83e−05)	5.76e−03*** (5.05e−04)	4.19e−05 (4.53e−05)	4.42e−04 (4.78e−04)	7.51e−03*** (7.03e−04)	7.63e−02*** (7.15e−03)
Assets	2.19e−02*** (7.96e−04)	1.90e−01*** (6.90e−03)	7.07e−03*** (7.55e−04)	7.45e−02*** (7.96e−03)	2.06e−01*** (1.57e−02)	2.09e+00*** (1.59e−01)
Profitability	3.94e−03*** (3.41e−04)	3.42e−02*** (2.95e−03)	1.18e−03*** (2.30e−04)	1.25e−02*** (2.43e−03)	1.02e−02** (4.73e−03)	1.04e−01** (4.81e−02)
Distance	−7.09e−03** (2.78e−03)	−6.14e−02** (2.41e−02)	−8.28e−03*** (2.49e−03)	−8.73e−02*** (2.63e−02)	−5.73e−03 (1.97e−02)	−5.82e−02 (2.00e−01)
Inflation	2.49e−03*** (6.92e−04)	2.16e−02*** (5.99e−03)	1.08e−03* (6.48e−04)	1.14e−02* (6.83e−03)	1.75e−02*** (4.77e−03)	1.78e−01*** (4.85e−02)
GDP	8.60e−03*** (2.18e−03)	7.45e−02*** (1.88e−02)	1.61e−03 (1.86e−03)	1.70e−02 (1.97e−02)	8.43e−02*** (1.55e−02)	8.57e−01*** (1.58e−01)
Trade	1.26e−03*** (2.53e−04)	1.09e−02*** (2.20e−03)	3.99e−04* (2.37e−04)	4.21e−03* (2.50e−03)	1.03e−02*** (1.74e−03)	1.05e−01*** (1.77e−02)
Risk	−8.93e−05 (3.18e−04)	−7.74e−04 (2.75e−03)	−1.29e−04 (2.84e−04)	−1.36e−03 (3.00e−03)	1.37e−03 (2.25e−03)	1.39e−02 (2.29e−02)

(continued)

Table 1 (continued). Regression Results: Baseline Specification

	All Banks		Small Banks		Large Banks	
	M.E. 1	**M.E. 2**	**M.E. 1**	**M.E. 2**	**M.E. 1**	**M.E. 2**
Time Fixed Effects Dummies for Bank Types	YES YES	YES YES	YES YES	YES YES	YES YES	YES YES
Freedom	−1.48e−03 (2.41e−03)	−1.29e−02 (2.09e−02)	−2.05e−03 (2.26e−03)	−2.16e−02 (2.38e−02)	7.46e−03 (1.67e−02)	7.58e−02 (1.70e−01)
Supervision	8.09e−04 (1.07e−03)	7.01e−03 (9.24e−03)	−1.06e−03 (9.54e−04)	−1.12e−02 (1.01e−02)	1.90e−02** (7.48e−03)	1.93e−01** (7.61e−02)
Transparency	1.60e−02*** (2.18e−03)	1.39e−01*** (1.89e−02)	7.15e−03*** (2.03e−03)	7.54e−02*** (2.14e−02)	1.14e−01*** (1.50e−02)	1.16e+00*** (1.53e−01)
Capital Controls	−5.53e−03 (4.50e−03)	−4.59e−02 (3.90e−02)	−1.01e−02** (5.00e−03)	−1.04e−01** (5.28e−02)	1.19e−02 (2.94e−02)	1.22e−01 (2.99e−01)
EU	−3.54e−03 (7.35e−03)	−3.08e−02 (6.37e−02)	−1.09e−02* (6.40e−03)	−1.17e−01* (6.75e−02)	6.07e−02 (5.27e−02)	6.10e−01 (5.36e−01)
Number of Non-German Banks	1.83e−03** (7.41e−04)	1.58e−02** (6.42e−03)	1.11e−03* (6.22e−04)	1.17e−02* (6.56e−03)	1.42e−02*** (5.46e−03)	1.44e−01*** (5.55e−02)
Banking System Assets/GDP	3.26e−06 (1.10e−05)	2.83e−05 (9.51e−05)	1.13e−05 (9.39e−06)	1.20e−04 (9.91e−05)	−8.83e−05 (7.78e−05)	−8.98e−04 (7.92e−04)
Return on Average Equity	−1.06e−05 (5.19e−05)	−9.20e−05 (4.50e−04)	−1.85e−05 (7.42e−05)	−1.95e−04 (7.83e−04)	−9.59e−06 (3.12e−04)	−9.75e−05 (3.18e−03)

(continued)

Table 1 (continued). Regression Results: Baseline Specification

	All Banks		Small Banks		Large Banks	
	M.E. 1	**M.E. 2**	**M.E. 1**	**M.E. 2**	**M.E. 1**	**M.E. 2**
Time Fixed Effects Dummies for Bank Types	YES YES	YES YES	YES YES	YES YES	YES YES	YES YES
Concentration	−8.80e−04*** (1.28e−04)	−7.63e−03*** (1.11e−03)	−6.10e−04*** (1.18e−04)	−6.44e−03*** (1.25e−03)	−4.03e−03*** (8.97e−04)	−4.09e−02*** (9.12e−03)
Value Added	−3.30e−03*** (1.01e−03)	−2.86e−02*** (8.74e−03)	−2.33e−03*** (8.41e−04)	−2.46e−02*** (8.87e−03)	−2.25e−02*** (7.36e−03)	−2.29e−01*** (7.49e−02)
Employment Share	1.84e−02*** (4.00e−03)	1.59e−01*** (3.46e−02)	7.66e−03** (3.38e−03)	8.09e−02** (3.57e−02)	1.50e−01*** (2.87e−02)	1.53+00*** (2.92e−01)
Constant	−8.29e−01*** (8.63e−02)	−7.19e+00*** (7.48e−01)	−1.81e−01** (7.14e−02)	−1.91e+00** (7.53e−01)	−8.33e+00*** (7.34e−01)	−8.47e+01*** (7.47e+00)
Number of Observations (N * T)	12,540	12,540	9,943	9,943	2,597	2,597
Adjusted R^2	0.19	0.19	0.14	0.14	0.17	0.17

Note: This table gives the results of tobit regressions for German banks' FDI. M.E. 1 = marginal effect on the probability of being uncensored, M.E. 2 = marginal effect on the expected value, conditional on being uncensored. The dependent variable, total assets, distance, GDP, and risk are in logs. All censored observations are left-censored at zero. Standard errors are shown in parentheses. *, **, and *** are significant at the 10 percent, 5 percent, and 1 percent levels, respectively. Note that 1.34e−02 $\equiv 1.34 \cdot 10^{-2} \equiv 0.0134$.

We find a positive coefficient. More-profitable banks have more cash flow to finance foreign investments. This is consistent with the Barron and Valev (2000) model, which implies that wealth constraints impede the international expansion of banks.

We include a measure for the degree of internationalization of the reporting bank. To compute this measure, we use the sum of cross-border lending and borrowing, scaled by total lending and borrowing. It might be objected that this variable is endogenous because our dependent variables capture proxies for the internationalization of banks as well. However, we do not believe that endogeneity is a serious concern because we use aggregated data for the individual bank rather than bilateral assets and liabilities in a given host country. Our results strongly suggest that more-international banks also hold larger investments abroad. Moreover, dropping the internationalization variable leaves all remaining results unaffected, with regard to both the signs and the significance levels of the other coefficients.

4.2.2 Characteristics of the Financial System

Whereas the characteristics of the individual bank affect the decision on *whether* to invest abroad, characteristics of the local banking and financial system are likely to affect the choice of *where* to invest. Hence, we include several proxies for the structure of the host country's banking system.

We use three measures for the size of the banking and financial system. The first, the size of the banking system assets relative to host-country GDP (*banking system assets/GDP*), is insignificant if we additionally include the employment in the financial system as a percentage of total employment. Employment in the financial system (*employment share*) is positive and significant throughout. If we exclude the employment share, the size of the banking system is positive and significant.[6] Hence, while the size of the banking sector matters, the effect comes through employment in the financial sector. This supports the hypothesis that specialized labor markets increase the attractiveness of locations for FDI by banks.

[6]We also experimented with a measure of stock market capitalization over GDP. This variable (*traded stocks*) has a negative impact on FDI of German banks, which would be consistent with the interpretation that German banks focus on countries with bank- rather than market-based financial systems.

As a third measure for the size of the financial system, we include value added in financial services (*value added*) as a percentage of total value added. Again, the expected impact is not clear cut. A high percentage of value added in financial services may indicate a large demand for financial services, but it may also indicate that the financial system is quite developed and that new entrants are finding it difficult to find a market niche. We indeed find a negative impact of value added in the financial services sector.

We include two additional measures of the degree of competition in the host country's banking system: the number of banks (*number of non-German banks*) and the degree of concentration (*concentration*). The number of banks serves as a proxy for the competitive environment in the host country. We exclude the number of German banks from this measure. The competitive impact of the presence of other banks may differ from that of German banks if German banks have a comparative advantage in servicing German nonfinancial firms.[7] The number of other, non-German banks is positive in the baseline regression, which would be consistent with the interpretation that a large number of banks increases the attractiveness of a particular country rather than increasing competitive pressure.

The degree of concentration can have two opposite effects on the profitability of entry. On the one hand, high concentration ratios can be an indication that profitability in the host-country banking system is high. This should encourage entry. On the other hand, high measures of concentration may indicate that the contestability of local markets is limited. This should discourage entry. Our results suggest that the latter effect dominates.

Finally, we include *return on average equity* as a measure of the profitability of the local banking system. This variable has no significant impact on German banks' entry decisions.

The degree of regulation in the host country's banking system is captured through different indicators. The degree of economic freedom (*freedom*) in banking assigns a lower index number to countries that heavily regulate banks. We expect to find a positive coefficient, but this variable is insignificant. *Capital controls* is a dummy

[7]Evidence in Berger et al. (2003) contradicts this expectation. They find that the foreign offices of multinationals are more likely to use a host-nation bank, rather than a home-nation bank, for the financial services they require.

that is set at 1 if countries impose controls on cross-border financial credits. This variable is insignificant as well, possibly because we are dealing with a relatively homogenous sample of OECD countries. Hence, there is relatively little cross-sectional variation in this variable.

We include two measures of the quality of the host country's supervisory system. Barth, Caprio, and Levine (2001) have compiled a comprehensive data set on banking supervision around the globe. From this database, we follow Buch and DeLong (2004) and construct two indices that capture the power of the banking supervision authorities to intervene in banks (*supervision*) and the transparency of the supervisory system (*transparency*). Both indicators assume higher values if the quality of the supervisory system improves. Results indicate that German banks appreciate greater transparency of the host-country banking system, while the effect of the power of banking supervisors is insignificant.

4.2.3 Country-Level Explanatory Variables

Besides the structure of the host country's financial system, general characteristics of the host country are likely to affect financial institutions' FDI. These characteristics of the host country can be grouped into proxies for market size; geographical, cultural, and economic distance; and the degree of (macroeconomic) stability.[8]

Gross domestic product (*GDP*) (in logs) is included to control for market size. Additionally, we use the ratio of bilateral trade (*trade*) between Germany and a given host country relative to host-country GDP as a proxy for the intensity of trade relations. This variable is a measure of the trade-related demand for banking services, and we expect a positive coefficient. Since we are using bank-level data as the dependent variable, potential endogeneity of bilateral trade is not an issue.

Both proxies for the size of the foreign market have a positive sign. One interpretation is that banks go abroad to realize economies of scale. A significant impact of trade on the internationalization of

[8]We do not include a dummy for the presence of a common border or a common language dummy, because countries sharing a common border with Germany, or which are German speaking, tend to be captured through the EU dummy and the distance variable.

banks has often been interpreted in terms of banks following their customers abroad, although the direction of causality has remained largely unexplored. Although we cannot directly link banks to their individual customers, we note that the positive impact of trade would be consistent with such a story.

The geographical *distance* between Berlin and the capital of the host country (in kilometers) is expected to reduce banks' FDI. Greater distances lead to higher communication and information costs, because they curtail face-to-face communication and networking. Moreover, greater distances reflect differences in culture, language, and institutions. Results confirm this expectation: distance is negative and significant.

We use *inflation* and a measure for political *risk* to control for the stability of the host country. The impact of inflation on FDI is not clear cut a priori. On the one hand, inflation could have a negative impact, since it implies increased macroeconomic instability. On the other hand, higher inflation might also have a positive impact on the nominal dependent variable we are using. In our data, the positive effect dominates. As a proxy for political risk, we include risk as a composite index of country risk, taken from various issues of *Euromoney*. We transform this variable so that it has a higher score when country risk is high. However, we find an insignificant coefficient.

Finally, we add a dummy variable *EU* that is set to 1 for countries that are members of the European Union. Contrary to expectations that the Single Market Program might have promoted cross-border entry, we find an insignificant sign. The reason could be that the Single Market Program has also eased the provision of services to foreign countries through cross-border lending, thereby reducing incentives to engage in FDI.

4.2.4 Small Banks versus Large Banks

Results in table 1 show that differences between large and small banks regarding the determinants of FDI are relatively minor. There are a few variables for which we obtain different results. The positive impact of the degree of banks' internationalization is driven by the large banks in the sample. For the small banks, internationalization is insignificant.

Likewise, the positive impact of GDP stems only from the larger banks. This is consistent with the hypothesis that smaller banks seek their market opportunities in (small) niche markets. These niche markets are not attractive to larger banks, because they do not provide sufficient opportunity to realize economies of scale. Also, we find the expected positive coefficient on the variable capturing the power of banking supervisors for the large banks only.

But there are also a few variables that are significant in the subsample of small banks only. The negative impact of distance is driven by the small banks. This would be consistent with an interpretation of distance as a proxy for the fixed costs of entry that are more difficult to cover for small banks. Likewise, capital controls discourage FDI by small banks but not by large banks. The negative EU effect for the small banks would be consistent with the hypothesis that the Single Market Program has eased cross-border lending more than it has lowered barriers for FDI.

In terms of explanatory power, we achieve the best fit for the full sample (pseudo R^2 of 0.19). The R^2 falls to 0.17 and 0.14 for the large and the small banks, respectively. Hence, some of the explanatory power that we obtain in the full sample is driven by the heterogeneity across banks of different size.

4.3 Do Banks Cluster?

We next investigate whether clustering is important in German banks' international investment decisions. We test whether banks are particularly attracted to host countries where other German banks are already active. To do so, we use the aggregated FDI of other German banks (*FDI of others*) as an additional explanatory variable (see Head and Mayer 2004 or Chang, Chaudhuri, and Jayaratne 1997 for a similar strategy). Investment of the bank under study is excluded from this number. To avoid problems of multicollinearity, we use the residual of a regression of aggregated FDI on the remaining explanatory variables.

Aggregated FDI would capture clustering effects if the presence of other German banks created positive spillover. It is, however, also conceivable that the presence of other banks captures omitted variables that attract *all* banks to a certain market. We additionally include a full set of country fixed effects to address this possibility.

4.3.1 Proxies for Clustering Effects

To proxy for the activities of other German banks in foreign markets, we distinguish between the impact of the number of foreign banks abroad (N) and the average amount of FDI in a particular market ($\overline{FDI}$). Hence, we split up the investment of other banks in market j in period t into two components:

$$FDI_{jt} = \sum_{\substack{k=1 \\ k \neq i}}^{N} FDI_{kjt} = \overline{FDI}_{jt} \cdot N_{jt}. \tag{3}$$

By splitting up the investment of other banks, we acknowledge that the impact of foreign entry on the profitability of domestic banks depends on the number of banks entering rather than on their market share, i.e., the amount that they have invested. Evidence in Claessens, Demirgüc-Kunt, and Huizinga (2001) on the impact of foreign entry on the profitability of the incumbents suggests that the number of competitors matters. Here, we look at a related issue, namely, the impact of the activity of other German banks on new entrants.

4.3.2 Aggregated FDI

Before splitting up the investment of other banks into its components, we use the sum of FDI of others (FDI_{jt}) as an additional regressor. Results are given in columns 1 and 2 of table 2.

Column 1 of table 2 presents the results without including country fixed effects, while column 2 has the results with a full set of country fixed effects. Column 1 shows a positive and significant effect of the FDI of others, but this effect disappears if we include country dummies. Hence, the positive effect reflects omitted variables that capture the general attractiveness of a country. Including country fixed effects even has a significant impact on the sign of the FDI of others: this variable switches from being significantly positive to being significantly negative. Our results thus suggest that the competition effect dominates.

One set of variables that is robust against the inclusion of country fixed effects is the set of bank-specific variables. These remain significant and retain their signs as well as an almost identical magnitude.

Table 2. Regression Results Including Other Banks' FDI

	All Banks	All Banks	All Banks	All Banks
Country Fixed Effects Time Fixed Effects Dummies for Bank Types	NO YES YES	YES YES YES	NO YES YES	YES YES YES
FDI of Others (Residual)	2.92*** (0.52)	−3.71*** (0.84)		
Number of Others (Residual)			0.01 (0.02)	−0.06*** (0.02)
Mean FDI of Others (Residual)			0.04 (0.03)	0.07 (0.05)
Internationalization	0.26*** (0.02)	0.25*** (0.02)	0.26*** (0.02)	0.26*** (0.02)
Assets	8.60*** (0.31)	8.31*** (0.30)	8.51*** (0.31)	8.42*** (0.30)
Profitability	1.56*** (0.13)	1.49*** (0.13)	1.53*** (0.13)	1.52*** (0.13)
Distance	−3.57*** (1.11)	−21.41*** (5.36)	−3.19*** (1.15)	−16.93*** (5.19)
Inflation	0.77*** (0.27)	0.22 (0.41)	0.90*** (0.29)	−0.06 (0.42)
GDP	3.37*** (0.85)	−16.65* (9.43)	3.35*** (0.84)	−3.41 (9.54)

(*continued*)

Table 2 (continued). Regression Results Including Other Banks' FDI

	All Banks	All Banks	All Banks	All Banks
Country Fixed Effects	NO	YES	NO	YES
Time Fixed Effects	YES	YES	YES	YES
Dummies for Bank Types	YES	YES	YES	YES
Trade	0.51***	−1.32***	0.52***	−0.80*
	(0.10)	(0.44)	(0.10)	(0.42)
Risk	−0.17	−0.13	−0.06	0.04
	(0.13)	(0.25)	(0.13)	(0.26)
Freedom	−1.53	4.75**	−1.10	3.52*
	(0.95)	(2.05)	(0.99)	(2.03)
Supervision	0.06	−11.73***	0.20	−9.48**
	(0.42)	(4.12)	(0.42)	(4.08)
Transparency	6.21***	9.58	6.19***	−4.40
	(0.85)	(11.22)	(0.85)	(11.82)
Capital Controls	−1.66	0.42	−2.05	2.00
	(1.74)	(2.96)	(1.75)	(3.02)
EU	−4.29	−35.47***	−1.77	−23.71***
	(2.90)	(9.58)	(2.98)	(8.91)
Number of Non-German Banks	−0.03	0.08	0.48	−0.15
	(0.31)	(2.01)	(0.32)	(2.01)
Banking System Assets/GDP	0.01	−0.01	0.00	0.01
	(0.00)	(0.02)	(0.00)	(0.02)

(continued)

Table 2 (continued). Regression Results Including Other Banks' FDI

	All Banks	All Banks	All Banks	All Banks
Country Fixed Effects Time Fixed Effects Dummies for Bank Types	NO YES YES	YES YES YES	NO YES YES	YES YES YES
Return on Average Equity	0.00 (0.02)	0.05* (0.03)	−0.01 (0.02)	0.01 (0.03)
Concentration	−0.40*** (0.05)	0.01 (0.39)	−0.36*** (0.05)	−0.19 (0.40)
Value Added	−0.38 (0.41)	−0.55 (0.83)	−1.08*** (0.41)	−0.91 (0.85)
Employment Share	3.11* (1.65)	−8.24 (5.08)	6.75*** (1.61)	−11.52** (5.67)
Constant	−300.96*** (34.00)	406.27 (277.78)	−313.21*** (33.89)	52.20 (275.37)
Number of Observations (N * T)	12,540	12,540	12,540	12,540
Adjusted R^2	0.20	0.21	0.19	0.21

Note: See also table 1. "FDI of Others" is the residual of a regression of the FDI of other German banks in a given market on the remaining explanatory variables. "Number of Others" is the residual of a regression of the number of other German banks' affiliates in a given market on the remaining explanatory variables. "Mean FDI of Others" is the corresponding mean amount of investment per banks. Investment of the bank under study has been excluded from these aggregates. Only OECD countries are included. Tobit coefficients are shown instead of marginal effects. Standard errors are shown in parentheses. *, **, and *** are significant at the 10 percent, 5 percent, and 1 percent levels, respectively.

This is not very surprising, given that the country fixed effects are unrelated to bank-specific factors.

Of the variables capturing country characteristics, only one variable is unaffected by the inclusion of country fixed effects: distance remains negative and significant. GDP, trade, and supervision, in contrast, tend to become negative. The indicator of economic freedom, by contrast, now has the expected positive sign. The reason for these changes in signs and significance is that the country-level variables are correlated with the country fixed effects.

4.3.3 Splitting Up Aggregated FDI

Including the aggregated FDI of other banks has the disadvantage of not enabling a distinction to be made between the effects of the number of competitors and those of the average size of their foreign affiliates. To give an example, there might be a country where only a few German banks are active but where these banks have made large foreign investments. Aggregated FDI in this country might be similar to that in a country where many banks operate but where the average volume of investment is small.

Moreover, the number of banks present in a foreign market—rather than the volume of their activities—might affect the competitive structure if banks serve as points of contact. Even if the local banks do not lend themselves, they might still arrange loans through their headquarters at home.

We split up aggregated investment abroad into the number of other German banks' affiliates (*number of others*) and the mean amount of FDI of those banks abroad (*mean FDI of others*), as described in equation (3).[9] Results are given in columns 3 and 4 of table 2. Both components of aggregated FDI are insignificant.[10] For the small banks, however, the average volume of investment of others

[9]Including the number of other banks in addition to the volume of investment also allows us to test the extent to which possible clustering effects are only valuation effects caused by exchange rate changes. Since we find similar results for the volume and the number of FDI, the co-movement of activities abroad is not due to exchange rate valuation effects.

[10]In panel probit regressions (not reported) and in regressions not including mean investment of others, the number of other banks is positive and significant if no country fixed effects are included.

is positive and significant.[11] The remaining results are practically unchanged compared to the baseline regression.

As before, however, the inclusion of a full set of country dummies changes the impact of the activities of other banks. The impact of the number of other banks' affiliates now becomes significantly negative. This effect is driven by the small banks. For the large banks, the effect of the number of other banks remains insignificant. For the small banks, the effect of other banks' mean investment is positive and significant, and this effect is not influenced by the country fixed effects.

Generally, these results are consistent with the hypothesis that the activities of other banks do not capture clustering effects but rather competition effects. The more active German banks are in a foreign market (measured either in terms of their investments or their number), the less attractive this market is to further entrants from Germany. The positive coefficients found in regressions that do not include country fixed effects reflect omitted country effects. At the same time, the positive effect of mean investments of other banks that we find for the small banks suggests that, if anything, clustering effects are more important to small banks than to large banks.

This would be consistent with the model by Barron and Valev (2000) that small banks are more wealth constrained and thus more likely to follow rather than to lead.

4.3.4 Robustness Tests

To check the robustness of our results, we apply a three-step approach. We split our banks into those with a high and a low share of noninterest income, we use a panel probit model and lagged variables to better exploit the time-series dimension of our data, and we include the activities of other nonbanks.

In a first step, we split the banks according to their noninterest income as a percentage of total income from operational business.

[11] This, and the following results of the comparison of large and small banks, is not reported but is available upon request. The results also come from a probit model since the corresponding tobit model did not converge for the small banks.

The purpose of this exercise is to check whether banks that are predominantly commercial banks behave differently from those that are predominantly investment banks. Since German banks are universal banks, no legal classification into commercial and investment banks is available to us. Therefore, banks that receive more than half of their revenue from noninterest income are classified as investment banks, and the others are referred to as commercial banks. Overall, commercial banks according to this definition dominate the sample, and they also dominate the baseline regression results (not reported). There are some interesting differences between the two groups of banks, though. Distance, GDP, and trade are insignificant for the investment banks. Also, regulatory factors such as the degree of transparency do not matter for these banks. Finally, FDI by commercial banks—but not investment banks' FDI—reacts positively to FDI by other German banks, but, as in the full sample, these effects become negative if we include country fixed effects.

In a second step, we run our model as a panel probit model, and we also include lagged terms to capture the time dimension of our data. The main results are unaffected. Also, we largely confirm our earlier finding that other banks' activities have a positive impact when no country fixed effects are included. This positive impact becomes insignificant or even negative, though, if we include country fixed effects.

In a third step, we use the number of nonbanks' affiliates abroad as an additional explanatory variable. The variable has a positive and significant impact on the activities of German banks, which would support the hypothesis that banks are more active in those markets where their customers are. However, after including country fixed effects that control for unobserved country characteristics, this variable becomes insignificant.

5. Summary

In this paper, we have studied why German banks' FDI is concentrated in particular countries. It could be because some countries are inherently attractive or because there are positive clustering effects between banks' activities. Our empirical analysis tries to disentangle these effects by including variables that capture features of the host-country financial and banking systems, proxies for clustering effects, and country fixed effects.

To analyze the determinants of German banks' FDI and to test whether clustering effects matter, we have used detailed bank-level data on the foreign direct investment patterns of German banks. Our study has three main findings.

First, banks are more highly invested in markets where other German banks are active as well. However, this is not due to agglomeration or clustering effects. If country fixed effects are included, other banks' activities have a negative impact on the foreign investment of German banks. These results would be consistent with a competition effect rather than a clustering effect.

Second, if anything, clustering is more important for small banks than for large banks. After including country fixed effects, activities of other banks have an insignificant impact on small banks' investment but a negative impact on large banks' investment. One reason could be that it is more difficult for small banks than large banks to obtain information on foreign markets and that they interpret the behavior of others as a signal regarding the profitability of investment.

Third, we confirm earlier literature with regard to the bank-level and the macroeconomic determinants of foreign banking activities. Larger, more-international, and more-profitable banks have numerous, and large, foreign affiliates. Larger countries and those with close trade links to Germany also attract more FDI from German banks. The impact of regulations and of variables capturing characteristics of the local banking market, though, has been more mixed. A higher degree of concentration and a higher share of value added in financial services, for instance, discourage entry. By contrast, a larger number of incumbent banks and a high share of employment in financial services encourage entry. These overall determinants of FDI are similar for small and large German banks alike.

Appendix. Descriptive Statistics and Regression Results

Table 3. Descriptive Statistics (2003)

A. Summary Statistics				
	Variable	**Observations**	**Mean**	**Standard Deviation**
All Banks	FDI (€ million)	3,080	29.0	709.0
	Profitability (%)	3,080	6.0	3.0
	Internationalization (%)	3,080	17.7	20.1
	Distance (km)	3,080	3,370.3	4,679.1
	Inflation (%)	3,080	3.2	4.2
	Freedom	3,080	3.1	0.8
	Supervision	2,790	3.7	1.6
	Transparency	2,790	2.0	0.8
	GDP (€ billion)	3,080	8,610.0	18,600.0
	Risk	3,080	15.8	13.8
	(Bilateral) Trade/GDP (%)	3,080	12.4	11.8
	Concentration (%)	3,080	76.0	19.1
	Value Added (%) [in 2002]	2,640	4.6	4.1
	Employment Share (%) [in 2002]	2,640	2.1	1.5
	Banking System Assets/GDP (%)	3,080	253.9	352.7
	Return on Average Equity	3,080	12.7	10.5

(continued)

Table 3 (continued). Descriptive Statistics (2003)

A. Summary Statistics (continued)

	Variable	**Observations**	**Mean**	**Standard Deviation**
Small banks	FDI (€ million)	2,324	0.8	8.6
	Profitability (%)	2,324	6.3	3.3
	Internationalization (%)	2,324	15.5	20.8
Large Banks	FDI (€ million)	756	116.0	1,430.0
	Profitability (%)	756	5.2	1.3
	Internationalization (%)	756	24.5	16.0

B. Internationalization of Small and Large Banks

	Small	**Large**	**All**
Number of Banks	83.0	27.0	110.0
FDI			
Amount (€ billion)	1.8	87.5	89.3
Affiliates (number)	99.0	700.0	799.0
Amount per Affiliate (€ million)	18.2	125.0	111.8
FDI/Total Assets (%)	0.35	2.79	2.44
FDI/Yields from Operational Business (%)	6.28	53.19	46.21

Note: We define small banks as those with total assets below €31.4 billion and large banks as those with assets exceeding that value. For the period under study, these cut-off points roughly correspond to the 75% quantile of banks reporting FDI. The number of observations is given as the number of banks times the number of countries times the number of years in the sample.

Table 4. Data Definitions

Variable	**Definition**	**Source**
	Bank-Level Variables	
FDI	Sum of primary and secondary direct investment in equity capital minus profits/losses for the current financial year (in €). For banks acting as direct investors, loans and trade credits owed by an affiliate (i.e., loan capital for nonbank investors) are typically not counted as FDI. We therefore only use FDI in equity capital. The original data include profit and losses for the current financial year, as the data are taken from the balance sheet before the allocation of net income. The "original" FDI data thus include profits to be distributed and thus part of the profits to be repatriated. Since we do not want to count these profits as FDI, profits or losses for the current financial year are deducted. Therefore, reinvested earnings appear in next year's revenue reserves or in the profits carried forward.	Deutsche Bundesbank MiDi Data (Micro Database Direct Investment)
Internationalization	Sum of cross-border claims and liabilities over total claims and liabilities (both in €).	Deutsche Bundesbank (Monthly Banking Statistics)
Profitability	Yields from operational business (interest income plus current income from shares/securities plus provisions) over total assets (all in €).	
Assets	Total assets (in €).	
Savings Bank	Dummy: 1 for savings banks; otherwise 0.	
Cooperative Bank	Dummy: 1 for cooperative banks; otherwise 0.	

(*continued*)

Table 4 (continued). Data Definitions

Variable	**Definition**	**Source**
	Market Size	
(Bilateral) Trade	Sum of bilateral trade (exports plus imports) (in €) over GDP (in USD converted to €).	Deutsche Bundesbank, OECD
GDP	Gross domestic product (in USD converted to €).	OECD
	Geographical and Cultural Distance	
Distance	Great circle distance between Berlin and other capital cities (in km).	U.S. Dept. of Agriculture, http://www.wcrl.ars.usda.gov/cec/java/capitals.htm
	Characteristics of Host-Country Financial Market	
All Non-German Banks	Total number of banks in the host country minus affiliates of German banks (in logs). Data are available for the years 1996–2003.	OECD (2005)
Share of Banks	Assets of the banking system (only banks with assets of more than €1 billion are included) relative to host-country GDP (in %). Data are available for the years 1998–2003.	Bankscope, OECD
Return on Average Equity	Only banks with assets of more than €1 billion are included. Data are available for the years 1998–2004.	Bankscope
Concentration	Assets of the five largest banks relative to total assets of the banking system (only banks with assets of more than €1 billion are included) (in %). Data are available for the years 1998–2004.	Bankscope

(continued)

Table 4 (continued). Data Definitions

Variable	**Definition**	**Source**
	Characteristics of Host-Country Financial Market (continued)	
Traded Stocks	Value of traded stocks relative to GDP (in %).	World Bank (2005)
Value Added	Share of value added in the financial services sector (ISIC Rev. 3 Sector 65: "Financial intermediation, except insurance and pension funding") relative to total value added (in %). Data are available for the years 1979–2002.	Groningen Growth and Development Centre, 60-Industry Database, February 2005, http://www.ggdc.net
Employment Share	Share of employment in the financial services sector (ISIC Rev. 3 Sector 65: "Financial intermediation, except insurance and pension funding") relative to total employment (in %). Data are available for the years 1979–2002.	
	Stability and Regulations	
Inflation	GDP deflator.	OECD
Risk	Composite index of country risk. The index is composed as follows: 25% political risk, 25% economic performance, 10% debt indicators, 10% debt in default/rescheduled, 10% credit ratings, 5% access to bank finance, 5% access to short-term finance, 5% access to capital markets, 5% discount on forfeiting. The original variable takes values from 100 (low risk) to 0 (high risk). The risk index used here has a lower score when country risk is small, i.e., we transformed the original data using $x' = 100 - x$.	*Euromoney* (various issues).
Freedom	Index of Economic Freedom in Banking. The index used here runs from 1 to 5, and a lower value indicates a more regulated system, i.e., we have transformed the original index values using $x' = 5 - x$.	Heritage Foundation (2005)

(*continued*)

Table 4 (continued). Data Definitions

Variable	Definition	Source
Stability and Regulations (continued)		
Capital Controls	0–1 dummy variable for the existence of controls for cross-border financial credits.	IMF (various issues)
EU	Dummy: 1 for EU member states; otherwise 0.	—
Supervision	Index of toughness of banking supervisors, which has been computed as the sum of 1–0 dummies capturing the following aspects: (i) Are supervisors legally liable for their actions? (ii) Can the supervisory agency supersede bank shareholder rights and declare a bank insolvent? (iii) Can the supervisory agency order directors/management to form provisions to cover actual/potential losses? (iv) Can the supervisory agency suspend dividends? (v) Can the supervisory agency suspend bonuses? (vi) Can the supervisory agency suspend management fees? The index runs from 0 to 6, and a higher value indicates greater supervisory power.	Barth, Caprio, and Levine (2001), own calculations
Transparency	Index of disclosure requirements in the banking industry, which has been computed as the sum of 1–0 dummies capturing the following aspects: (i) Are consolidated accounts covering bank and any nonbank financial subsidiaries required? (ii) Are off-balance-sheet items disclosed to the public? (iii) Must banks disclose risk management procedures to the public? (iv) Do regulations require credit ratings for commercial banks? The index runs from 0 to 4, and a higher value indicates greater transparency.	Barth, Caprio, and Levine (2001), own calculations

Note: All data denominated in foreign currencies (e.g., the data retrieved from the World Bank's *World Development Indicators* CD-ROM) are converted into euros. For the 1997–98 period, foreign currencies are converted into Deutsche marks and then into euros, using the fixed conversion rate for the Deutsche mark, which is DM 1.95583/€1. For year-end data, year-end exchange rates are used, whereas other data such as the GDP numbers are converted using the average exchange rates of the year in question.

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Factor Model Forecasts for New Zealand*

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This paper focuses on forecasting four key New Zealand macroeconomic variables using a dynamic factor model and a large number of predictors. We compare the (simulated) real-time forecasting performance of the factor model with a variety of other time-series models (including the Reserve Bank of New Zealand's published forecasts), and we gauge the sensitivity of our results to alternative variable-selection algorithms. We find that the factor model performs particularly well at longer horizons.

JEL Codes: C32, E47.

1. Introduction

Each quarter, the Reserve Bank of New Zealand assesses the state of the economy and publishes forecasts in its *Monetary Policy Statement*. The Bank has a multitude of economic and financial data at its disposal (over 6,000 series), all of which can be used to glean information about the economy. Yet, experience suggests that the usefulness of these data varies widely, both across the different series and over time. Indicators with good predictive ability over history may break down when used in forecasting, while indicators that were not so useful in the past may prove to be the most useful in the future. Forecasting is thus fraught with difficulties; the informational content of each piece of data is small and, importantly, unknown to the forecaster in real time.

*I have benefited from discussions with various members of the Economics Department of the Reserve Bank of New Zealand. I would especially like to thank Anne Guan and Madeline Penny for their excellent research assistance, and Shaun Vahey and Christie Smith for useful comments on earlier drafts. Any errors and omissions are entirely my own, and the views expressed in the paper are not necessarily those of the Reserve Bank of New Zealand. Author contact: E-mail: troy.matheson@rbnz.govt.nz; Tel: 64 4 471 3859.

The time-series models used in forecasting typically only incorporate a small handful of variables, chosen using a variety of different selection procedures. The final variables selected are thus considered representative of a larger population of potentially useful series. Recently, however, methods have been developed to distill information from a very large data set into a few variables (called factors). Forni et al. (2000, 2004) and Stock and Watson (1998), for example, examine the properties of generalized dynamic factor models, based on the dynamic factor models of Sargent and Sims (1977) and Geweke (1977). In a series of papers, Stock and Watson (1998, 1999, 2002) use factor models to combine information from large panels of macroeconomic data in the United States, then use the estimated factors to forecast future realizations of a variety of macroeconomic series. In factor models a huge variety of series are used to identify the latent drivers—the factors—that are common to all of the series. These factors can then be used to forecast particular series of interest, such as GDP and inflation. Stock and Watson find that this two-step procedure yields forecasts that compare favorably to a large number of other univariate, bivariate, and multivariate benchmarks (according to comparisons of mean-squared forecast errors, or MSFEs). Stock and Watson's (1999) results are particularly striking when forecasting inflation.

With similarly impressive results, Forni et al. (2001) and Marcellino, Stock, and Watson (2003) use factor models to analyze large panels of euro-area data, while Artis, Banerjee, and Marcellino (2002) use factor models to forecast economic and financial variables for the United Kingdom.

In this paper, we examine—for the first time—the forecasting performance of factor models in the New Zealand context. We also analyze the forecasting performance of a range of other univariate, bivariate, and multivariate forecasts. Forecasts are made for four key macroeconomic variables (the consumer price index, gross domestic product, the ninety-day interest rate, and the trade-weighted nominal exchange rate), and the performance of competing models is tested using fully recursive real-time out-of-sample forecast simulations. In all cases, our forecasts are compared with a relatively sophisticated benchmark—the real-time forecasts published by the Reserve Bank of New Zealand.

The data set is important in determining the quality of factor model forecasts. Boivin and Ng (2003) show that extracting factors from larger data sets does not always yield better forecasting performance, and they propose some rules to reduce the size of their data set before factors are extracted. They show that forecasting performance can be improved by removing (or downweighting) series with highly cross-correlated errors in the factor model and by categorizing the data into subgroups with an economic interpretation (real and nominal variables, for example). Conceptually, it seems reasonable to exclude series that deteriorate the overall quality of the data set. Boivin and Ng also note that the choice of data is not innocuous. The factors are defined with respect to a specific data set and depend on the exercise at hand: two researchers can end up with different factor estimates by choosing different data sets at the outset of the estimation exercise.

Stock and Watson (1999), for example, show that a single factor extracted from a broad-based data set produces very good forecasts of inflation one year ahead. But the factors extracted from Stock and Watson's data set are by no means guaranteed to be good at forecasting other macroeconomic variables or even inflation at a horizon other than one year ahead.

This paper aims to forecast a variety of variables at different horizons. Since it is not at all clear how to go about finding the appropriate data to use when constructing factor model forecasts in these circumstances, we propose two simple rules that link the dimension of the data set to the particular variable and the particular horizon being forecast. Effectively, our rules group series together based on their past predictive performance, thereby aiming to tailor each data set to the particular task at hand—forecasting.

We find that the factor model performs well and can serve as a useful complement to the Reserve Bank's current forecasting methodologies, especially at longer horizons. We also find that our data-reduction rules yield superior forecasts at some horizons.

The paper proceeds as follows. We begin with a general description of the factor model. This is followed by a description of our data. We then outline an algorithm that we use to vary the size of the data set from which the factors are extracted. In section 4 we lay out our forecasting models, and section 5 describes our out-of-sample forecasting exercise. Section 6 contains our empirical findings, and we conclude in section 7.

2. An Approximate Dynamic Factor Model

2.1 The Factor Model

In this section, we outline the generalized factor model. For a more detailed description of factor models, their estimation, and their use in forecasting, see Stock and Watson (1998).

Let X_{it} be the observed data for the ith macroeconomic time series at time t, for $i = 1, \ldots, N$ and $t = 1, \ldots, T$. Now suppose X_{it} has an approximate linear dynamic factor representation with $\bar{r}$ common dynamic factors (f_t):

$$X_{it} = \lambda_i(L) f_t + e_{it}, \tag{1}$$

where e_{it} is an idiosyncratic component, and $\lambda_i(L)$ are polynomials of nonnegative powers of the lag operator L, where $Ly_t = y_{t-1}$. This model is the dynamic factor representation of the data; see, for example, Geweke (1977), Sargent and Sims (1977), and Forni et al. (2000, 2004). If the lag polynomials $\lambda_i(L)$ are assumed to have finite orders of at most q, (1) can be written in static form:

$$X_t = \Lambda F_t + e_t. \tag{2}$$

In the above equation, $X_t = (X_{1t}, X_{2t}, \ldots, X_{Nt})'$, $\Lambda = (\lambda_1, \lambda_2, \ldots, \lambda_N)'$, $F_t = (f_t', \ldots, f_{t-q}')'$, and $e_t = (e_{1t}, e_{2t}, \ldots, e_{Nt})'$ (Stock and Watson 1998). Note that the factors F_t, the loadings Λ, and the disturbances e_t are not observable. When the idiosyncratic components e_{it} are allowed to be correlated across i, the model is said to have an approximate factor structure. Approximate factor models are more general than the strict factor model used in classical factor analysis, which assumes e_{it} is uncorrelated across i (Bai and Ng 2002).

2.2 Estimation

When N is small, factor models are often expressed in state-space form and estimated using the Kalman filter (Stock and Watson 1989). The drawback with this is that the number of parameters to be estimated, and the difficulty of the estimation problem, increases with N. Stock and Watson (1998), however, show that common factors can be consistently estimated in large panels using asymptotic principal components. The number of factors that can be estimated using this method is then $\min\{N, T\}$—much larger than is permitted by state-space models. We use asymptotic principal components to estimate our factors.

An estimated factor can be thought of as a weighted average of the variables in a data set, where the weights (the loadings) can be either positive or negative and reflect how correlated each variable is with each factor. Factors are extracted in a sequential fashion, with the first factor explaining the most variation in the data set, the second factor explaining the next most variation (not explained by the first factor), and so on. Factor models thus aim to summarize the information contained in a data set in a parsimonious fashion. The idea is to reduce the size of the data set to a few variables that can be considered representative of the key features of the data set as a whole.

Bai and Ng (2002) propose several information criteria for estimating the number of factors that should be extracted. However, in preliminary work, we found that these criteria typically retained a large number of factors—too many to include in the forecasting equation without running low on degrees of freedom. Instead of using the Bai and Ng criteria, we thus extract a fixed number of factors from the data and allow the final number of factors to be determined by a criterion that minimizes the MSFEs, as in Stock and Watson (1998, 2002).

3. Data

This section describes the macroeconomic variables that we forecast. It also describes how we vary the size of the data set, based on the past predictive ability of the indicators (explained below).

We forecast four series (z_t): the growth rate of the consumer price index excluding credit charges (CPI); the growth rate of real gross domestic product (GDP); the level of ninety-day bank-bill interest rates; and the growth rate of the nominal trade-weighted exchange rate index. All data are analyzed at a quarterly frequency. Our sample period ranges from 1992:2 to 2004:3. We forecast at horizons between one and eight quarters ahead, $h = (1, \ldots, 8)$.

The raw indicator set contains 384 series drawn from a variety of sources (appendix 1). The set of indicators is compiled from the Reserve Bank's databases and consists of both monthly and quarterly data. All monthly data are aggregated into quarterly data using monthly averages.

Both forward-looking and backward-looking indicators of economic activity and prices are incorporated into the data set, although special attention is given to activity-related, forward-looking variables.[1] Some of the series were included at the finest level of disaggregation possible, as well as in aggregate form, while other series were only included as aggregates. Broadly speaking, the forward-looking series are included at their finest level of disaggregation, and the backward-looking variables are included only as aggregates. Series considered to display excessive volatility in disaggregate form were only included as aggregates.

All series in the raw data set are seasonally adjusted using X12 (additive). The series are then transformed to account for stochastic and deterministic trends; the I(1) series are logged and then differenced, and the I(0) series are left as levels.

3.1 Varying the Size of the Data Set Based on Past Predictive Performance

So how does the number of series in the data set influence the factor model's forecasting performance? This remains an open question in the empirical literature. Thus far, the empirical work tends to favor using as much data as possible to estimate factors, and for good reason—the theory of factor model estimation was developed for large N and T. Boivin and Ng (2003), however, show that extracting factors from larger data sets does not always yield better forecasting performance, especially when the added data increases cross-section correlation in the idiosyncratic errors. Indeed, conceptually, it seems reasonable to exclude those series that are in some sense idiosyncratic—those series whose inclusion deteriorates the overall quality of the data set.

[1] Stock and Watson (1999) found that data relating to real activity performed well when forecasting inflation.

Boivin and Ng (2003) reduce the size of their empirical data set using rules based on removing (or downweighting) series with highly cross-correlated errors in the factor model and rules based on categorizing the data into subgroups with an economic interpretation (real and nominal variables, for example). They show that both of these methods can produce more efficient estimates of the factors and better forecasts.

Nevertheless, estimated factors are data dependent and not guaranteed to be good at forecasting, certainly not over a variety of variables at different horizons. We thus propose a simple approach that aims to tailor the data to the particular variable and the particular horizon being forecast.

Explicitly, for each forecast horizon h, each stationary forecast variable y_t, and each potential indicator $x_{i,t}$, where $h = (1, \ldots, 8)$ and $i = (1, \ldots, 384)$, the following equation is estimated using OLS:

$$y_t = \beta_0 + \beta_1 x_{i,t-h} + e_{i,t}. \tag{3}$$

The R-squareds (the coefficients of determination) from these bivariate regressions are then used to sort the indicators from most to least informative.

We then reduce the size of our data set by categorizing our data based on past predictive performance. Specifically, we choose to "cut off" the top proportion θ of the ranked indicators and only allow these indicators to enter into our data set, with $\theta = (5\%, 10\%, 50\%, 100\%)$. The smallest data set contains the top 5 percent of the ranked indicators, and the largest data set contains all 386 indicators. We then extract factors from these different-sized data sets.

We also report a variation on this procedure that combines Boivin and Ng's (2003) idea of estimating the factor model first (before reducing the size of the data set) with the rule suggested above. In this second rule, the factor model is estimated over the entire data set, and then the common component of each indicator (the projection of each indicator on the factors) is used in (3), instead of the indicator itself.[2] The ranked indicators resulting from

[2]Thanks to an anonymous referee for suggesting this hybrid criterion. Eight factors are extracted in the initial step.

this rule are ensured to have large common components from the entire data set relative to the previous rule. However, if there is some useful information for forecasting purposes outside the common components, it may be that this rule does not perform as well.

We call the first selection criterion the *one-step* rule (estimate (3) using each indicator) and the second selection criterion the *two-step* rule (estimate the factor model, then estimate (3) using the common component from each indicator). Note that the rules are identical when $\theta = 100\%$.

Effectively, by allowing all of the indicators, $\theta = 100\%$, into a data set, we assume that all of the data have some information useful for forecasting the particular variable at the particular horizon we are interested in. Conversely, by trimming the size of the data sets based on R-squared, we impose a zero weight on those indicators that share lower common variance with the variable and horizon being forecast. In this way we hope to better estimate the factors driving each variable on a case-by-case basis—we hope to tailor each data set to the particular forecasting problem at hand.

Analysis of the first two factors extracted from the entire data set, $\theta = 100\%$, shows that the first factor loads highly on indicators of real economic activity. The time profile of the first factor also looks similar to real GDP growth over our sample period, suggesting that it can be broadly interpreted as a measure of real economic activity, consistent with Stock and Watson's (2002) findings for the United States (figure 1). The second factor, on the other hand, loads highly on more direct measures of pricing pressure—price and inflation expectations, etc.

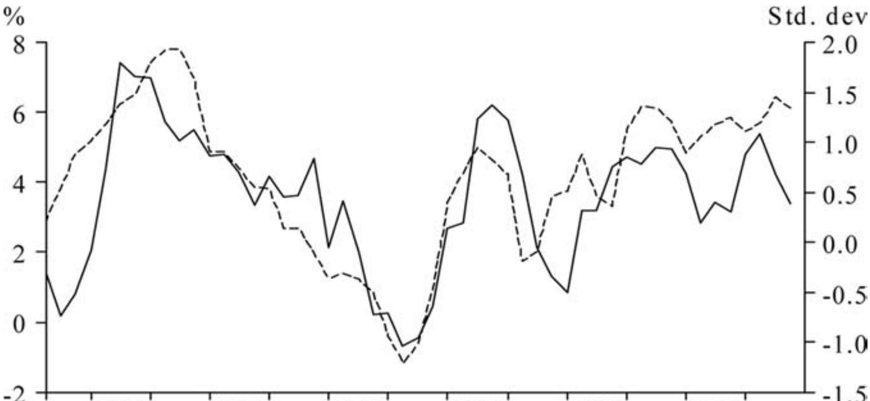
4. Forecasts

This section outlines the forecasts we compare in our analysis, beginning with a general description of our forecasting model.

4.1 The h-step-ahead Forecast

Aside from the vector autoregressive and the Reserve Bank of New Zealand forecasts, all of the forecasts that we analyze are based

Figure 1. The First Factor from the Entire Data Set and GDP Growth



on h-step-ahead linear projections. Specifically, the h-step-ahead variable y^h_{t+h} is forecast using the following regression model:

$$y^h_{t+h} = \phi + \beta(L) f_t + \gamma(L) y_t + e^h_{t+h}, \tag{4}$$

where e^h_{t+h} is an error term, ϕ is a constant, $\beta(L)$ and $\gamma(L)$ are lag polynomials, and f_t is a vector of predictor variables; the interpretation of f_t depends on the particular model being used. The construction of y^h_{t+h} depends on whether the series of interest z^h_{t+h} is modeled as being I(0) or I(1). If z^h_{t+h} is modeled as I(0),

$$y^h_{t+h} = z^h_{t+h} \text{ and } y_t = z_t. \tag{5}$$

If z^h_{t+h} is modeled as I(1),

$$y^h_{t+h} = \ln\left(\frac{z^h_{t+h}}{z^h_t}\right) \text{ and } y_t = \ln\left(\frac{z_t}{z_{t-1}}\right) \tag{6}$$

or

$$y^h_{t+h} = z^h_{t+h} - z^h_t \text{ and } y_t = z_t - z_{t-1}. \tag{7}$$

We model the CPI, the GDP, and the exchange rate using (6), and we model the interest rate using (7).[3]

4.2 Forecasting Models

The range of different forecast models that we estimate is discussed below.

4.2.1 Autoregressive Forecasts

The autoregressive forecast *far* is based on (4), excluding f_t. As is commonplace in the literature, we choose the lag length according to a Schwartz Bayesian information criterion (BIC), with lags varying from zero to four: the largest autoregressive model possible includes four lags and a constant, and the smallest includes only a constant.

4.2.2 Bivariate Forecasts

We construct bivariate forecasts for each indicator. In the bivariate regressions, f_t in (4) becomes a single indicator $x_{i,t}$. For each bivariate forecast, we allow one to four lags of $x_{i,t}$ and zero to four lags of the dependent variable y_t, with all the lags selected using the BIC. The BICs for all bivariate indicator equations are then ranked. The best bivariate indicator *fbiv_best* is found, along with the mean *fbiv_mean* and median *fbiv_med* forecasts from the top 5 percent and 10 percent of the ranked bivariate indicators.[4] These 5 percent and 10 percent cut-off points correspond to the first two θ cut-offs that we use to vary the size of our data set when we extract factors.

4.2.3 Factor Model Forecasts

We analyze three different variants of factor model forecasts, similar to Stock and Watson (2002). The first variant excludes lagged dependent variables and explores forecasts when different numbers of

[3] Modeling the ninety-day interest rate in differences is supported by evidence of a falling neutral real interest rate in New Zealand over our sample period (Basdevant, Björksten, and Karagedikli 2004).

[4] In a cross-country forecasting exercise, Stock and Watson (2004) found that the simple average of indicator forecasts outperformed a wide range of different methods of combining forecasts, when forecasting output growth.

contemporaneous factors k are included. In this group of forecasts, equation (4) is estimated with k contemporaneous factors, with k ranging from one to four *fdi_k*. In (4) $\beta(L)f_t$ becomes βf_t, where f_t is a $k \times 1$ vector of factors. We then define *fdi_bic* to be the forecast where k is chosen by the BIC.

The second set of factor forecasts is similar to the first but allows the BIC to select between zero and four lags of the dependent variables. These forecasts are denoted *fdiar_k* for fixed k and *fdiar_bic* where k is chosen by the BIC.

The third factor forecast, *fdiarlag_bic*, is the most general. Here, we allow the BIC to determine the number of factors (one to four), the number of lagged factors (zero to two), and the number of lags of the dependent variable (zero to four). Together, we estimate forty-four different factor models for each horizon (and for each data-reduction rule): the eleven models outlined above over the four different data set cut-offs (θ).

4.2.4 Vector Autoregressive (VAR) Forecasts

The VAR forecasts, *fvar*, are computed from a system containing each of our four forecast variables. The VAR is estimated in levels, and the number of lags of the endogenous variables is set at two. VAR forecasts are made by iterating forecasts forward, unlike in the h-step-ahead method we use for our other forecasting models.

4.2.5 Reserve Bank Forecasts

The Reserve Bank forecasts, denoted *rbnz*, are the real-time forecasts published in the Reserve Bank's quarterly *Monetary Policy Statement*. The forecasts are a combination of model-based forecasts and judgment. There is a distinction between how the Reserve Bank forecasts over the near term (one to two quarters ahead) and how it forecasts over longer horizons. The Reserve Bank's near-term forecasts can be characterized as being more judgment and indicator based. The longer-term forecasts, on the other hand, are made with the help of a large-scale macroeconomic model, the Reserve Bank's Forecasting and Policy System (FPS).[5]

[5]See Drew and Hunt (1998) for a detailed description of FPS.

5. Out-of-Sample Forecast Comparisons

Our forecasts are compared using a fully recursive simulated out-of-sample methodology. For these simulations, we transform all data and estimate all equations for each quarter from 1999:4 to 2004:3. These forecasts are then tested against the ex post data from 2000:1 to 2004:4. The real-time exercise is more "pure" than is common in the literature since the raw data are seasonally adjusted each quarter, thereby mimicking the real-time problems associated with estimating seasonal factors. Also, we use real-time vintages of our forecast series in estimation—the data that were available when such forecasts would have been made.

For each of our forecasts, we compute the implied levels of the forecast variables; the CPI growth forecasts, for example, are transformed into CPI level forecasts, i.e., $z^h_{t+h} = z_t(1 + y^h_{t+h})$. We then construct annual percentage changes for the CPI, the GDP, and the exchange rate, leaving the interest rate in levels. These are the forecasts that we compare in our real-time simulations: y^h_{t+h} for the CPI becomes the annual percentage change of the CPI in period $t + h$; likewise for the other variables, except interest rates, which are left as levels. The data against which we compare our real-time forecasts are displayed in figure 2.

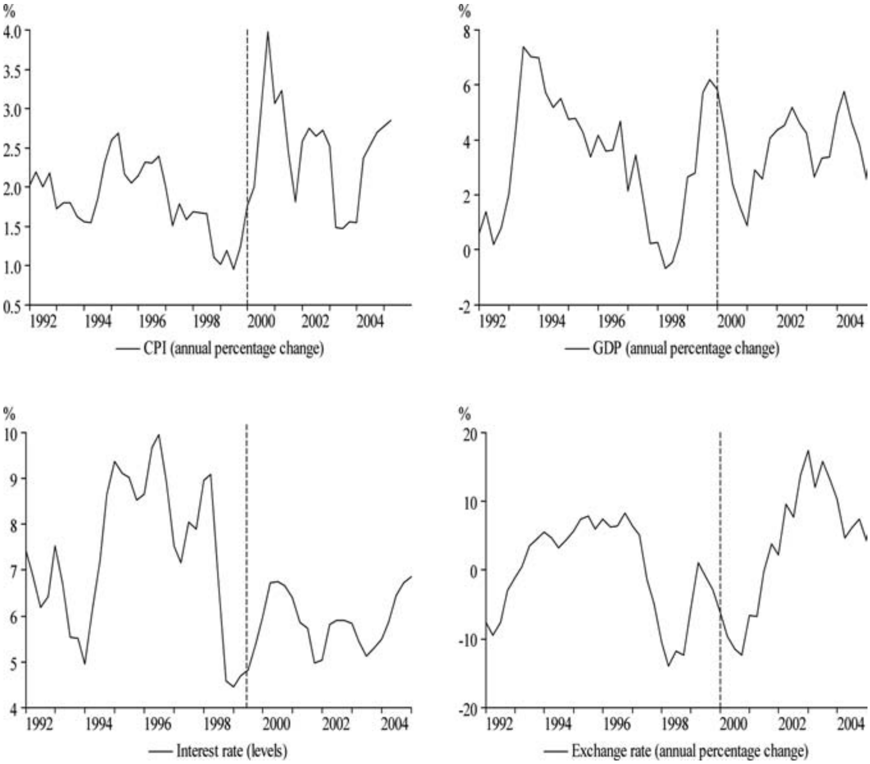
The forecasting performance of a candidate forecast is evaluated by comparing its out-of-sample MSFE to a Reserve Bank of New Zealand benchmark. For an h-step-ahead forecast, the MSFE of a candidate model i relative to the benchmark Reserve Bank forecast 0 is

$$MSFE\_relative = \frac{\sum_{t=T_1}^{T_2-h}\left(\hat{y}^h_{i,t+h} - y_{t+h}\right)^2}{\sum_{t=T_1}^{T_2-h}\left(\hat{y}^h_{0,t+h} - y_{t+h}\right)^2}, \tag{8}$$

where T_1 and $T_2 - h$ are the first and last dates over which the out-of-sample forecasts are compared, respectively. We test whether the MSFE of the candidate model is significantly smaller than that of the Reserve Bank using methods described in Diebold and Mariano (1995). Specifically, we test whether the difference in MSFEs between the benchmark and the candidate model is negative, i.e.,

$$\text{Null Hypothesis: } E[\varepsilon_t] = 0 \tag{9}$$

Figure 2. The Ex Post Data



against

$$\text{Alternative Hypothesis: } E[\varepsilon_t] < 0, \tag{10}$$

where

$$\varepsilon_t = \left(\hat{y}^h_{i,t+h} - y_{t+h}\right)^2 - \left(\hat{y}^h_{0,t+h} - y_{t+h}\right)^2. \tag{11}$$

As above, the subscript i refers to a candidate model and the subscript 0 refers to forecasts from the Reserve Bank of New Zealand.[6]

[6]The variance of the mean difference in MSFEs is estimated using the Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) estimator, with a truncation lag of $(h-1)$. The test statistic is compared to a Student-t distribution with $(T-1)$ degrees of freedom.

6. Empirical Results

In this section, we include a table displaying the results for the models other than the factor model (*far*, *fvar*, *fbiv_best*, *fbiv_mean*, and *fbiv_med*) (table 1) and a table displaying the results for the simplest factor model forecast (*fdi_1*) (table 2). All other results can be found in appendix 2. We report the forecast comparisons for each of the macroeconomic variables. Our statistical tests yield disappointingly few significant results, even though we use quite liberal levels of significance. We thus prefer to discuss the results in a descriptive manner. We leave a more rigorous statistical analysis of the competing models (and data sets) for the future, when more time-series data are available.

6.1 CPI Inflation

In general, the Reserve Bank forecasts have lower MSFEs at shorter horizons, $h < 5$. At longer horizons, however, some of the forecasting models begin to outperform the benchmark. As noted by Stock and Watson (2002) for the United States, we find that models that incorporate one or two factors (with or without autoregressive terms) generally perform better than models that allow for more factors. Models that allow for multifactors and lags of the factors *fdiarlag_bic* perform the worst out of the competing models. Similarly, forecasting using the best bivariate indicator at each horizon *fbiv_best* yields poor results.

The mean and median bivariate forecasts, *fbiv_mean* and *fbiv_med*, and the VAR forecast, *fvar,* compare favorably to both the Reserve Bank and the factor model forecasts, especially at longer horizons. It also seems that small gains can be made by averaging or taking the median of a larger number of bivariate indicators, i.e., when $\theta = 10\%$, rather than $\theta = 5\%$. At longer horizons, the simple autoregressive model *far* also performs well relative to most models—including the Reserve Bank benchmark.

At shorter horizons, extracting factors from the entire data set, $\theta = 100\%$, leads to better forecasts than when the factor model is restricted to a smaller data set of "better" indicators. When $h = 8$, however, the factor models seem to perform better with fewer indicators. Thus, there does not seem to be any clear relationship

Table 1. MSFEs Relative to Reserve Bank

				$\theta = 5\%$		$\theta = 10\%$	
	far	**fvar**	**fbiv_best**	**fbiv_mean**	**fbiv_med**	**fbiv_mean**	**fbiv_med**
CPI							
$h = 1$	3.28	3.42	4.18	3.71	3.66	3.66	3.60
2	1.55	1.83	1.96	1.70	1.62	1.70	1.63
3	1.38	1.30	2.29	1.58	1.56	1.54	1.48
4	1.29	1.14	2.80	1.53	1.46	1.54	1.47
5	**0.84**	**0.76**	1.51	**0.98**	**0.99**	1.00	**0.98**
6	**0.64****	**0.45**	1.69	**0.88**	**0.89**	**0.88**	**0.85**
7	**0.57***	**0.58**	2.73	**0.61**	**0.54**	**0.53***	**0.56***
8	**0.61**	**0.98**	3.25	**0.81**	**0.74**	**0.65**	**0.53**
GDP							
$h = 1$	2.12	1.69	2.53	2.07	2.02	2.02	1.98
2	1.54	1.75	2.15	1.33	1.53	1.28	1.49
3	1.23	1.81	1.95	1.11	1.22	1.07	1.08
4	**0.96**	2.08	1.00	**0.60***	**0.66**	**0.64***	**0.71**
5	**0.57***	**0.90**	**0.87**	**0.72**	**0.75**	**0.54***	**0.59**
6	**0.59****	1.29	1.14	**0.63**	**0.65**	**0.65**	**0.71**
7	**0.87**	1.25	7.56	1.59	1.23	1.45	1.05
8	1.07	1.59	6.29	1.69	1.21	1.32	1.22
Interest Rate							
$h = 1$	16.19	27.50	50.45	23.55	22.49	18.67	19.32
2	4.18	7.30	20.25	7.94	7.20	5.92	5.45
3	2.07	4.96	11.19	3.41	3.65	2.98	3.09
4	1.25	3.94	1.99	1.29	1.65	1.30	1.49
5	**0.76**	2.72	1.70	**0.72**	**0.93**	**0.56**	**0.75**
6	**0.40****	2.62	2.36	**0.59**	**0.70**	**0.49**	**0.55**
7	**0.25****	3.52	2.06	**0.76**	**0.71**	**0.58**	**0.60**
8	**0.21**	4.20	2.58	**0.75**	**0.62**	**0.72**	**0.66**

(*continued*)

Table 1 (continued). MSFEs Relative to Reserve Bank

				$\theta = 5\%$		$\theta = 10\%$	
	far	**fvar**	**fbiv_best**	**fbiv_mean**	**fbiv_med**	**fbiv_mean**	**fbiv_med**
Exchange Rate							
$h = 1$	8.34	9.03	12.18	7.06	7.65	6.97	7.33
2	1.69	2.04	2.24	1.20	1.22	1.21	1.28
3	1.28	1.94	2.15	1.00	1.02	1.03	1.07
4	1.32	1.88	2.17	1.46	1.50	1.30	1.36
5	1.13	1.79	2.49	1.54	1.46	1.22	1.31
6	1.39	2.32	1.92	1.82	1.69	1.68	1.68
7	2.23	3.52	5.22	2.28	2.25	2.00	2.11
8	2.13	3.88	5.77	2.12	2.39	2.34	2.43

Note: ** denotes significance at the 5 percent level. * denotes significance at the 10 percent level.

Table 2. MSFEs Relative to Reserve Bank—*fdi_1*

Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
CPI							
$h = 1$	3.50	3.41	3.05	3.60	3.80	3.03	2.87
2	2.05	1.84	1.68	2.09	1.99	1.71	1.60
3	1.41	1.48	1.53	1.79	1.66	1.55	1.42
4	1.45	1.47	1.45	1.91	1.70	1.48	1.38
5	1.14	1.05	**0.94**	1.33	1.25	**0.96**	**0.89**
6	1.07	**0.97**	**0.73**	1.10	1.06	**0.76**	**0.69**
7	**0.89**	**0.77**	**0.65**	**0.87**	**0.82**	**0.66**	**0.62***
8	**0.67**	**0.71**	**0.73**	**0.68**	**0.72**	**0.72**	**0.74**

(continued)

Table 2 (continued). MSFEs Relative to Reserve Bank—*fdi_1*

Cut-Off Criterion	One-Step			Two-Step			None
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
GDP							
$h = 1$	2.02	2.00	1.83	1.92	2.04	1.80	1.73
2	1.67	1.63	1.36	1.67	1.62	1.31	1.35
3	1.28	1.21	**0.93**	1.22	1.21	**0.93**	**0.97**
4	**0.97**	**0.84**	**0.66**	**0.94**	**0.81**	**0.64**	**0.66**
5	**0.57****	**0.56****	**0.48****	**0.67***	**0.60****	**0.48****	**0.46****
6	**0.55****	**0.61***	**0.74**	1.02	**0.88**	**0.74**	**0.65***
7	**0.67****	**0.71**	1.05	1.20	**0.88**	1.04	**0.99**
8	**0.77****	**0.82**	1.28	1.63	**0.95**	1.27	1.28
Interest Rate							
$h = 1$	25.10	24.58	21.25	25.72	24.63	21.83	20.52
2	7.53	7.06	5.55	7.19	6.86	5.86	5.28
3	4.53	4.08	3.19	5.79	4.70	3.29	2.92
4	2.62	2.16	2.05	3.20	2.71	2.01	2.03
5	1.45	1.14	1.11	1.38	1.40	1.10	1.25
6	1.11	**0.75**	**0.67**	1.08	**0.85**	**0.67**	**0.77**
7	1.13	**0.73**	**0.50**	1.30	**0.90**	**0.52**	**0.54**
8	**0.77**	**0.65**	**0.45**	1.33	**0.83**	**0.47**	**0.40**
Exchange Rate							
$h = 1$	7.45	6.62	5.71	6.71	6.10	5.77	5.71
2	1.35	1.20	1.08	1.27	1.22	1.06	1.09
3	1.05	**0.99**	**0.93**	1.08	**0.93**	**0.89**	**0.95**
4	1.20	1.09	1.05	1.14	1.07	1.02	1.11
5	**0.91**	**0.87**	**0.95**	**0.86**	**0.77**	**0.90**	1.01
6	1.16	1.06	1.14	**0.95**	**0.93**	1.12	1.22
7	1.59	1.56	1.59	1.36	1.45	1.60	1.64
8	2.17	2.32	2.00	2.24	2.03	2.03	2.04

Note: ** denotes significance at the 5 percent level. * denotes significance at the 10 percent level.

between the size of the data set, as represented by θ, and forecast performance. Likewise, it is not clear which data-reduction rule (the one-step rule or the two-step rule) produces the best factor model forecasts; for some models and some horizons the one-step rule seems to be preferable, and for other models and other horizons the two-step rule appears to be better.

6.2 GDP Growth

Similar to CPI inflation, the Reserve Bank forecasts outperform the competing models at shorter horizons ($h < 3$), and at longer horizons the competing models begin to outperform the Reserve Bank benchmark forecasts. Also, it appears that including only one or two factors (with or without autoregressive terms) generally leads to better forecasts. The VAR model *fvar*, models that allow for multifactors and lags of the factors *fdiarlag_bic*, and the best bivariate model at each horizon *fbiv_best* yield poor forecasts.

As with the results for CPI inflation, the mean, median, and autoregressive forecasts—*fbiv_mean*, *fbiv_med*, and *far*—compare favorably to both the Reserve Bank and the factor model forecasts, especially at longer horizons. It also appears that small gains can be made when averages or medians are taken over a larger number of bivariate forecasts.

Again, the ideal size of the data set from which factors are extracted is not clear cut. At shorter horizons, it appears that including all of the indicators, $\theta = 100\%$, improves the forecasting performance of models with one or two factors. Yet, at longer horizons, some of the better factor models perform better with fewer indicators. For example, when $h = 6$ the model with one factor extracted from the data set reduced using the one-step rule *fdi_1* outperforms the benchmark by more when the factor model is applied to fewer indicators. Generally speaking, the one-step and two-step rules have comparable forecasting performance across most factor models and forecast horizons.

6.3 Interest Rate

The results for the interest rate are broadly the same as for CPI inflation. That is, the competing models are outperformed by the Reserve

Bank benchmark at shorter horizons, $h < 5$, and are comparable or better to the benchmark forecasts at longer horizons. The optimal number of factors to incorporate in the interest rate models (with or without autoregressive terms) is difficult to determine. The mean and median bivariate forecasts *fbiv_mean* and *fbiv_med* compare favorably to both the Reserve Bank and the factor model forecasts at longer horizons; the best bivariate model *fbiv_best*, allowing for lags of the factors *fdiarlag_bic*, and the VAR *fvar* all performed poorly.

Although it is not entirely clear cut, it seems that the better factor model forecasts tend to use the entire data set, $\theta = 100\%$, at shorter horizons. At longer horizons, the better factor model forecasts generally use only half of the indicators, $\theta = 50\%$: the two-step rule and the one-step rule produce comparable forecasts in these cases. It is also worth noting that the univariate autoregressive model *far* performs particularly well at longer horizons, $h > 5$, and generally yields the lowest MSFE of the competing models.

6.4 Exchange Rate Growth

Our results for forecasting the exchange rate are disappointing; our models are outperformed by the Reserve Bank benchmark over most horizons.

Comparing our forecasts, the same themes emerge. The models with one or two factors and the average and median forecasts seem to perform best. The VAR *fvar*, the best bivariate forecasts *fbiv_best*, and the models that allow lagged factors *fdiarlag_bic* perform worst. Similar to the results for interest rates, the better factor model forecasts tend to use only half of the indicators, $\theta = 50\%$: the two-step rule seems to perform slightly better than the one-step rule in these cases.

7. Summary and Conclusions

Two conclusions emerge from our empirical results. First, across most of the variables we forecast, with the exception of the exchange rate, the forecasting models that use a large number of predictors (either factor models with one or two factors, or the mean/median of a range of bivariate forecasts) seem to outperform the Reserve Bank benchmark at longer horizons—one year ahead and beyond.

Likewise, at longer horizons, a simple autoregressive forecast generally performs well relative to the Reserve Bank benchmark. Thus, these models appear to be tough benchmarks for future forecasting model comparisons in New Zealand.

Second, it seems that at short horizons it is better to allow the factor model to use all of the indicators than to impose a zero weight to the indicators with relatively poor predictive performance in the past. At longer horizons, the evidence is less clear cut. This may have implications for the degree of data mining that can take place before factors are extracted from the data and, as a consequence, for the size of the data set from which factors are extracted. While our data-reduction rules were ad hoc, they still yielded superior forecasts at some horizons. These rules, together with the rules outlined in Boivin and Ng (2003), may help guide future researchers in determining how to choose data for factor model forecasts.

Overall, we find merits in using a large number of predictors to forecast in New Zealand, especially at longer horizons. It should be noted, however, that our out-of-sample forecasting exercises were conducted with a very short sample of data. Our results will thus need to be revisited in the future.

Appendix 1. Data

#	Source and Series
	Statistics New Zealand
	National Accounts
1	Real GDP – Total Expenditure
2	Real GDP – Total Production
3	Real GDP – Exports Total
4	Real GDP – Imports Total
5	Real GDP – Agriculture
6	Real GDP – Forestry, Fishing, Mining
7	Real GDP – Fishing & Hunting
8	Real GDP – Forestry & Logging
9	Real GDP – Mining & Quarrying
10	Real GDP – Primary Industries
11	Real GDP – Manufacturing – Primary Food
12	Real GDP – Manufacturing – Other Food

13 Real GDP – Manufacturing – Primary Food, Beverage, Tobacco
14 Real GDP – Manufacturing – Textiles & Apparel
15 Real GDP – Manufacturing – Wood & Paper Products
16 Real GDP – Manufacturing – Printing & Publishing & Recorded Media
17 Real GDP – Manufacturing – Chemicals, Plastics, Petroleum, Rubber
18 Real GDP – Manufacturing – Non-metallic Mineral Products
19 Real GDP – Manufacturing – Basic Metal Products
20 Real GDP – Manufacturing – Machinery & Equipment
21 Real GDP – Manufacturing – Furniture & Other Manufacturing
22 Real GDP – Manufacturing – Total
23 Real GDP – Electricity, Gas & Water
24 Real GDP – Construction
25 Real GDP – Goods-Producing Industries
26 Real GDP – Wholesale & Retail, Accommodation, Cafes, Restaurants
27 Real GDP – Wholesale Trade
28 Real GDP – Retail Trade, Including Motor Vehicle Repairs
29 Real GDP – Retail Trade, Accommodation, Cafes, Restaurants
30 Real GDP – Accommodation, Restaurants, Cafes
31 Real GDP – Transport, Communications, Business & Personal Services
32 Real GDP – Transport, Storage
33 Real GDP – Communications
34 Real GDP – Transport, Storage & Communications
35 Real GDP – Finance & Insurance
36 Real GDP – Real Estate & Business Services
37 Real GDP – Finance, Insurance, Property & Business Services
38 Real GDP – Education, Health, Cultural, Recreation, Personal & Other
39 Real GDP – Owner-Occupied Dwellings
40 Real GDP – General Govt Services – Govt Administration and Defence

41 Real GDP – General Govt Services – Local Govt Services
42 Real GDP – General Government Services
43 Real GDP – Service Industries
44 Real GDP – Unallocated
45 Consumption Deflator
46 GDP Deflator
47 GDP Deflator (excluding exports)

Consumers Price Index

48 Headline CPI
49 Non-tradable CPI
50 Tradable CPI
51 Non-tradable – Weighted Median
52 Non-tradable – Trimmed Mean
53 Tradable – Weighted Median
54 Tradable – Trimmed Mean

Retail Trade Survey

55 Retail Trade Deflator (excluding auto)
56 Retail Trade Deflator

Quarterly Employment Survey

57 Total Paid Hours – Total All Industries
58 Labour Productivity
59 Total Paid Hours – Forestry & Mining
60 Total Paid Hours – Manufacturing
61 Total Paid Hours – Electricity, Gas & Water Supply
62 Total Paid Hours – Construction
63 Total Paid Hours – Wholesale Trade
64 Total Paid Hours – Retail Trade
65 Total Paid Hours – Accommodation, Cafes & Restaurants
66 Total Paid Hours – Transport, Storage and Communication Services
67 Total Paid Hours – Finance & Insurance
68 Total Paid Hours – Property & Business Services
69 Total Paid Hours – Government Administration & Defence
70 Total Paid Hours – Education
71 Total Paid Hours – Health & Community Services
72 Total Paid Hours – Cultural & Recreational Services
73 Total Paid Hours – Personal & Other Services

74 Average Hourly Earnings (ord + o/time) – Accom., Cafes & Restaurants
75 Average Hourly Earnings (ord + o/time) – Construction
76 Average Hourly Earnings (ord + o/time) – Cultural & Recreational Services
77 Average Hourly Earnings (ord + o/time) – Education
78 Average Hourly Earnings (ord + o/time) – Electricity, Gas & Water
79 Average Hourly Earnings (ord + o/time) – Finance & Insurance
80 Average Hourly Earnings (ord + o/time) – Forestry & Mining
81 Average Hourly Earnings (ord + o/time) – Govt Admin and Defence
82 Average Hourly Earnings (ord + o/time) – Health & Community Services
83 Average Hourly Earnings (ord + o/time) – Manufacturing
84 Average Hourly Earnings (ord + o/time) – Personal & Other Services
85 Average Hourly Earnings (ord + o/time) – Property & Business Services
86 Average Hourly Earnings (ord + o/time) – Retail Trade
87 Average Hourly Earnings (ord + o/time) – Total
88 Average Hourly Earnings (ord + o/time) – Transport, Storage, Communication
89 Average Hourly Earnings (ord + o/time) – Wholesale Trade
90 Average Hourly Earnings (ordinary time) – Private Sector
91 Average Hourly Earnings (ordinary time) – Public Sector
92 Average Hourly Earnings (ordinary time) – All Sectors

Building Consents

93 Houses and Flats – Number
94 Total Additions and Alterations – Number
95 Total New/Altered – Number
96 New Residential Buildings – Total
97 Apartment Buildings – Number

Building Work Put in Place

98 Real Building Work Put in Place – Residential
99 Real Building Work Put in Place – Non-residential

Car Registrations

100 New Vehicles – Including Cars Previously Registered Overseas

Producers' Price Indexes

101 PPI Inputs – All Industries
102 PPI Outputs – All Industries

Merchandise Trade Indexes

103 Terms of Trade Index
104 Export Volume Index – All Merchandise
105 Export Price Index – All Merchandise
106 Volume of Total Merchandise Imports
107 Import Price Index Total Merchandise Imports

External Migration

108 Net Short-Term Migration
109 Net Permanent & Long-Term Migration
110 Short-Term Visitor Arrivals

Energy Production Data

111 Electricity Generation – Sale to Consumers (Hydro)
112 Electricity Generation – Sale to Consumers (Thermal)
113 Gas Production
114 Electricity Generation

Slaughter Numbers

115 Livestock Slaughter, by Weight, Millions kg
116 Cattle Slaughter, by Total Number
117 Sheep Slaughter, by Total Number
118 Lamb Slaughter, by Total Number

Reserve Bank of New Zealand
Money and Credit Aggregates

119 Official Series of M1
120 Official Series of M2
121 Official Series of M3
122 Official Series of PSCR
123 Official Series of DC
124 Household Claims

Interest and Exchange Rates

125 Monetary Conditions Index
126 Trade Weighted Index
127 NZD/AUD Exchange Rate (average 11am)
128 NZD/GBP Exchange Rate (average 11am)
129 NZD/JPY Exchange Rate (average 11am)
130 NZD/USD Exchange Rate (average 11am)
131 Real Exchange Rate
132 Real Exchange Rate (deviation from equilibrium)
133 Real 90-Day Interest Rate (deviation from equilibrium)
134 Nominal 90-Day Interest Rate (deviation from equilibrium)
135 Yield Spread (90-day rate – 10-year bond yield)
136 Australia 10-Year Bond
137 Australia 90-Day Bank Bill
138 Australia Yield Spread (90-day rate – 10-year bond yield)
139 US 10-Year Bond
140 US 90-Day Bank Bill
141 US Yield Spread (90-day rate – 10-year bond yield)
142 World Long Interest Rates
143 World Short Interest Rates
144 World Yield Spread (90-day rate – 10-year bond yield)

Output and Prices

145 World Real GDP – Trade Weighted
146 Growth Difference between NZ and ROW (APC)
147 World CPI Trade Weighted

Marketscope Survey

148 Expected Current Inflation – Mean
149 Net % Exp Higher Inflation (12 Months)
150 Expected Inflation (12 Months) – Mean

Survey of Expectations

151 Exp Quarterly CPI – Next Quarter
152 Exp Annual CPI – 1 Year from Now
153 Exp Annual CPI – 2 Years from Now
154 Exp HLFS Unemployment Rate – 1 Year Ahead

Datastream
Prices

155 PPI (manufacturing) – Australia
156 PPI (manufacturing) – Japan
157 PPI (manufacturing) – UK
158 PPI (manufacturing) – US
159 PPI (total) – Japan
160 Consumers Price Index – Australia
161 Consumers Price Index – Euro
162 Consumers Price Index – Japan
163 Consumers Price Index – UK
164 Consumers Price Index – US

Output

165 GDP (constant prices) – Australia
166 GDP (constant prices) – Europe
167 GDP (constant prices) – Japan
168 GDP (constant prices) – US

Oil Prices

169 Brent oil prices ($US/barrel)

Real Estate Institute of New Zealand
Housing-Related Data

170 Median Dwelling Price
171 Median List Price
172 No. of Dwelling Sales
173 Median Days to Sell

Quotable Value New Zealand
House Prices

174 Quarterly House Price Index

New Zealand Institute of Economic Research
Quarterly Survey of Business Opinion

175 ECONOMY-WIDE – PAST 3 MONTHS – Average Costs
176 ECONOMY-WIDE – NEXT 3 MONTHS – Average Costs
177 ECONOMY-WIDE – PAST 3 MONTHS – Average Selling Price

178 ECONOMY-WIDE – NEXT 3 MONTHS – Average Selling Price
179 ECONOMY-WIDE – Capacity Utilisation
180 ECONOMY-WIDE – PAST 3 MONTHS – Domestic Trading Activity
181 ECONOMY-WIDE – NEXT 3 MONTHS – Domestic Trading Activity
182 ECONOMY-WIDE – Find. Labour: Skilled
183 ECONOMY-WIDE – Find. Labour: Unskilled
184 ECONOMY-WIDE – General Business Situation
185 ECONOMY-WIDE – New Investment: Buildings
186 ECONOMY-WIDE – New Investment: Plant & Machinery
187 ECONOMY-WIDE – Limiting Factor – Capital
188 ECONOMY-WIDE – Limiting Factor – Finished orders
189 ECONOMY-WIDE – Limiting Factor – Labour
190 ECONOMY-WIDE – Limiting Factor – Materials
191 ECONOMY-WIDE – Limiting Factor – New orders
192 ECONOMY-WIDE – Limiting Factor – Other
193 ECONOMY-WIDE – PAST 3 MONTHS – No. Employed
194 ECONOMY-WIDE – NEXT 3 MONTHS – No. Employed
195 ECONOMY-WIDE – PAST 3 MONTHS – Profitability
196 ECONOMY-WIDE – NEXT 3 MONTHS – Profitability
197 ECONOMY-WIDE – PAST 3 MONTHS – Overtime Wkd
198 ECONOMY-WIDE – NEXT 3 MONTHS – Overtime Wkd

199 BUILDERS – PAST 3 MONTHS – Average Costs
200 BUILDERS – NEXT 3 MONTHS – Average Costs
201 BUILDERS – PAST 3 MONTHS – Average Selling Price
202 BUILDERS – NEXT 3 MONTHS – Average Selling Price
203 BUILDERS – Capacity Utilisation
204 BUILDERS – Find. Labour: Skilled
205 BUILDERS – Find. Labour: Unskilled
206 BUILDERS – General Business Situation
207 BUILDERS – New Investment: Buildings
208 BUILDERS – New Investment: Plant & Machinery
209 BUILDERS – Limiting Factor – Capital
210 BUILDERS – Limiting Factor – Finished Orders
211 BUILDERS – Limiting Factor – Labour
212 BUILDERS – Limiting Factor – Materials

213 BUILDERS – Limiting Factor – New Orders
214 BUILDERS – Limiting Factor – Other
215 BUILDERS – PAST 3 MONTHS – No. Employed
216 BUILDERS – NEXT 3 MONTHS – No. Employed
217 BUILDERS – PAST 3 MONTHS – New Orders
218 BUILDERS – NEXT 3 MONTHS – New Orders
219 BUILDERS – PAST 3 MONTHS – Output
220 BUILDERS – NEXT 3 MONTHS – Output
221 BUILDERS – PAST 3 MONTHS – Profitability
222 BUILDERS – NEXT 3 MONTHS – Profitability
223 BUILDERS – PAST 3 MONTHS – Overtime Wkd
224 BUILDERS – NEXT 3 MONTHS – Overtime Wkd

225 BUILDING & CONSTRUCTION – PAST 3 MONTHS – Deliveries in NZ
226 BUILDING & CONSTRUCTION – NEXT 3 MONTHS – Deliveries in NZ
227 BUILDING & CONSTRUCTION – Find. Labour: Skilled
228 BUILDING & CONSTRUCTION – Find. Labour: Unskilled
229 BUILDING & CONSTRUCTION – General Business Situation
230 BUILDING & CONSTRUCTION – New Investment: Buildings
231 BUILDING & CONSTRUCTION – New Investment: Plant & Machinery
232 BUILDING & CONSTRUCTION – PAST 3 MONTHS – No. Employed
233 BUILDING & CONSTRUCTION – NEXT 3 MONTHS – No. Employed
234 BUILDING & CONSTRUCTION – PAST 3 MONTHS – New Orders
235 BUILDING & CONSTRUCTION – NEXT 3 MONTHS – New Orders
236 BUILDING & CONSTRUCTION – PAST 3 MONTHS – Output
237 BUILDING & CONSTRUCTION – NEXT 3 MONTHS – Output

238 BUILDING & CONSTRUCTION – PAST 3 MONTHS – Profitability
239 BUILDING & CONSTRUCTION – NEXT 3 MONTHS – Profitability

240 BUILDING MATERIALS – General Business Situation
241 BUILDING MATERIALS – PAST 3 MONTHS – No. Employed
242 BUILDING MATERIALS – NEXT 3 MONTHS – No. Employed
243 BUILDING MATERIALS – PAST 3 MONTHS – New Orders
244 BUILDING MATERIALS – NEXT 3 MONTHS – New Orders
245 BUILDING MATERIALS – PAST 3 MONTHS – Profitability
246 BUILDING MATERIALS – NEXT 3 MONTHS – Profitability

247 MANUFACTURERS – PAST 3 MONTHS – Average Costs
248 MANUFACTURERS – NEXT 3 MONTHS – Average Costs
249 MANUFACTURERS – PAST 3 MONTHS – Average Selling Price
250 MANUFACTURERS – NEXT 3 MONTHS – Average Selling Price
251 MANUFACTURERS – Capacity Utilisation
252 MANUFACTURERS – PAST 3 MONTHS – Deliveries in NZ
253 MANUFACTURERS – NEXT 3 MONTHS – Deliveries in NZ
254 MANUFACTURERS – Find. Labour: Skilled
255 MANUFACTURERS – Find. Labour: Unskilled
256 MANUFACTURERS – General Business Situation
257 MANUFACTURERS – New Investment: Buildings
258 MANUFACTURERS – New Investment: Plant & Machinery
259 MANUFACTURERS – Limiting Factor – Capital
260 MANUFACTURERS – Limiting Factor – Finished Orders

261 MANUFACTURERS – Limiting Factor – Labour
262 MANUFACTURERS – Limiting Factor – Materials
263 MANUFACTURERS – Limiting Factor – New Orders
264 MANUFACTURERS – Limiting Factor – Other
265 MANUFACTURERS – PAST 3 MONTHS – No. Employed
266 MANUFACTURERS – NEXT 3 MONTHS – No. Employed
267 MANUFACTURERS – PAST 3 MONTHS – New Orders
268 MANUFACTURERS – NEXT 3 MONTHS – New Orders
269 MANUFACTURERS – PAST 3 MONTHS – Output
270 MANUFACTURERS – NEXT 3 MONTHS – Output
271 MANUFACTURERS – PAST 3 MONTHS – Profitability
272 MANUFACTURERS – NEXT 3 MONTHS – Profitability
273 MANUFACTURERS – PAST 3 MONTHS – Overtime Wkd
274 MANUFACTURERS – NEXT 3 MONTHS – Overtime Wkd
275 MANUFACTURERS & BUILDERS – PAST 3 MONTHS – Profitability
276 MANUFACTURERS & BUILDERS – NEXT 3 MONTHS – Profitability
277 MANUFACTURERS & BUILDERS – PAST 3 MONTHS – Overtime Wkd
278 MANUFACTURERS & BUILDERS – NEXT 3 MONTHS – Overtime Wkd

279 MERCHANTS – PAST 3 MONTHS – Average Costs
280 MERCHANTS – NEXT 3 MONTHS – Average Costs
281 MERCHANTS – PAST 3 MONTHS – Average Selling Price
282 MERCHANTS – NEXT 3 MONTHS – Average Selling Price
283 MERCHANTS – Find. Labour: Skilled
284 MERCHANTS – Find. Labour: Unskilled
285 MERCHANTS – General Business Situation
286 MERCHANTS – New Investment: Buildings
287 MERCHANTS – New Investment: Fix. F
288 MERCHANTS – Limiting Factor – Capital
289 MERCHANTS – Limiting Factor – Finished Orders
290 MERCHANTS – Limiting Factor – Labour
291 MERCHANTS – Limiting Factor – Material
292 MERCHANTS – Limiting Factor – New Orders

293 MERCHANTS – Limiting Factor – Other
294 MERCHANTS – PAST 3 MONTHS – No. Employed
295 MERCHANTS – NEXT 3 MONTHS – No. Employed
296 MERCHANTS – PAST 3 MONTHS – New Forward Orders
297 MERCHANTS – NEXT 3 MONTHS – New Forward Orders
298 MERCHANTS – PAST 3 MONTHS – Sales in NZ
299 MERCHANTS – NEXT 3 MONTHS – Sales in NZ
300 MERCHANTS – Volume of Sales Next 6 Months
301 MERCHANTS – PAST 3 MONTHS – Profitability
302 MERCHANTS – NEXT 3 MONTHS – Profitability
303 MERCHANTS – PAST 3 MONTHS – Overtime Wkd
304 MERCHANTS – NEXT 3 MONTHS – Overtime Wkd

305 SERVICES – PAST 3 MONTHS – Average Cost per Service
306 SERVICES – NEXT 3 MONTHS – Average Cost per Service
307 SERVICES – Find. Labour: Skilled
308 SERVICES – Find. Labour: Unskilled
309 SERVICES – General Business Situation
310 SERVICES – New Investment: Buildings
311 SERVICES – New Investment: Plant & Machinery
312 SERVICES – Limiting Factor – Capital
313 SERVICES – Limiting Factor – Demand
314 SERVICES – Limiting Factor – Finished Orders
315 SERVICES – Limiting Factor – Labour
316 SERVICES – Limiting Factor – Other
317 SERVICES – Limiting Factor – Supply
318 SERVICES – PAST 3 MONTHS – No. Employed
319 SERVICES – NEXT 3 MONTHS – No. Employed
320 SERVICES – PAST 3 MONTHS – Volume of Services
321 SERVICES – NEXT 3 MONTHS – Volume of Services
322 SERVICES – PAST 3 MONTHS – Profitability
323 SERVICES – NEXT 3 MONTHS – Profitability
324 SERVICES – PAST 3 MONTHS – Overtime Wkd
325 SERVICES – NEXT 3 MONTHS – Overtime Wkd

326 FINANCIAL SERVICES – PAST 3 MONTHS – Average Cost per Service

327 FINANCIAL SERVICES – NEXT 3 MONTHS – Average Cost per Service
328 FINANCIAL SERVICES – Find. Labour: Skilled
329 FINANCIAL SERVICES – Find. Labour: Unskilled
330 FINANCIAL SERVICES – General Business Situation
331 FINANCIAL SERVICES – New Investment: Buildings
332 FINANCIAL SERVICES – New Investment: Plant & Machinery
333 FINANCIAL SERVICES – Limiting Factor – Capital
334 FINANCIAL SERVICES – Limiting Factor – Demand
335 FINANCIAL SERVICES – Limiting Factor – Finished Orders
336 FINANCIAL SERVICES – Limiting Factor – Labour
337 FINANCIAL SERVICES – Limiting Factor – Other
338 FINANCIAL SERVICES – Limiting Factor – Supply
339 FINANCIAL SERVICES – PAST 3 MONTHS – No. Employed
340 FINANCIAL SERVICES – NEXT 3 MONTHS – No. Employed
341 FINANCIAL SERVICES – PAST 3 MONTHS – Volume of Services
342 FINANCIAL SERVICES – NEXT 3 MONTHS – Volume of Services
343 FINANCIAL SERVICES – PAST 3 MONTHS – Profitability
344 FINANCIAL SERVICES – NEXT 3 MONTHS – Profitability
345 FINANCIAL SERVICES – PAST 3 MONTHS – Overtime Wkd
346 FINANCIAL SERVICES – NEXT 3 MONTHS – Overtime Wkd

National Bank of New Zealand
Business Outlook Survey

347 INFLATION EXPECTATIONS – Next 12 Months – Retail
348 INFLATION EXPECTATIONS – Next 12 Months – Manufacturing
349 INFLATION EXPECTATIONS – Next 12 Months – Agriculture

350 INFLATION EXPECTATIONS – Next 12 Months – Construction
351 INFLATION EXPECTATIONS – Next 12 Months – Services
352 INFLATION EXPECTATIONS – Next 12 Months – Total (All Sectors)

353 BUSINESS CONFIDENCE – Next 12 Months – Retail
354 BUSINESS CONFIDENCE – Next 12 Months – Manufacturing
355 BUSINESS CONFIDENCE – Next 12 Months – Agriculture
356 BUSINESS CONFIDENCE – Next 12 Months – Construction
357 BUSINESS CONFIDENCE – Next 12 Months – Services
358 BUSINESS CONFIDENCE – Next 12 Months – Total (All Sectors)

359 ACTIVITY OUTLOOK – Next 12 Months – Retail
360 ACTIVITY OUTLOOK – Next 12 Months – Manufacturing
361 ACTIVITY OUTLOOK – Next 12 Months – Agriculture
362 ACTIVITY OUTLOOK – Next 12 Months – Construction
363 ACTIVITY OUTLOOK – Next 12 Months – Services
364 ACTIVITY OUTLOOK – Next 12 Months – Total (All Sectors)

365 PRICING INTENTIONS – Next 3 Months – Total (All Sectors)
366 PRICING INTENTIONS – Next 3 Months – Retail
367 PRICING INTENTIONS – Next 3 Months – Manufacturing

ANZ Banking Group Ltd
Commodity Price Indexes

368 COMMODITY PRICE INDEX – NZ$
369 COMMODITY PRICE INDEX – NZ$ – Meat, Skins & Wool
370 COMMODITY PRICE INDEX – NZ$ – Dairy Products

371 COMMODITY PRICE INDEX – NZ$ – Horticultural Products
372 COMMODITY PRICE INDEX – NZ$ – Forestry Products
373 COMMODITY PRICE INDEX – NZ$ – Seafood
374 COMMODITY PRICE INDEX – NZ$ – Aluminium

Westpac Banking Corporation
Westpac-McDermott-Millar
375 Consumer Confidence Index

Television New Zealand
One News Colmar Brunton Poll
376 Consumer Confidence

AON Consulting Ltd
Economist Survey
377 CPI Inflation – In 1 Year's Time
378 CPI Inflation – In 4 Years' Time
379 CPI Inflation – In 7 Years' Time
380 Increase Avg. Weekly Wage – In 1 Year's Time
381 Increase Avg. Weekly Wage – In 4 Years' Time
382 Increase Avg. Weekly Wage – In 7 Years' Time

Cement and Concrete Assoc (NZ)
383 Cement Sales

National Institute of Water and Atmospheric Research
384 Southern Oscillation Index

Appendix 2. Relative Mean-Squared Forecast Errors (MSFEs)

Notes for Appendix B

For each model, the mean-squared forecast error relative to the Reserve Bank's MSFE is reported. As discussed in the text, $\theta = 5, 10, \ldots, 100$ is the proportion of series used to derive the factors. The forecasts in the rows of the tables are as follows:

rbnz	Reserve Bank of New Zealand benchmark
far	Autoregressive model, with BIC selection of 0 to 4 lags
fvar	VAR model, with lags set at 2
fbiv_best	The best bivariate indicator, allowing one to four lags of the indicator and zero to four lags of the dependent variable (BIC selection of both)
fbiv_mean	Mean of the top 5 percent and 10 percent of BIC-ranked bivariate indicators
fbiv_med	Median of the top 5 percent and 10 percent of BIC-ranked bivariate indicators
fdi_k	Factor model with (suffix) $k = 1, 2, 3, 4$ factors
fdi_bic	Factor model using BIC selection of factors (1 to 4)
fdiar_k	Factor model with (suffix) $k = 1, 2, 3, 4$ factors and one to four lags of the dependent variable (BIC selection of lag numbers)
fdiar_bic	Factor model with one to four factors and zero to four lags of the dependent variable (BIC selection of factors and lags)
fdiarlag_bic	Factor model with one to four factors, one to three lags of the factors, and one to four lags of the dependent variable (BIC selection of all three)
RMSFEs	Root Mean-Squared Forecast Errors

Significance Tests

Asterisks denote that the mean-squared errors of the given test are significantly smaller than those of the Reserve Bank of New Zealand.

** shows significance at the 5 percent level
* shows significance at the 10 percent level

The variance of the mean difference in MSFEs is estimated using the Newey and West (1987) HAC estimator, with a truncation lag of $(h - 1)$. The test statistic is compared to a Student-t distribution with $(T - 1)$ degrees of freedom.

Table 3. CPI Inflation (Year on Year)

$h = 1$	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	3.50	3.41	3.05	3.60	3.80	3.03	2.87
fdi_2	3.61	3.55	3.10	3.53	3.45	3.10	2.83
fdi_3	4.14	4.13	3.68	3.47	3.55	3.81	3.32
fdi_4	3.88	4.30	4.20	3.55	3.53	4.64	3.99
fdi_bic	4.01	3.57	3.17	3.43	3.88	3.13	3.22
fdiar_1	4.53	4.34	3.05	3.99	4.64	3.03	3.34
fdiar_2	4.41	4.19	3.92	4.28	4.14	3.76	3.47
fdiar_3	5.51	4.87	4.30	4.17	3.99	4.43	4.25
fdiar_4	5.18	5.71	4.43	4.23	4.09	5.24	4.93
fdiar_bic	5.60	4.75	3.91	4.14	4.30	3.98	3.79
fdiarlag_bic	5.69	5.92	5.73	6.03	5.62	6.43	3.75
	Other Forecasts						
far	3.28						
fvar	3.42						
fbiv_best	4.18						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	3.71	3.66					
fbiv_med	3.66	3.60					
RMSFE rbnz	0.23						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

***h* = 2**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	2.05	1.84	1.68	2.09	1.99	1.71	1.60
fdi_2	2.04	2.12	1.64	2.03	2.07	1.68	1.56
fdi_3	2.19	2.47	2.44	2.21	2.03	2.01	2.11
fdi_4	2.09	2.58	2.72	2.15	1.98	2.53	2.52
fdi_bic	2.25	2.33	2.21	2.09	1.99	2.30	2.16
fdiar_1	2.24	2.01	1.68	2.02	2.09	1.71	1.60
fdiar_2	1.99	2.01	1.57	2.12	2.04	1.51	1.52
fdiar_3	2.13	2.24	1.97	2.36	2.59	1.62	2.35
fdiar_4	2.17	2.48	2.01	2.47	2.36	1.96	2.49
fdiar_bic	2.12	2.27	1.93	2.07	2.40	1.56	1.80
fdiarlag_bic	2.31	2.27	1.93	2.37	3.00	2.14	1.91
	Other Forecasts						
far	1.55						
fvar	1.83						
fbiv_best	1.96						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.70	1.70					
fbiv_med	1.62	1.63					
RMSFE rbnz	0.48						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

***h* = 3** Cut-Off Criterion	Factor Model Forecasts						
	One-Step			**Two-Step**			**None**
θ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.41	1.48	1.53	1.79	1.66	1.55	1.42
fdi_2	1.56	1.70	1.50	1.65	1.68	1.55	1.37
fdi_3	1.50	1.83	2.43	1.28	1.52	2.39	2.26
fdi_4	1.74	1.74	2.43	1.17	1.66	2.50	2.59
fdi_bic	1.50	1.49	2.32	1.71	1.66	2.27	2.13
fdiar_1	1.73	1.72	1.69	2.13	1.92	1.71	1.57
fdiar_2	1.70	1.58	1.48	1.87	1.93	1.51	1.69
fdiar_3	1.99	1.96	2.07	1.68	1.79	2.10	2.47
fdiar_4	2.00	2.05	2.16	1.43	2.00	2.28	2.57
fdiar_bic	1.97	1.97	2.07	1.77	2.24	2.07	2.33
fdiarlag_bic	2.14	2.25	2.12	2.18	2.55	2.05	2.83
	Other Forecasts						
far	1.38						
fvar	1.30						
fbiv_best	2.29						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	1.58	1.54					
fbiv_med	1.56	1.48					
RMSFE rbnz	0.66						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

$h = 4$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.45	1.47	1.45	1.91	1.70	1.48	1.38
fdi_2	1.50	1.50	1.48	1.85	1.72	1.49	1.46
fdi_3	1.53	1.84	2.13	1.80	1.68	2.17	2.10
fdi_4	1.72	2.02	2.26	1.79	1.34	2.15	2.12
fdi_bic	1.53	1.54	1.79	1.69	1.70	2.05	2.00
fdiar_1	1.55	1.55	1.47	1.91	1.84	1.49	1.41
fdiar_2	1.45	2.01	1.64	1.98	1.66	1.86	1.53
fdiar_3	1.56	1.93	2.10	2.08	2.02	1.93	2.41
fdiar_4	2.56	2.43	2.01	1.82	1.67	1.98	2.02
fdiar_bic	1.97	1.95	1.78	1.72	1.73	1.90	1.81
fdiarlag_bic	2.36	2.46	1.78	1.74	1.87	1.89	1.74
	Other Forecasts						
far	1.29						
fvar	1.14						
fbiv_best	2.80						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	1.53	1.54					
fbiv_med	1.46	1.47					
RMSFE rbnz	0.78						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

$h = 5$	Factor Model Forecasts						
Cut-Off Criterion	One-Step			Two-Step			None
θ (%) =	5	10	50	5	10	50	100
fdi_1	1.14	1.05	0.94	1.33	1.25	0.96	0.89
fdi_2	1.13	1.12	1.15	1.28	1.27	1.14	1.11
fdi_3	1.20	1.36	1.49	1.30	1.28	1.55	1.39
fdi_4	1.51	1.56	1.52	1.29	1.27	1.39	1.44
fdi_bic	1.06	1.00	1.36	1.34	1.21	1.06	1.20
fdiar_1	1.31	1.18	1.18	1.55	1.43	1.22	1.21
fdiar_2	1.24	1.21	1.70	1.67	1.45	1.87	1.56
fdiar_3	1.26	1.27	2.16	1.77	1.67	2.11	2.44
fdiar_4	1.81	1.51	2.37	1.60	1.46	2.27	2.12
fdiar_bic	1.72	1.32	1.51	1.57	1.74	1.53	1.63
fdiarlag_bic	2.67	2.12	1.64	1.72	1.37	1.46	1.71
	Other Forecasts						
far	0.84						
fvar	0.76						
fbiv_best	1.51						
Cut-off **(%)=**	**5**	**10**					
fbiv_mean	0.98	1.00					
fbiv_med	0.99	0.98					
RMSFE rbnz	0.82						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

***h* = 6**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
***θ* (%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.07	0.97	0.73	1.10	1.06	0.76	0.69
fdi_2	1.25	1.39	1.25	1.34	1.16	1.24	1.24
fdi_3	1.38	1.90	1.35	2.00	1.19	1.39	1.38
fdi_4	1.73	1.84	1.40	1.77	1.03	1.22	1.14
fdi_bic	1.71	2.06	1.10	2.05	1.06	1.04	0.99
fdiar_1	1.18	1.04	1.19	1.04	1.09	1.23	1.10
fdiar_2	1.30	1.45	1.57	1.43	1.26	1.65	1.50
fdiar_3	1.55	1.86	1.34	1.88	1.70	1.49	1.38
fdiar_4	1.79	1.86	1.61	1.80	1.51	1.46	1.22
fdiar_bic	1.77	1.87	1.51	2.06	1.32	1.40	1.53
fdiarlag_bic	2.64	2.12	2.01	4.06	2.18	1.47	2.87
	Other Forecasts						
far	0.64**						
fvar	0.45						
fbiv_best	1.69						
***Cut-off* (%)=**	**5**	**10**					
fbiv_mean	0.88	0.88					
fbiv_med	0.89	0.85					
RMSFE rbnz	0.88						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

$h = 7$	Factor Model Forecasts						
Cut-Off Criterion	One-Step			Two-Step			None
θ (%) =	5	10	50	5	10	50	100
fdi_1	0.89	0.77	0.65	0.87	0.82	0.66	0.62*
fdi_2	1.16	1.21	1.31	1.45	1.27	1.23	1.34
fdi_3	1.65	2.01	1.54	2.20	1.82	1.56	1.91
fdi_4	1.72	1.60	2.91	2.59	2.24	2.28	2.08
fdi_bic	1.74	1.65	2.50	2.22	1.23	2.27	2.00
fdiar_1	0.80	0.81	0.88	0.67	0.64	0.82	0.82*
fdiar_2	1.04	1.12	1.19	1.21	1.08	1.22	0.95
fdiar_3	1.44	1.79	0.84	2.11	1.47	0.86	0.96
fdiar_4	1.42	1.13	2.46	2.34	1.17	1.64	1.28
fdiar_bic	1.58	1.23	2.38	1.66	0.83	1.53	1.32
fdiarlag_bic	3.05	3.48	5.83	5.70	3.67	8.07	6.23
	Other Forecasts						
far	0.57*						
fvar	0.58						
fbiv_best	2.73						
Cut-off (%) =	5	10					
fbiv_mean	0.61	0.53*					
fbiv_med	0.54	0.56*					
RMSFE rbnz	0.85						

(*continued*)

Table 3 (continued). CPI Inflation (Year on Year)

$h = 8$	Factor Model Forecasts						
Cut-Off Criterion	One-Step			Two-Step			None
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.67	0.71	0.73	0.68	0.72	0.72	0.74
fdi_2	0.68	0.73	1.13	0.94	0.88	0.90	1.17
fdi_3	1.66	1.88	1.07	0.99	0.80	1.03	0.81
fdi_4	2.25	1.47	3.34	1.14	1.19	2.91	1.70
fdi_bic	2.14	1.18	3.24	0.84	0.80	3.07	2.02
fdiar_1	0.56	0.69	0.76	0.75	0.78	0.75	0.87
fdiar_2	1.17	1.48	1.18	1.49	1.72	0.97	1.13
fdiar_3	1.86	1.85	1.39	1.80	1.40	1.03	0.98
fdiar_4	2.26	1.98	3.56	2.08	1.31	2.96	1.81
fdiar_bic	1.77	1.16	2.57	1.50	1.34	2.96	2.09
fdiarlag_bic	3.58	3.37	6.47	7.06	5.16	12.05	7.41
	Other Forecasts						
far	0.61						
fvar	0.98						
fbiv_best	3.25						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	0.81	0.65					
fbiv_med	0.74	0.53					
RMSFE rbnz	0.80						

Table 4. GDP Growth (Year on Year)

$\boldsymbol{h=1}$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
$\boldsymbol{\theta}$ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	2.02	2.00	1.83	1.92	2.04	1.80	1.73
fdi_2	2.44	2.00	1.88	2.14	2.02	1.91	1.74
fdi_3	2.57	2.52	2.23	2.20	2.28	2.03	1.87
fdi_4	2.61	2.61	2.77	2.32	2.57	2.22	1.97
fdi_bic	2.18	2.42	2.29	2.09	2.28	1.96	1.79
fdiar_1	2.18	2.15	1.97	1.90	2.22	1.94	1.87
fdiar_2	2.43	2.34	1.95	2.25	2.24	1.94	1.83
fdiar_3	2.51	2.74	2.22	2.18	2.29	2.03	2.02
fdiar_4	2.52	2.66	2.76	2.39	2.67	2.25	2.07
fdiar_bic	2.27	2.51	2.46	2.05	2.39	1.94	1.94
fdiarlag_bic	2.31	2.44	2.53	2.14	2.39	2.13	1.97
	Other Forecasts						
far	2.12						
fvar	1.69						
fbiv_best	2.53						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	2.07	2.02					
fbiv_med	2.02	1.98					
RMSFE rbnz	0.67						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

***h* = 2**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.67	1.63	1.36	1.67	1.62	1.31	1.35
fdi_2	1.61	1.66	1.41	1.68	1.84	1.40	1.32
fdi_3	1.59	1.71	1.65	1.80	1.99	1.77	1.61
fdi_4	1.64	1.89	1.64	1.61	1.96	1.61	1.46
fdi_bic	1.67	1.63	1.47	1.67	1.62	1.49	1.43
fdiar_1	1.32	1.28	0.97	1.67	1.33	0.94	1.27
fdiar_2	1.24	1.26	1.09	1.68	1.49	1.10	1.27
fdiar_3	1.14	1.13	1.01	1.63	1.88	1.11	1.49
fdiar_4	1.12	1.71	1.01	1.42	1.84	1.06	1.44
fdiar_bic	1.28	1.28	1.08	1.67	1.33	1.01	1.21
fdiarlag_bic	1.30	1.10	1.10	1.65	1.82	0.96	1.15
	Other Forecasts						
far	1.54						
fvar	1.75						
fbiv_best	2.15						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.33	1.28					
fbiv_med	1.53	1.49					
RMSFE rbnz	1.03						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

$h=3$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.28	1.21	0.93	1.22	1.21	0.93	0.97
fdi_2	1.25	1.22	1.13	1.33	1.21	1.09	1.06
fdi_3	1.32	1.67	1.11	1.24	1.51	1.11	1.09
fdi_4	1.36	1.65	1.15	1.58	1.74	1.07	1.18
fdi_bic	1.28	1.21	1.22	1.42	1.38	1.09	1.19
fdiar_1	1.21	1.24	1.21	1.22	1.25	1.28	1.25
fdiar_2	1.26	1.33	1.37	1.30	1.40	1.40	1.37
fdiar_3	1.18	1.58	1.20	1.20	1.45	1.30	1.34
fdiar_4	1.39	1.45	1.35	1.47	1.67	1.15	1.33
fdiar_bic	1.25	1.18	1.46	1.31	1.32	1.34	1.40
fdiarlag_bic	2.58	1.78	1.13	1.34	1.56	2.36	2.48
	Other Forecasts						
far	1.23						
fvar	1.81						
fbiv_best	1.95						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	1.11	1.07					
fbiv_med	1.22	1.08					
RMSFE rbnz	1.39						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

***h* = 4**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.97	0.84	0.66	0.94	0.81	0.64	0.66
fdi_2	0.92	0.89	1.22	0.88	0.79	1.03	1.20
fdi_3	1.00	1.22	0.92	0.92	0.69	1.06	1.09
fdi_4	1.00	1.60	1.15	1.07	0.91	1.48	1.35
fdi_bic	0.97	0.84	1.11	0.94	0.81	1.44	1.47
fdiar_1	0.83	0.67*	0.75	0.94	0.77	0.79	0.79
fdiar_2	0.81	0.66	0.97	0.88	0.71	0.95	1.10
fdiar_3	0.77	0.88	0.99	0.92	0.64	1.07	1.14
fdiar_4	0.93	1.12	1.16	1.05	0.90	1.53	1.32
fdiar_bic	0.96	0.66*	0.78	1.03	0.76	1.02	1.66
fdiarlag_bic	1.21	1.12	1.33	1.04	2.16	0.97	1.99
	Other Forecasts						
far	0.96						
Fvar	2.08						
fbiv_best	1.00						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	0.60*	0.64*					
fbiv_med	0.66	0.71					
RMSFE rbnz	1.65						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

$h = 5$ Cut-Off Criterion	Factor Model Forecasts						
	One-Step			Two-Step			None
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.57**	0.56**	0.48**	0.67*	0.60**	0.48**	0.46**
fdi_2	0.71**	0.80	1.02	0.70**	0.68	0.80	1.08
fdi_3	1.12	1.72	0.66*	0.77*	1.31	0.72	0.78
fdi_4	1.18	1.53	1.54	0.84	1.72	1.60	1.09
fdi_bic	1.11	1.22	1.84	0.51**	0.60**	1.80	1.32
fdiar_1	0.62**	0.67	1.25	0.67*	0.61**	1.25	0.83
fdiar_2	0.82	0.53*	0.88	0.70**	0.68	0.88	1.27
fdiar_3	0.59	0.96	0.92	0.77*	1.58	0.87	0.83
fdiar_4	1.21	2.19	1.68	1.06	2.03	1.76	1.17
fdiar_bic	1.10	2.30	2.01	0.65**	0.90	1.67	1.75
fdiarlag_bic	3.41	4.66	3.61	1.74	1.96	1.79	5.31
	Other Forecasts						
far	0.57*						
fvar	0.90						
fbiv_best	0.87						
Cut-off (%) =	**5**	**10**					
fbiv_mean	0.72	0.54*					
fbiv_med	0.75	0.59					
RMSFE rbnz	1.90						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

***h* = 6** **Cut-Off Criterion**	**Factor Model Forecasts**						
	One-Step			**Two-Step**			**None**
$\boldsymbol{\theta}$ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.55**	0.61*	0.74	1.02	0.88	0.74	0.65*
fdi_2	1.24	0.58**	1.58	1.29	1.00	1.00	1.74
fdi_3	2.26	5.30	3.01	1.22	1.55	2.55	2.41
fdi_4	1.83	4.13	4.01	1.53	1.98	5.70	3.40
fdi_bic	1.49	3.05	5.41	1.07	1.62	5.92	4.22
fdiar_1	0.65*	0.79	1.50	1.22	1.11	1.49	0.48**
fdiar_2	0.73	0.76	1.40	1.17	1.04	1.40	1.39
fdiar_3	1.22	3.81	3.28	1.14	0.75	2.64	2.55
fdiar_4	2.26	3.83	4.16	1.35	1.05	6.02	3.52
fdiar_bic	1.67	3.87	5.35	1.10	0.82	6.13	4.38
fdiarlag_bic	4.68	4.31	5.26	5.52	13.27	8.74	10.97
	Other Forecasts						
far	0.59**						
fvar	1.29						
fbiv_best	1.14						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	0.63	0.65					
fbiv_med	0.65	0.71					
RMSFE rbnz	1.63						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

$h = 7$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.67**	0.71	1.05	1.20	0.88	1.04	0.99
fdi_2	1.84	0.53**	1.43	3.53	4.17	0.93	1.68
fdi_3	5.90	5.75	5.71	4.08	6.82	4.26	2.95
fdi_4	5.47	5.63	6.35	4.86	5.72	6.89	3.64
fdi_bic	4.37	5.14	9.37	3.17	6.81	9.39	4.62
fdiar_1	1.02	0.98	1.07	1.29	1.00	1.33	1.28
fdiar_2	1.56	0.86	1.81	3.74	4.99	1.41	1.30
fdiar_3	3.04	4.43	5.62	4.95	6.84	4.67	3.02
fdiar_4	5.28	5.21	6.62	6.71	5.70	7.66	3.53
fdiar_bic	4.76	4.51	7.56	4.85	4.37	9.62	4.71
fdiarlag_bic	10.52	6.99	8.26	19.92	10.07	17.42	11.20
	Other Forecasts						
far	0.87						
fvar	1.25						
fbiv_best	7.56						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	1.59	1.45					
fbiv_med	1.23	1.05					
RMSFE rbnz	1.62						

(*continued*)

Table 4 (continued). GDP Growth (Year on Year)

$h = 8$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.77**	0.82	1.28	1.63	0.95	1.27	1.28
fdi_2	2.48	1.20	1.37	2.96	3.12	0.92	1.30
fdi_3	3.35	4.16	2.92	5.12	3.13	2.20	1.88
fdi_4	3.15	7.07	2.97	7.24	3.46	3.04	1.71
fdi_bic	2.41	4.35	2.83	3.92	3.39	4.08	1.88
fdiar_1	0.75	0.63**	1.08	2.15	1.02	0.85	1.46
fdiar_2	2.46	1.49	1.95	3.78	2.84	0.92	1.45
fdiar_3	2.76	3.97	3.22	5.64	2.83	2.66	2.39
fdiar_4	2.78	3.53	2.62	7.57	4.04	2.68	1.72
fdiar_bic	2.24	3.70	4.33	2.48	3.03	5.23	2.87
fdiarlag_bic	5.96	4.91	13.27	14.45	21.84	16.33	14.66
	Other Forecasts						
far	1.07						
fvar	1.59						
fbiv_best	6.29						
Cut-off (%) =	**5**	**10**					
fbiv_mean	1.69	1.32					
fbiv_med	1.21	1.22					
RMSFE rbnz	1.72						

Table 5. Interest Rate (90-Day Bank Bill)

$h = 1$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	25.10	24.58	21.25	25.72	24.63	21.83	20.52
fdi_2	31.83	28.76	23.92	24.72	25.11	25.72	21.71
fdi_3	34.98	26.41	20.69	20.45	29.27	32.90	24.87
fdi_4	31.47	24.09	59.19	23.74	31.88	49.57	57.12
fdi_bic	31.87	24.71	48.41	25.08	28.47	35.33	20.52
fdiar_1	24.94	23.45	19.26	22.67	21.95	19.33	19.00
fdiar_2	31.50	33.79	35.79	23.69	24.43	35.41	39.02
fdiar_3	36.39	26.87	34.50	19.74	28.50	45.67	33.42
fdiar_4	38.58	25.20	61.96	23.61	30.78	57.20	60.28
fdiar_bic	32.82	32.20	50.06	23.50	27.88	29.90	26.89
fdiarlag_bic	27.91	31.99	98.54	22.12	70.88	49.42	29.90
	Other Forecasts						
far	16.19						
fvar	27.50						
fbiv_best	50.45						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	23.55	18.67					
fbiv_med	22.49	19.32					
RMSFE rbnz	0.09						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

***h* = 2**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
***θ* (%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	7.53	7.06	5.55	7.19	6.86	5.86	5.28
fdi_2	8.98	9.75	5.84	15.27	11.22	6.20	6.36
fdi_3	8.63	14.15	16.78	14.89	15.85	14.35	10.93
fdi_4	9.00	14.49	15.15	14.62	17.18	12.01	15.52
fdi_bic	9.77	15.21	13.43	13.89	12.56	5.86	5.28
fdiar_1	7.53	7.06	6.64	7.27	6.86	5.98	6.55
fdiar_2	9.22	10.92	14.13	15.27	15.63	13.14	14.45
fdiar_3	8.63	14.56	23.69	14.88	25.84	9.25	10.12
fdiar_4	9.00	14.49	19.87	14.61	23.66	11.16	11.41
fdiar_bic	9.77	15.21	15.59	11.50	16.98	12.28	11.54
fdiarlag_bic	10.07	31.26	14.19	19.73	19.34	14.31	11.13
	Other Forecasts						
far	4.18						
fvar	7.30						
fbiv_best	20.25						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	7.94	5.92					
fbiv_med	7.20	5.45					
RMSFE rbnz	0.35						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

***h* = 3**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	4.53	4.08	3.19	5.79	4.70	3.29	2.92
fdi_2	4.84	5.31	4.91	8.09	7.96	5.05	5.16
fdi_3	7.11	8.78	14.25	7.85	7.50	12.52	12.63
fdi_4	10.84	10.83	12.25	6.75	6.83	12.98	13.63
fdi_bic	9.22	6.27	11.88	7.47	6.63	11.87	11.93
fdiar_1	4.54	4.40	4.04	5.70	4.70	4.18	3.76
fdiar_2	7.97	6.98	6.79	7.45	7.29	7.13	6.14
fdiar_3	8.98	10.50	15.77	7.34	6.86	8.73	5.80
fdiar_4	12.24	13.16	13.25	6.24	7.23	8.68	6.30
fdiar_bic	10.76	10.33	15.63	7.29	6.47	7.84	5.99
fdiarlag_bic	10.38	19.23	8.78	9.95	7.78	14.33	7.05
	Other Forecasts						
far	2.07						
fvar	4.96						
fbiv_best	11.19						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	3.41	2.98					
fbiv_med	3.65	3.09					
RMSFE rbnz	0.61						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

***h* = 4**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
***θ* (%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	2.62	2.16	2.05	3.20	2.71	2.01	2.03
fdi_2	2.58	2.95	3.94	2.89	3.29	3.77	3.97
fdi_3	4.16	4.53	9.45	2.75	3.22	8.77	9.90
fdi_4	5.09	5.67	7.75	3.82	4.16	8.44	10.83
fdi_bic	4.36	4.98	8.01	2.72	2.69	6.41	9.37
fdiar_1	2.78	2.44	2.70	3.42	3.03	2.77	2.64
fdiar_2	4.41	2.78	3.22	3.19	4.62	3.98	3.58
fdiar_3	5.30	3.80	4.91	3.00	4.16	4.99	4.40
fdiar_4	6.84	4.64	4.60	3.90	5.14	5.07	3.80
fdiar_bic	6.07	3.68	3.62	3.69	3.22	4.02	3.81
fdiarlag_bic	2.96	2.33	3.20	4.64	5.57	9.09	5.08
	Other Forecasts						
far	1.25						
fvar	3.94						
fbiv_best	1.99						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.29	1.30					
fbiv_med	1.65	1.49					
RMSFE rbnz	0.84						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

$h = 5$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.45	1.14	1.11	1.38	1.40	1.10	1.25
fdi_2	1.37	1.34	2.42	1.25	1.11	2.01	2.46
fdi_3	1.73	1.62	3.82	1.34	1.49	3.17	4.53
fdi_4	1.93	1.78	2.80	1.24	1.53	3.76	4.09
fdi_bic	1.45	1.19	2.65	1.38	1.40	2.01	3.01
fdiar_1	1.46	1.15	1.38	1.43	1.49	1.46	1.55
fdiar_2	1.99	1.79	1.37	1.99	2.21	1.49	1.62
fdiar_3	2.11	2.40	0.66	1.87	2.22	1.37	1.62
fdiar_4	2.28	3.23	0.55	2.33	2.06	1.59	1.32
fdiar_bic	2.02	2.75	1.45	1.67	2.09	1.76	1.80
fdiarlag_bic	4.85	1.43	7.50	2.23	5.83	2.56	2.96
	Other Forecasts						
far	0.76						
Fvar	2.72						
fbiv_best	1.70						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	0.72	0.56					
fbiv_med	0.93	0.75					
RMSFE rbnz	1.08						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

***h* = 6**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.11	0.75	0.67	1.08	0.85	0.67	0.77
fdi_2	1.09	0.94	1.74	1.37	0.88	1.50	2.02
fdi_3	1.05	1.51	1.47	1.84	1.60	1.16	1.98
fdi_4	0.96	2.43	2.04	2.05	1.54	1.40	1.78
fdi_bic	1.11	0.75	2.07	1.12	1.51	1.50	2.18
fdiar_1	1.10	0.77	0.74	1.06	0.90	0.74	0.89
fdiar_2	1.09	0.93	1.00	0.98	1.42	0.90	1.32
fdiar_3	1.03	1.25	0.64	1.26	2.20	0.55	0.82
fdiar_4	1.06	1.52	1.22	1.86	1.98	1.18	0.72
fdiar_bic	1.02	1.01	1.30	1.06	1.71	1.08	0.83
fdiarlag_bic	2.73	0.93	2.14	1.48	3.47	1.87	3.77
	Other Forecasts						
far	0.40**						
fvar	2.62						
fbiv_best	2.36						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	0.59	0.49					
fbiv_med	0.70	0.55					
RMSFE rbnz	1.25						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

$h = 7$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.13	0.73	0.50	1.30	0.90	0.52	0.54
fdi_2	1.20	0.97	2.17	1.63	1.16	1.79	2.18
fdi_3	1.26	1.49	1.60	1.58	1.01	1.20	1.71
fdi_4	1.93	1.22	3.62	1.65	2.20	3.93	2.24
fdi_bic	1.13	0.73	3.43	1.30	0.92	3.62	2.37
fdiar_1	1.16	0.75	0.52	1.29	0.88	0.54	0.62
fdiar_2	0.82	0.69	1.82	1.62	1.00	1.44	2.18
fdiar_3	0.82	1.13	1.54	1.59	0.92	0.84	1.41
fdiar_4	1.27	0.96	3.15	1.49	2.09	3.77	1.92
fdiar_bic	1.16	0.75	2.95	1.30	0.91	3.40	2.12
fdiarlag_bic	5.30	3.19	3.41	1.35	2.86	6.65	22.78
	Other Forecasts						
far	0.25**						
fvar	3.52						
fbiv_best	2.06						
Cut-off (%) =	**5**	**10**					
fbiv_mean	0.76	0.58					
fbiv_med	0.71	0.60					
RMSFE rbnz	1.26						

(*continued*)

Table 5 (continued). Interest Rate (90-Day Bank Bill)

$h = 8$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.77	0.65	0.45	1.33	0.83	0.47	0.40
fdi_2	0.81	0.86	2.45	1.64	1.04	2.04	2.78
fdi_3	0.99	2.58	2.62	1.55	1.41	1.26	1.50
fdi_4	1.02	2.84	5.26	1.78	1.99	2.74	1.97
fdi_bic	0.77	1.61	3.51	1.36	0.83	2.41	1.82
fdiar_1	0.77	0.66	0.47	1.33	0.83	0.48	0.49
fdiar_2	1.22	0.86	2.51	1.64	1.04	2.04	3.07
fdiar_3	1.40	3.69	2.62	1.55	1.52	1.24	1.50
fdiar_4	1.45	4.61	11.50	1.78	2.31	3.02	1.97
fdiar_bic	1.26	4.00	3.54	1.36	1.10	2.69	1.82
fdiarlag_bic	1.49	11.71	6.05	4.05	4.56	14.30	21.36
	Other Forecasts						
far	0.21						
fvar	4.20						
fbiv_best	2.58						
Cut-off (%) =	**5**	**10**					
fbiv_mean	0.75	0.72					
fbiv_med	0.62	0.66					
RMSFE rbnz	1.25						

Table 6. Exchange Rate (Year-on-Year Growth)

$h = 1$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	7.45	6.62	5.71	6.71	6.10	5.77	5.71
fdi_2	7.60	7.29	6.39	7.50	6.79	6.63	5.81
fdi_3	8.06	7.57	8.19	8.02	7.24	7.45	6.82
fdi_4	8.55	9.01	8.48	9.35	8.44	7.58	6.34
fdi_bic	7.79	8.34	8.40	6.71	6.72	6.52	6.08
fdiar_1	7.45	6.62	6.19	6.71	6.10	6.23	6.01
fdiar_2	7.66	7.02	6.72	7.50	6.79	6.92	6.26
fdiar_3	8.03	6.99	7.95	8.72	7.24	7.45	6.82
fdiar_4	8.55	9.01	9.97	10.10	8.44	7.58	6.34
fdiar_bic	7.84	7.87	9.22	6.71	6.72	7.03	6.01
fdiarlag_bic	6.89	7.93	11.97	7.47	6.24	7.44	7.43
	Other Forecasts						
far	8.34						
fvar	9.03						
fbiv_best	12.18						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	7.06	6.97					
fbiv_med	7.65	7.33					
RMSFE rbnz	1.43						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

$h = 2$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.35	1.20	1.08	1.27	1.22	1.06	1.09
fdi_2	1.35	1.48	1.24	1.35	1.25	1.29	1.19
fdi_3	1.29	1.33	1.73	1.42	1.52	1.23	1.50
fdi_4	1.54	1.45	1.55	1.55	1.73	1.57	1.38
fdi_bic	1.45	1.51	2.02	1.27	1.13	1.19	1.27
fdiar_1	1.30	1.20	1.08	1.27	1.22	1.06	1.09
fdiar_2	1.25	1.53	1.24	1.22	1.21	1.29	1.19
fdiar_3	1.22	1.40	1.85	1.17	1.63	1.36	1.50
fdiar_4	1.41	1.28	1.40	1.33	1.51	1.47	1.42
fdiar_bic	1.16	1.44	1.86	1.27	1.10	1.31	1.27
fdiarlag_bic	2.23	1.61	1.80	1.57	1.38	1.32	1.35
	Other Forecasts						
far	1.69						
fvar	2.04						
fbiv_best	2.24						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.20	1.21					
fbiv_med	1.22	1.28					
RMSFE rbnz	5.02						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

$h = 3$	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.05	0.99	0.93	1.08	0.93	0.89	0.95
fdi_2	1.35	1.52	0.94	1.24	1.50	0.98	1.04
fdi_3	1.54	1.35	1.27	1.37	1.46	1.42	1.24
fdi_4	1.37	1.15	0.99	1.45	1.69	1.03	1.18
fdi_bic	1.27	1.05	1.11	1.16	1.57	0.85	1.29
fdiar_1	1.05	0.99	0.93	0.99	0.93	0.89	0.95
fdiar_2	1.40	1.52	0.94	1.23	1.76	0.98	1.04
fdiar_3	1.73	1.43	1.29	1.35	1.85	1.22	1.24
fdiar_4	1.70	1.12	0.91	1.42	1.87	1.65	1.18
fdiar_bic	1.43	1.05	0.95	1.07	1.52	0.89	1.29
fdiarlag_bic	3.67	1.06	0.81	1.73	1.50	0.91	1.40
	Other Forecasts						
far	1.28						
fvar	1.94						
fbiv_best	2.15						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	1.00	1.03					
fbiv_med	1.02	1.07					
RMSFE rbnz	6.96						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

***h* = 4**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.20	1.09	1.05	1.14	1.07	1.02	1.11
fdi_2	1.77	1.51	0.91	1.39	1.85	0.95	1.13
fdi_3	2.29	1.99	1.51	1.78	2.05	1.91	1.15
fdi_4	2.09	1.66	1.14	1.38	1.73	1.11	1.18
fdi_bic	2.12	1.68	1.46	1.44	1.91	1.69	1.28
fdiar_1	1.20	1.09	1.05	1.14	1.07	1.02	1.11
fdiar_2	1.77	1.51	0.83	1.39	1.85	0.86	1.13
fdiar_3	2.29	1.99	1.54	1.78	2.05	1.96	0.94
fdiar_4	2.09	1.66	1.22	1.38	1.73	1.64	0.94
fdiar_bic	2.12	1.68	1.62	1.44	1.91	1.83	1.28
fdiarlag_bic	2.76	2.28	1.97	1.07	1.50	1.96	1.96
	Other Forecasts						
far	1.32						
fvar	1.88						
fbiv_best	2.17						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	1.46	1.30					
fbiv_med	1.50	1.36					
RMSFE rbnz	8.35						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

***h* = 5**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
$\boldsymbol{\theta}$ **(%) =**	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	0.91	0.87	0.95	0.86	0.77	0.90	1.01
fdi_2	1.77	1.36	0.63*	1.05	1.44	0.63	0.90
fdi_3	2.24	1.85	1.68	1.09	1.40	1.61	0.88
fdi_4	1.98	1.89	1.37	1.07	1.01	1.22	0.82
fdi_bic	1.92	2.23	1.37	0.94	0.91	1.05	1.10
fdiar_1	1.04	1.02	0.95	1.21	0.97	0.90	1.01
fdiar_2	2.06	1.75	1.15	1.16	1.94	1.13	1.12
fdiar_3	2.51	2.64	1.89	1.30	1.91	3.06	0.70
fdiar_4	1.97	1.59	1.64	1.15	1.25	1.84	0.70
fdiar_bic	1.83	1.49	1.58	1.17	1.21	1.82	1.11
fdiarlag_bic	2.83	2.30	1.31	2.10	0.83	2.29	1.86
	Other Forecasts						
far	1.13						
fvar	1.79						
fbiv_best	2.49						
Cut-off **(%) =**	**5**	**10**					
fbiv_mean	1.54	1.22					
fbiv_med	1.46	1.31					
RMSFE rbnz	9.40						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

***h* = 6** Cut-Off Criterion	Factor Model Forecasts						
	One-Step			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.16	1.06	1.14	0.95	0.93	1.12	1.22
fdi_2	2.36	1.64	0.58**	1.42	1.32	0.56**	0.88
fdi_3	2.23	2.31	2.74	1.81	1.28	2.02	1.07
fdi_4	2.26	2.14	3.40	1.99	1.01	2.53	1.21
di_bic	1.82	1.57	2.71	1.85	0.95	1.71	1.01
fdiar_1	1.51	1.14	1.05	1.56	1.30	1.05	1.09
fdiar_2	2.97	2.49	1.40	2.42	1.76	1.55	1.13
fdiar_3	2.90	4.62	3.10	2.57	1.85	2.56	1.13
fdiar_4	2.91	2.76	4.39	2.26	1.31	3.00	1.58
fdiar_bic	2.84	2.69	3.33	2.18	1.76	2.46	1.10
fdiarlag_bic	3.43	3.83	3.50	6.66	2.44	2.45	1.12
	Other Forecasts						
far	1.39						
fvar	2.32						
fbiv_best	1.92						
Cut-off (%) =	**5**	**10**					
fbiv_mean	1.82	1.68					
fbiv_med	1.69	1.68					
RMSFE rbnz	8.96						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

***h* = 7**	**Factor Model Forecasts**						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	1.59	1.56	1.59	1.36	1.45	1.60	1.64
fdi_2	3.19	1.79	0.95	1.72	1.85	0.87	1.24
fdi_3	1.85	2.60	2.44	2.16	2.55	2.24	1.54
fdi_4	2.00	2.49	4.93	2.06	2.52	3.50	1.23
fdi_bic	2.29	2.08	3.41	2.13	2.24	2.18	1.70
fdiar_1	2.00	1.98	1.83	1.83	1.83	1.82	1.88
fdiar_2	4.33	3.06	1.07	2.70	2.65	1.07	1.43
fdiar_3	1.95	5.08	2.74	3.42	4.76	2.70	1.85
fdiar_4	1.79	5.23	5.69	4.01	4.85	3.47	1.84
fdiar_bic	1.99	5.05	3.67	4.42	4.55	3.09	1.94
fdiarlag_bic	5.78	6.87	8.23	5.96	6.82	5.21	2.65
	Other Forecasts						
far	2.23						
fvar	3.52						
fbiv_best	5.22						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	2.28	2.00					
fbiv_med	2.25	2.11					
RMSFE rbnz	8.25						

(*continued*)

Table 6 (continued). Exchange Rate (Year-on-Year Growth)

***h* = 8**	Factor Model Forecasts						
Cut-Off Criterion	**One-Step**			**Two-Step**			**None**
θ (%) =	**5**	**10**	**50**	**5**	**10**	**50**	**100**
fdi_1	2.17	2.32	2.00	2.24	2.03	2.03	2.04
fdi_2	1.87	1.86	2.05	2.84	1.28	1.84	2.02
fdi_3	1.90	1.67	1.09	2.88	1.92	1.65	0.83
fdi_4	2.74	2.71	4.38	2.94	2.56	3.52	1.55
fdi_bic	2.36	1.99	1.67	2.39	1.51	1.70	1.17
fdiar_1	2.03	2.32	1.79	2.15	1.93	1.83	1.84
fdiar_2	1.96	1.93	1.23	2.96	1.71	1.13	1.47
fdiar_3	2.00	2.94	1.59	3.10	2.90	2.27	0.85
fdiar_4	2.61	3.70	5.46	3.07	4.21	3.71	1.96
fdiar_bic	2.69	2.36	2.30	2.53	3.43	2.86	2.05
fdiarlag_bic	6.45	7.64	6.32	17.92	15.55	7.38	5.32
	Other Forecasts						
far	2.13						
fvar	3.88						
fbiv_best	5.77						
***Cut-off* (%) =**	**5**	**10**					
fbiv_mean	2.12	2.34					
fbiv_med	2.39	2.43					
RMSFE rbnz	8.07						

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