Bank Market Power and Monetary Policy Transmission*

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This paper examines empirically the role of bank market power as an internal factor influencing banks' reaction in terms of lending and risk taking to monetary policy impulses. The analysis is carried out for the U.S. and euro-area banking sectors over the period 1997–2010. Market power is estimated at the bank-year level, using a method that allows the efficient estimation of marginal cost of banks also at the bank-year level. The findings show that banks with even moderate levels of market power are able to buffer the negative impact of a monetary policy change on bank loans and credit risk. This effect is somewhat more pronounced in the euro area compared with the United States. However, following the sub-prime mortgage crisis of 2007, the level of market power needed to shield bank loans and credit risk from the impact of a change in monetary policy increased substantially. This is clear evidence that the financial crisis reinforced the mechanisms of the bank lending and the risk-taking channels.

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1. Introduction

Understanding the transmission mechanism is crucial for monetary policy. In this respect, the special role of banking institutions in this mechanism has been studied extensively both at a theoretical and empirical level. The existing evidence shows that there are two channels of monetary policy that can influence the lending and risk-taking behavior of banks, namely the bank lending and risk-taking channels of monetary policy. In turn, the potency of both channels is heavily affected by certain bank characteristics, like capitalization and liquidity. This paper introduces bank market power as one of the most important bank characteristics affecting the pass-through of a monetary policy change in the U.S. and euro-area banking sectors over the period 1997–2010.

The aim of this paper is related to a long tradition in the literature of the transmission mechanism that accords banks a special role. Bernanke and Blinder (1988), among other proponents of the so-called bank lending channel, suggest that the effect of monetary policy on aggregate demand through interest rates (the interest rate channel) can be enhanced by financial market imperfections and the existence of imperfect substitutability between loans and securities in bank portfolios and also as a means of borrowing for firms. The corresponding impact of monetary policy changes on banks' credit risk is the subject of more recent research studies. The premise of this channel is that a decrease in interest rates increases risk-taking incentives of banks due to the associated lower yield of the lending activity, as well as the downsizing of agency costs and of banks' own estimates of default probabilities (Borio and Zhu 2012). Indeed, the empirical work of Jimenez et al. (2007), Ioannidou, Ongena, and Peydro (2008), and Delis, Hasan, and Mylonidis (2011) confirms the theoretical proposition of the risk-taking channel.

One of the identification schemes for the lending channel involves estimation of reduced-form bank loan equations, where loan supply shifts are traced by using bank-level data on bank characteristics (Kashyap and Stein 2000; Ashcraft 2006). The idea is that monetary policy will have a differential effect on loans for banks of different size, or with different levels of capitalization and liquidity (see, e.g., Kashyap and Stein 2000; Gambacorta 2005). For example, consider two banks that are alike except for their holdings of liquid assets and are hit by a contractionary monetary policy shock. The bank with the low share of liquid assets in its portfolio will be forced to reduce lending because of the decrease in insured deposits that is caused by the monetary contraction. In contrast, the bank with the high share of liquid assets will be able to somewhat buffer the impact of the monetary shock by using part of this liquidity to finance future lending activity. The same mechanism holds for the impact of monetary policy on banks' credit risk, which is directly related to bank loans.

Here we propose a new important bank characteristic that generates a differential effect of monetary policy on bank lending and risk taking, namely bank market power. We provide three theoretical arguments that give market power a special role in the monetary transmission mechanism through banks. First, banks with high market power should have easier access to uninsured finance, which would make their lending less dependent on central bank funding and therefore on monetary policy shocks. Second, high market power is usually associated with higher profits, and this implies that the respective banks may be less interested in engaging in very risky activities. Thus, an expansionary monetary policy will imply that the search-for-yield mechanism of the risk-taking channel may be less potent for these banks. Third, and related to the above, standard microeconomic theory suggests that in perfectly competitive markets the level of prices (here lending rates) is directly affected by the marginal cost of the production of loans. In turn, marginal cost is directly affected by the overnight rates, which banks use to obtain loanable funds. If banks with market power do not have to rely on these loanable funds, but have access to alternative sources of finance or can attract short-term deposits more easily, then the short-term increase in the marginal cost of loan production, owing to a contractionary monetary policy, will not have a major impact on the lending and risk-taking behavior of these banks.

Given these theoretical arguments, our empirical analysis explores the role of bank market power in the bank lending and risk-taking channels of monetary policy in the euro area and the United States. We first estimate market power at the bank-year level, using a technique that allows efficient estimation of marginal cost also at the bank-year level (Delis 2012; Delis, Iosifidi, and Tsionas 2012).

This is important because this method captures changes in the marginal cost for each bank at each point in time, which could be in part attributed to changes in monetary policy as discussed above. Subsequently, we estimate bank loan and credit risk equations that include interaction terms between the monetary policy variable and bank market power.

The empirical results show that a monetary policy tightening has a negative effect on both bank loans and credit risk. However, the potency of these relationships weakens for banks that have even moderate levels of market power. Specifically, only about 1 percent higher market power, relative to that of the average bank in our sample, is sufficient to completely buffer the negative effect of the monetary policy variable on bank lending or risk taking. If we distinguish between the euro area and the United States, we still find that market power plays a very important role in reducing the effect of monetary policy. Notably, this reduction in the effect of monetary policy change is somewhat more pronounced in the euro area, while in the United States the degree of market power required to buffer the impact of a change in monetary policy is about 7 percent and 5 percent higher than that of the average U.S. bank for the bank loan and credit risk equations, respectively. We confirm that these results are robust to the measure of monetary policy used, to different specifications and estimation methods, and show that bank market power emerges as a key element affecting the potency of the bank lending and the risk-taking channels.

In the empirical analysis, we also examine whether the relationships identified above changed in the years following the eruption of the sub-prime mortgage crisis in 2007. We find that during the period 2007–10, the market power required to completely buffer the negative impact of a change in monetary policy on bank loans and credit risk is quite higher than the average market power in the banking industry. This has two important interrelated implications. First, after 2007, a moderate level of market power is not enough anymore to insulate bank portfolios from the effect of a change in monetary policy. Second, market power seems to have been the main bank characteristic reducing the potency of the bank lending and risk-taking channels prior to 2007 in our panel. Given the first implication, this suggests that the potency of the bank lending and the risk-taking channel has increased since 2007.

The rest of this paper is organized as follows. Section 2 provides a brief analysis of the bank lending and risk-taking channels; it also analyzes the theory behind choosing market power as an important element in the nexus between monetary policy changes on the one hand, and bank lending and risk taking on the other. Section 3 describes the empirical setup, the data set, and the way market power is estimated. Section 4 presents the empirical results, and section 5 concludes the paper.

2. Theoretical Considerations

The literature that studies bank behavior and monetary policy is multifaceted, and each of the approaches merits a discussion in its own right. Here we focus on the theoretical framework that assigns banks a special role in the monetary policy transmission mechanism via two channels, namely the bank lending and risk-taking channels. We further link this literature to the role of bank market power in shaping a heterogeneous response of banks in their lending and risk-taking behavior following a change in monetary policy.

2.1 Channels of Monetary Policy Transmission through Banks

According to the traditional lending channel view, monetary policy affects bank loan supply, and this in turn has an independent and significant effect on aggregate economic activity. In general, two conditions must be fulfilled for a bank lending channel to exist (Bernanke and Blinder 1988). On the one hand, borrowers are not able to fully insulate their real spending from a decline in the availability of bank loans, i.e., bank loans are imperfect substitutes for other sources of finance. On the other hand, banks are not able to fully insulate their loan supply from a monetary-policy-induced change in their reserves, i.e., there are no perfect substitutes for loans in bank portfolios. Both conditions have been subject to considerable debate in the literature. For instance, Romer and Romer (1990) suggest that if banks are able to obtain funds by tapping financial markets, monetary policy would affect banks only through changes in interest rates and, therefore, no bank lending channel would be at work.[1] Empirically, the bank lending channel has been explored by many studies with mixed results (for the U.S. case, see Kashyap and Stein 2000; for the euro area, see the collection of papers in Angeloni, Kashyap, and Mojon 2003). There is consensus, however, that in financial systems that are more market based, the higher degree of asset substitutability makes the bank lending channel less potent.

More recently, the notion of another channel, namely the risk-taking channel, has been put forward. Elements of this channel can be traced in Gibson (1997), who suggests that monetary policy has a greater effect on banks at times when their balance sheets have a riskier composition of assets. Several dimensions of how the risk-taking channel can work have been proposed. Matsuyama (2007) suggests that expansionary monetary policy reinforces the incentives of intermediaries to finance riskier projects. In a similar vein, Dell'Ariccia and Marquez (2006) and Rajan (2006) provide evidence that during lending booms loan quality deteriorates, as both lenders and borrowers are willing to take on higher risks. Further, in addition to this effect working through the risk taking of banks, it has been argued that the monetary policy of low interest rates followed in recent years, by affecting asset prices, has led some institutional investors to invest increasingly in credit-related assets in search of higher yield (European Central Bank 2008). This has allowed banks to increasingly fund themselves by selling loans in the secondary market, thus potentially boosting the supply of new loans. However, this may also have contributed to a higher value of non-performing loans.

Empirical evidence to support the above theoretical arguments on the risk-taking channel is quite recent. Jimenez et al. (2007) use a sample of Spanish banks and a variety of duration models to find that lower short-term interest rates prior to loan origination result in banks granting more risky new loans. Ioannidou, Ongena, and Peydro (2008) examine the Bolivian case (it has a dollarized banking system) and find that a decrease in the U.S. federal funds rate prior

[1] Unlike what is observed with the Bernanke and Blinder (1988) framework, in Romer and Romer (1990) bonds (securities issued outside the banking system) do not appear in banks' balance sheets and can be perfect substitutes for either certificates of deposit (a bank liability) or loans (a bank asset).

to loan origination raises the monthly probability of default on individual bank loans. Delis, Hasan, and Mylonidis (2011), using quarterly U.S. bank-level and loan-level data for the period 1990–2010, find evidence of a highly significant negative relationship between changes in monetary policy rates and bank risk taking.

An important element missing from the empirical work on the bank lending and risk-taking channels of monetary is the potential role that bank market power plays in the transmission process. We discuss this role in the following sub-section.

2.2 The Role of Bank Market Power

The empirical studies of the bank lending channel test for differential effects of monetary policy on the lending of individual banks using the bank characteristics of liquidity, capitalization, and size (see, e.g., papers in Angeloni, Kashyap, and Mojon 2003; Gambacorta 2005). The main contribution of this literature is the use of bank characteristics and, hence, of panel data to solve the identification problem of the lending channel, i.e., distinguishing between shifts in loan demand and shifts in loan supply.[2]

In the present study we depart from using size as the third basic bank balance sheet characteristic influencing banks' reaction to changes in policy rates. The main argument for the use of bank size is that one would expect the largest banks to have an easier time raising uninsured finance, which would make their lending less dependent on monetary policy shocks, irrespective of other bank characteristics (Kashyap and Stein 1997, 2000). However, this implicitly suggests that certain banks have market power in raising finance from alternative sources, something that may or may not be the result of size. This feature is carried over to the asset side of bank balance sheets, causing deviations from perfectly competitive behavior. It is also noteworthy that Lensink and Sterken (2002), in editing a special issue of the *Journal of Banking and Finance*, suggest that future

[2]This strategy relies on the hypothesis that bank characteristics influence only loan supply movements, while loan demand is independent of these characteristics. Brissimis and Delis (2009) also used panel data to overcome the identification problem, while Brissimis and Magginas (2005) offered a solution to the problem using time-series data.

work should identify whether bank competition plays an important role in the monetary transmission mechanism.

Besides the argument that banks with high market power have better access to alternative sources of finance, there are other important mechanisms backing up our study of the role of market power in the bank lending and risk-taking channels. In principle, higher market power of banks increases future lending opportunities, leading to higher loan growth and risk taking. However, a rather established literature on bank competition and risk taking (e.g., Keeley 1990; Koetter, Kolari, and Spierdijk 2012) is skeptical about this conclusion. The premise is that high market power leads to a "quiet life," a situation where these banks already earn considerable profit and are not as interested in extending their future funding opportunities, given the additional risk that these bear. If this mechanism prevails, the effect of market power in the bank lending and risk-taking channels is then straightforward. Following, e.g., an expansionary monetary policy, banks with less market power will take on higher credit risk and increase loans in search for yield, while banks with high market power will engage in such activities to a lesser extent because they already extract rents.

The two mechanisms above are interrelated with the simple microeconomics of banking in propagating differential effects of monetary policy changes on bank lending through bank market power. Specifically, existing empirical evidence (e.g., Kahn, Pennacchi, and Sopranzetti 2005) shows that in more concentrated banking markets, lending rates appear to be quite sticky to changes in marginal cost.[3] The intuition is that the marginal cost of loan production is directly affected by changes in monetary policy, which alter the interest rates banks have to pay for obtaining loanable funds in the short-term market. Under perfect competition, a change in the central bank rate will, ceteris paribus, match the change in the marginal cost of loan production and the change in lending rates. Under a noncompetitive structure (e.g., oligopolistic), bank lending will be less sensitive to changes in the marginal cost for the production of new loans. This is likely to hold, as the marginal cost itself will be less sensitive to a change in central bank rates, given that banks with

[3]Note that this study uses concentration as a proxy for competition and this choice is open to criticism (e.g., Beck, Demirguc-Kunt, and Levine 2006).

market power will have access to alternative sources of finance or will be living a "quiet life." In both cases, the impact of monetary policy on bank lending and risk taking decreases with higher levels of bank market power.

At a more aggregate level, Baglioni (2007) investigates a theoretical model of the banking industry under both monopolistic competition and a Cournot oligopoly. The results suggest that under monopolistic competition the aggregate effect of monetary policy on the economy is amplified, while under an oligopolistic structure it is weakened. The result for the monopolistically competitive structure is derived from the assumption that the response of each bank is amplified by the reaction of other competitive banks, introducing a multiplier effect. Note that empirical evidence from the European banking industry suggests that most banking systems in euro-area countries are characterized by monopolistic competition (see Bikker and Haaf 2002; Claessens and Laeven 2004), while some banking systems of newly acceded EU countries feature oligopolistic behavior (see Brissimis, Delis, and Papanikolaou 2008). Bearing these issues in mind, we now proceed to the discussion of the empirical framework.

3. Data and Empirical Setup

The starting point in the estimation procedure is the setup of the econometric model. We opt to estimate bank loan and credit risk equations with a view to identifying the role of bank market power in the relationship between changes in monetary policy and loan growth or changes in credit risk. The equations to be estimated are directly obtained from the literature. The first equation considers the response of bank loans to monetary policy and follows from the bank lending channel literature (e.g., Kashyap and Stein 2000). The second considers the impact of monetary policy on credit risk and follows from the literature that explains credit risk (e.g., Delis, Hasan, and Mylonidis 2011). Thus, the estimated equations are of the following general form:

$$\begin{aligned}\Delta L_{it} = a_0 + a_1\Delta L_{i,t-1} + a_2\Delta M_{t-1} + a_3 B_{i,t-1} \\ + a_4\Delta M_{t-1}B_{i,t-1} + u_{it}^1 \end{aligned} \tag{1}$$

$$\Delta R_{it} = b_0 + b_1 \Delta R_{i,t-1} + b_2 \Delta M_{t-1} + b_3 B_{i,t-1} + b_4 \Delta M_{t-1} B_{i,t-1} + u^2_{it}, \quad (2)$$

where Δ denotes change, L is lending of bank i in period t (in logarithmic terms), R is a measure of bank credit risk, M is the monetary policy variable, B is a vector of bank characteristics that include market power, and u is the error term. The above empirical model suggests that in both equations the coefficient of the monetary policy variable depends directly on the level of market power (among other bank characteristics) of individual banks. Also, both equations include the first lag of the dependent variable to account for the inherent dynamics of bank data and are in differences to reduce first-order serial correlation, which is present in bank panel data.

3.1 Data

To estimate equations (1) and (2), we build a panel data set that covers the U.S. and euro-area (the first twelve EU countries that participated in the euro area) banking sectors for the period 1997–2010. Annual bank-level data are obtained from the Bankscope database. The final data set is unbalanced and is built by applying two selection criteria. First, all types of banks that take deposits (commercial, savings, cooperative, and bank holding companies) are included in the sample. Investment banks are not included because they do not take deposits and, therefore, do not fall into the theoretical discussion provided above. Second, an outlier rule is applied to the main bank-level variables so as to disregard the 2 percent of both edges of their distribution. This deletes all bank observations for which data on the main variables of this study are unreasonable (e.g., negative value of bank assets, loans, and expenses).

Third, and most important, we account for corporate events like mergers and acquisitions (M&A's) and failures. We went through all these corporate events one by one and made sure that both banks appear separately in the sample before, e.g., the M&A and only the merged entity or the acquiring bank is included in the sample after the event. Also, in the United States there are quite a few separate banks that have the same name but are active in a different state. To solve this issue, we relate the value of total assets of, say, bank i in the last year this bank appears in our sample with Bankscope's identification number for bank i. The final working sample consists of 21,406 observations for the United States and 26,430 observations for the euro-area banking sector for the less demanding specifications—therefore 47,836 observations in total. As we add control variables in more demanding specifications, the number of observations falls due to missing observations for some of these control variables.

We note here that Bankscope data are annual, and an immediate question arises as to why annual data are used to study monetary policy. Most work on the lending channel cited in section 2.1 employs quarterly data. In two relatively recent papers, Gambacorta (2005) and Ashcraft (2006) point out that results obtained from bank loan equations are robust to the use of annual data. In addition, Delis and Kouretas (2011) confirm that this is the case when examining the impact of monetary policy on bank credit risk.

3.2 Estimation of Bank Market Power

Before estimating the bank loan and credit risk equations, we need to measure bank market power. The Global Financial Development Report (World Bank 2013) offers a number of indicators of banking-sector competition at the country-year level. However, and consistent with Clerides, Delis, and Kokas (2013), we decided to estimate our own indicators for two main reasons. First, we need estimates of market power at the bank-year level to increase the number of observations and the power of our results. Second, in line with the discussion in section 3.1, we need a careful cleansing of the data to remove double-counting of banks stemming from mergers and acquisitions, ownership issues, and inflexible features of the Bankscope database.

We resort to the estimation of the two indicators that are the most favored in the empirical literature of bank market power, namely the Lerner index and the Boone indicator.[4] Boone, Griffith, and Harrison (2005) and Boone (2008) criticize certain aspects of the

[4]Previous studies have also used the H-statistic of Panzar and Rosse (1987) to measure bank competition. However, several recent studies (e.g., Bikker, Shaffer, and Spierdjik 2012) show that there are serious problems associated with this approach, especially in viewing the H-statistic as a continuous measure of market power.

Lerner index as a proxy for competition, especially when they consider highly concentrated markets. However, Schiersch and Schmidt-Ehmcke (2010) show that the empirical equivalent of Boone's (2008) model is inferior to the Lerner index when applied to a rich data set of manufacturing firms. As the relative empirical merits of these measures of competition are still unknown, we examine the sensitivity of our results by using both measures.

The Lerner index is given by the equation

$$Lerner_{it} = \frac{p_{it} - mc_{it}}{p_{it}}, \tag{3}$$

where mc_{it} is the marginal cost of bank i at time t and p_{it} denotes the price of the banking product. The Lerner index ranges between 0 and 1, where larger values are interpreted as indicating more market power (less competition). In turn, the Boone indicator of market power can be estimated from the following equation:

$$\ln \pi_{it} = \alpha + \beta \ln mc_{it}, \tag{4}$$

where π_{it} is the profit of bank i at time t and β is the Boone indicator. In principle, β should be negative, given that profits and marginal cost have a negative relationship. Hence, a larger β reflects a less competitive industry. An analytical derivation of the Boone indicator is presented in appendix 1.

For the estimation of equations (3) and (4), we need estimates of marginal cost from a simple cost function. A critical element of the theoretical models underlying both indices is that estimates of marginal cost must be obtained at the bank-year (observation) level. This has two empirical implications. First, imposing a common parametric functional form for the cost function across all banks in our panel is a very strong assumption, because this implies that all banks in the thirteen countries considered and across time share the same production technology. Second, even if we obtain estimates of marginal cost at the bank-year level from, e.g., a translog specification, the Boone indicator β will not be estimated at the bank-year level.

A solution to these issues is proposed by Delis (2012), Delis, Iosifidi, and Tsionas (2012), and Clerides, Delis, and Kokas (2013), who use a non-parametric estimation method for the estimation of marginal cost. Specifically, these studies employ the semi-parametric smooth-coefficient model, which allows estimation of the model's parameters at the observation (here bank-year) level. This is important because both marginal cost and the Boone parameter β vary for each available observation. Further, this class of non-parametric models are completely flexible and, therefore, do not impose a specific functional form on the cost function.

More formally, we rely on the estimation of the cost equation

$$c_{it} = b + dq_{it} + \sum_{n=1}^{3} \phi_n w_{n,it} + e_{it}, \tag{5}$$

where c is the total cost that bank i incurs at time t to produce output q, using three inputs of production with associated prices w_n, where $n = 1, 2, 3$. As the choice of the functional form is not an issue, we use the more general linear form, which allows obtaining marginal cost simply as $d_{it.}$ In other words, estimation of equation (5) with the smooth-coefficient model yields bank-year estimates of $mc_{it} = \partial c_{it}/\partial q_{it} = d_{it}$. In panel A of table 1, we define the variables used to estimate this cost equation and report summary statistics. For the definition of bank output and input prices, we follow the intermediation approach, which assumes that deposits are inputs used in the production process to produce bank loans (Berger and Humphrey 1997; Koetter, Kolaris, and Spierdijk 2012).

We estimate equation (5) using the procedure of Delis (2012) and Delis, Iosifidi, and Tsionas (2012). As we replicate the econometric procedure of these papers, we do not include here all the technical details for the estimation process, but we provide a brief description in appendix 2. Subsequently, we use the estimates of marginal cost and equation (3) to calculate the Lerner index at the bank-year level. The price of bank output p (i.e., the lending rate) is defined as the ratio of total income to total earning assets. For the Boone indicator, we use the same marginal cost obtained from equation (5) and estimate equation (4) again with the smooth-coefficient model. This yields bank-year estimates β_{it} of the Boone indicator.

In table 2 we present averages for these bank-year Lerner and Boone indices across country and year. As figure 1 indicates, fluctuations across time are not large, but the trend is increasing for both indices up to 2006. During the crisis of 2007–8, both indices reflect a decrease in average bank market power, and in 2009–10 there is again

Table 1. Summary Statistics of the Variables Used in the Empirical Analysis

Notation	Measure	Mean	St. Dev.	Min.	Max.
A. Variables Used to Estimate Market Power					
Total Cost (c)	ln(real total expenses)	76,319.7	1,111,541	94.76	99,300,000
Earning Assets (q)	ln(real earning assets)	1,477,392	19,300,000	935.29	1,010,000,000
Price of Funds (w_1)	ln(interest expenses/total customer deposits)	0.067	0.092	0.001	1.030
Price of Labor (w_2)	ln(personnel expenses/total assets)	0.015	0.006	0.001	0.089
Price of Physical Capital (w_3)	ln(overheads/fixed assets)	1.444	3.045	0.130	56.66
Lending Rate (p)	ln(total income/earning assets)	0.070	0.026	0.016	0.704
Bank Profits (π)	ln(real profits before tax)	13,827.5	254,150	10,300,000	19,000,000
B. Variables Used in the Lending and Risk Equations					
Loans	ln(real total loans)	944,785	11,400,000	157.98	643,000,000
Problem Loans	Non-performing loans/total loans	0.009	0.019	0.000	0.758
CB Rate	Central bank rate	2.453	1.663	0.160	12.750
Liquidity	Liquid assets/total assets	0.206	0.099	0.000	0.923
Capitalization	Equity capital/total assets	0.087	0.056	−0.469	1.000
Provisions	Loan loss provisions/total loans	0.028	1.092	0.000	0.603
Profitability	Profits before tax/total assets	0.008	0.013	−0.500	0.301
Growth	Annual growth rate	1.777	2.259	−8.354	10.900

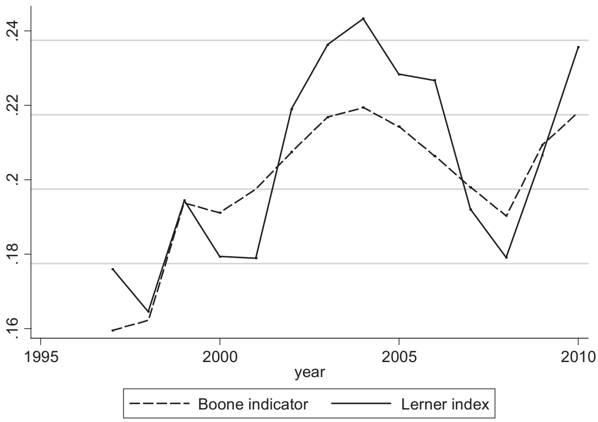
Notes: The table reports the notation, the measure, and summary statistics (mean, standard deviation, minimum, and maximum) for the variables used in the empirical analysis. Panel A reports statistics for the variables used to estimate bank market power (the Lerner index and the Boone indicator). Panel B reports statistics for the variables used in the bank loan and credit risk equations. The summary statistics for all variables in panel A and for the loan variable in panel B are not in logarithmic terms. The variables that are not ratios are in thousand US$.

Table 2. Estimates of Bank Market Power (Country and Year Averages)

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Mean
A. Lerner Index															
Austria	0.20	0.19	0.21	0.23	0.19	0.20	0.23	0.22	0.23	0.22	0.20	0.17	0.20	0.23	0.21
Belgium	0.13	0.16	0.17	0.18	0.17	0.15	0.16	0.15	0.16	0.16	0.11	0.11	0.18	0.18	0.16
Finland	0.25		0.34	0.35			0.32	0.29	0.19	0.15	0.18	0.07	0.24	0.20	0.23
France	0.13	0.14	0.15	0.15	0.16	0.18	0.18	0.21	0.22	0.22	0.20	0.18	0.24	0.26	0.19
Germany	0.17	0.15	0.17	0.14	0.13	0.16	0.18	0.19	0.18	0.22	0.16	0.15	0.19	0.23	0.17
Greece	0.15	0.17	0.44	0.36		0.33	0.26	0.26	0.25	0.22	0.19	0.19	0.20	0.19	0.25
Ireland	0.19	0.18	0.26	0.21	0.15	0.14	0.23	0.27	0.13	0.18	0.19	0.19	0.19	0.21	0.19
Italy	0.16	0.20	0.17	0.21	0.19	0.17	0.19	0.22	0.22	0.26	0.25	0.21	0.23	0.20	0.21
Luxembourg	0.12	0.12	0.15	0.15	0.14	0.14	0.16	0.22	0.24	0.23	0.20	0.15	0.27	0.31	0.19
Netherlands	0.14	0.15	0.17	0.20	0.16	0.10	0.11	0.16	0.17	0.14	0.20	0.18	0.16	0.27	0.17
Portugal	0.07	0.08	0.06	0.17	0.27	0.35	0.31	0.35	0.17	0.20	0.17	0.20	0.20	0.18	0.20
Spain	0.13	0.18	0.21	0.16	0.16	0.19	0.27	0.25	0.25	0.25	0.25	0.21	0.26	0.20	0.21
United States	0.20	0.20	0.23	0.21	0.22	0.25	0.25	0.22	0.25	0.23	0.20	0.19	0.21	0.22	0.22
Mean	0.16	0.16	0.21	0.21	0.18	0.20	0.22	0.23	0.20	0.21	0.19	0.17	0.21	0.22	0.20
B. Boone Indicator															
Austria	−0.41	−0.41	−0.40	−0.41	−0.40	−0.39	−0.38	−0.38	−0.38	−0.38	−0.40	−0.42	−0.39	−0.39	−0.40
Belgium	−0.50	−0.45	−0.42	−0.43	−0.42	−0.43	−0.40	−0.40	−0.43	−0.42	−0.45	−0.46	−0.42	−0.39	−0.43
Finland	−0.36	−0.37	−0.37	−0.34			−0.37	−0.36	−0.36	−0.36	−0.35	−0.38	−0.36	−0.36	−0.36
France	−0.43	−0.44	−0.43	−0.43	−0.42	−0.42	−0.39	−0.41	−0.42	−0.43	−0.44	−0.45	−0.44	−0.41	−0.43
Germany	−0.40	−0.39	−0.39	−0.39	−0.39	−0.38	−0.37	−0.37	−0.37	−0.37	−0.37	−0.37	−0.37	−0.37	−0.38
Greece	−0.39	−0.39	−0.38	−0.34	−0.30	−0.30	−0.32	−0.33	−0.34	−0.36	−0.38	−0.38	−0.36	−0.36	−0.35
Ireland	−0.51	−0.48	−0.46	−0.46	−0.35	−0.36	−0.40	−0.43	−0.52	−0.47	−0.52	−0.52	−0.47	−0.35	−0.45
Italy	−0.41	−0.39	−0.37	−0.38	−0.38	−0.38	−0.38	−0.39	−0.37	−0.37	−0.40	−0.43	−0.37	−0.36	−0.38
Luxembourg	−0.52	−0.53	−0.49	−0.49	−0.45	−0.45	−0.43	−0.43	−0.43	−0.43	−0.42	−0.41	−0.40	−0.40	−0.45
Netherlands	−0.58	−0.58	−0.56	−0.57	−0.58	−0.52	−0.49	−0.54	−0.49	−0.51	−0.45	−0.41	−0.37	−0.36	−0.50
Portugal	−0.56	−0.61	−0.50	−0.46	−0.51	−0.47	−0.52	−0.46	−0.43	−0.50	−0.47	−0.49	−0.42	−0.39	−0.49
Spain	−0.44	−0.43	−0.39	−0.43	−0.41	−0.44	−0.43	−0.39	−0.38	−0.42	−0.48	−0.50	−0.45	−0.38	−0.43
United States	−0.39	−0.39	−0.40	−0.40	−0.40	−0.40	−0.38	−0.36	−0.36	−0.37	−0.37	−0.37	−0.36	−0.36	−0.38
Mean	−0.45	−0.45	−0.43	−0.43	−0.42	−0.41	−0.40	−0.40	−0.41	−0.41	−0.42	−0.43	−0.40	−0.38	−0.42

Notes: The table reports average values (by country and year) of bank-level estimates of market power. Panel A reports averages for the Lerner index and panel B averages for the Boone indicator. Higher values for both indices reflect lower competition (higher market power).

Figure 1. Averages of the Lerner and Boone Indicators over Time



Notes: The figure shows the annual average for the Lerner index and the Boone indicator for our panel. The Boone indicator is rescaled to have comparable values with the Lerner index.

an increase in market power to the levels of the pre-crisis period. Our findings are consistent with the equivalent ones from the Global Financial Development Report (World Bank 2013) and the new data set on bank competition by Clerides, Delis, and Kokas (2013). For example, there is a 0.41 and 0.60 correlation coefficient between our Lerner index and the Lerner indices of the Global Financial Development Report and Clerides, Delis, and Kokas (2013), respectively. The trends discussed above for our Lerner and Boone indices are also quite similar with those in the existing literature.

Both our Lerner and Boone indices show that countries like Belgium, Luxembourg, and the Netherlands have quite competitive banking sectors. Greece, Italy, and Finland are examples of countries with less competitive banking sectors, even though the two indices do not agree entirely on this front. The two indices have a strong positive pairwise correlation coefficient that is equal to 0.37 and statistically significant at the 1 percent level. In the rest of the empirical analysis, we use primarily the Lerner index, as this is the one usually employed in the literature, and conduct sensitivity analysis with the Boone index.

3.3 Dependent and Other Explanatory Variables

Panel B of table 1 provides definitions and summary statistics for the main variables used to estimate equations (1) and (2). Bank loans are measured by total customer loans, and bank credit risk by the ratio of problem loans to total loans. Let us briefly comment here on our choice for the risk variable. In equation (2) R represents ex post credit risk, i.e., the realized variation in net income and the market value of equity resulting from a non-payment or delayed payment by borrowers. Whenever a bank grants a loan, it assumes the risk that the borrower will default—that is, he will not repay the principal and interest on a timely basis—and, thus, our measure reflects the quality of bank loans. Since a portion of non-performing loans will probably result in losses for the bank, a high value for this ratio is unwanted. Credit risk represents the major cause of most bank failures and is directly related to the theoretical discussion of section 2 because it refers to the risk of lending.

Following Bernanke and Blinder (1992) and Ashcraft (2006), we utilize the federal funds rate as a measure of monetary policy in the United States. For the euro area, we utilize the ECB key policy rate from 1999 onwards (2001 for Greece) and before 1999 the official refinancing operation rate for each country separately. We name this monetary policy variable "CB rate." We also examine the sensitivity of our results to the use of Taylor-rule residuals instead of the central bank rates. We obtain Taylor-rule residuals by regressing the overnight interbank rate on GDP growth and inflation, using panel least-squares regressions for the United States and the euro area (e.g., Maddaloni and Peydro 2011).

Turning to the rest of the bank characteristics that may affect loan supply, we first use the ratio of equity to total assets to measure the capitalization of banks and the ratio of liquid assets to total assets to measure their liquidity (see also studies in Angeloni, Kashyap, and Mojon 2003; Gambacorta 2005). Further, we use the ratio of net profits to total assets (i.e., the return on assets, ROA) to capture the income generated from both traditional and non-traditional banking activities. In some specifications, we also control for the perceptions of the banks' management about credit risk using the ratio of loan-loss provisions to total loans. This variable captures the level of risk aversion of bank managers. We experiment with many other bank characteristics like bank size (measured by the natural logarithm of total assets), the ratio of loans to total assets, the ratio of loans to deposits, the ratio of non-interest income to total income, etc. The empirical results from the inclusion of most of these variables do not affect the pass-through of monetary policy to bank loans or credit risk and, thus, the corresponding estimates are only available on request.

In all estimated equations, we use bank fixed effects to control for all missing bank-level characteristics, as well as country-specific time effects to control for within-country shocks common to all banks that might affect bank lending or risk taking. As we have thirteen countries in our sample, we also use country fixed effects to capture time-invariant common effects across all banks in a single country. Finally, in some of the estimated equations we use GDP growth, but this and other macroeconomic variables tend to be redundant after controlling for country-specific time effects.[5]

4. Empirical Results

Equations (1) and (2) include the first lag of the dependent variable and, thus, we resort to dynamic panel data estimation techniques. We use both the generalized method of moments (GMM) of Blundell and Bond (1998) for dynamic panels and the limited-information maximum-likelihood (LIML) method. For the GMM estimator, we use the two-step procedure with corrected standard errors (Windmeijer 2005). GMM is optimal for panels with a relatively small time dimension, but is overly sensitive to the use of different instruments. LIML is also used with corrected standard errors and seems to be the optimal estimator as the time dimension of the panel increases (Baltagi 2005, p. 153). As we have data for fourteen years, LIML seems to be a good alternative to GMM. For the estimation process we instrument the CB rate and the associated interaction terms with the bank-level variables, using only the second and third lags of the interaction terms including market power, capitalization, and liquidity

[5]We also experiment with a number of other macroeconomics variables like the ratio of stock market capitalization to GDP, the ratio of bank credit to the private sector to GDP, etc. Changes in our results are not significant.

as IV-style instruments.[6] These instruments yield acceptable values for all of the Sargan over-identification tests for the GMM regressions, as well as for all of the under-, weak-, and over-identification tests of the LIML regressions. We report these tests along with the estimated coefficients and t-statistics in the relevant specifications. Further, use of the same set of instruments in the GMM and the LIML regressions allows a direct comparison of the results from the two methods.

4.1 Loan Equations

We present the results from our basic bank loan equations in table 3. We should note here that all explanatory variables that appear in interaction terms were demeaned so as to interpret the coefficient estimates as the response of the dependent variables to a unit change in the predictor when the other predictors involved in the interaction terms are at their mean values. For expositional brevity, we only report the coefficient estimates and t-statistics on the main effect of the change in the CB rate and on the interaction terms between the change in the CB rate and bank characteristics, as these estimates are of particular interest here. The full set of results is available on request.

The first three regressions are the ones estimated with GMM. In column 1 we include the Lerner index of bank market power as the only bank characteristic. The coefficient on ΔCB rate is negative and statistically significant at the 1 percent level and shows that a one-point increase in the CB rate will decrease bank loans by 18 percent, which is a very large decrease. However, the coefficient on the interaction term between the ΔCB rate and the Lerner index is positive and statistically significant, showing that the bank lending channel is less potent for banks with higher market power. In columns 2 and 3 we reduce omitted-variable bias by adding more bank characteristics, and this also reduces the value of the coefficient on ΔCB rate to more reasonable levels. The interaction term of the

[6] Use of GMM-style instruments under the method of Blundell and Bond (1998) produces Sargan tests that reject the hypothesis of over-identifying restrictions in our panel. For more on these issues, see Roodman (2006).

Table 3. Bank Loan Equations: Full Sample

	GMM Results			LIML Results				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
ΔCB Rate	−0.179***	−0.193***	−0.074***	−0.119***	−0.072***	−0.075***	−0.076***	−0.072***
	(−83.577)	(−82.349)	(−9.083)	(−5.558)	(−6.421)	(−6.985)	(−6.313)	(−5.968)
ΔCB Rate * Lerner Index	0.215***	0.238***	0.213***	0.452***	0.375***	0.354***	0.397***	
	(3.349)	(8.038)	(3.603)	(6.732)	(3.562)	(4.680)	(11.636)	
ΔCB Rate * Liquidity		0.106*	0.222***		0.249***	0.252***	0.210***	0.204***
		(1.701)	(4.570)		(11.298)	(4.853)	(14.852)	(14.167)
ΔCB Rate * Capitalization		0.176***	0.027		0.443***	0.487***	0.428**	0.467***
		(22.809)	(0.613)		(10.991)	(5.557)	(4.994)	(4.270)
ΔCB Rate * Provisions			−0.653***			−0.458***	−0.583***	−0.106**
			(−7.843)			−(4.783)	(−10.490)	(−2.206)
ΔCB Rate * Profitability			0.869***			0.415*	0.871***	0.819**
			(7.009)			(1.895)	(9.491)	(2.550)
Growth							0.006	0.0005
							(0.563)	(0.478)
ΔCB Rate * Boone Indicator								0.174***
								(7.442)
Constant Term	2.704***	2.940***	2.703***	0.210***	0.206***	0.290***	0.221***	0.210***
	(97.216)	(91.203)	(64.957)	(27.765)	(26.565)	(17.472)	(22.034)	(19.149)
Observations	47,836	47,832	42,044	47,836	47,832	42,044	42,044	42,118
Sargan Test (p-value)	0.156	0.147	0.214					
UI Test (p-value)				0.00	0.00	0.00	0.00	0.00
WIT Test (p-value)				33.28	31.10	27.50	28.24	30.01
OIT Test (p-value)				0.302	0.407	0.355	0.306	0.362

Notes: The table reports estimated coefficients and t-statistics (in parentheses). The dependent variable is the annual loan growth. The explanatory variables are defined in table 1 and are all lagged one year. Δ in front of the CB rate denotes annual change. Regressions 1–3 are estimated with GMM for dynamic panels and regressions 4–8 with LIML for dynamic panels. All regressions include country-specific time effects. Sargan is the p-value of the over-identification test by Sargan, which requires a value higher than 0.05 to reject the null hypothesis at the 5 percent level. UIT is the p-value of the under-identification LM test by Kleibergen and Paap, which requires a value lower than 0.05 to reject the null hypothesis at the 5 percent level. WIT is the Wald F-statistic of the weak identification test by Kleibergen and Paap, which must be higher than approximately 10 to reject the null hypothesis. OIT is the p-value of the over-identification test by Hansen, which requires a value higher than 0.05 to reject the null hypothesis at the 5 percent level. ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

monetary policy variable with the Lerner index remains highly significant. The values of the coefficients on the rest of the interaction terms and their statistical significance are not very stable among the regressions reported in columns 2 and 3. In fact, even slight changes in the instrumental variables yield very large differences in the results, causing some uncertainty about the applicability of the GMM procedure to our panel.

In columns 4–8, we estimate equation (1) using LIML. An immediate observation is that, with the exception of regression 4, which suffers from an obvious omitted-variable bias, the rest of the regressions yield fairly stable coefficient estimates. Specifically, the coefficient estimate on ΔCB rate in column 6 implies that a one-point increase in the CB rate will increase loans by 7.5 percent. However, this effect decreases considerably for banks with high market power. Given the coefficient estimate of 0.354 on the interaction term between ΔCB rate and the Lerner index, we can calculate the level of the Lerner index required for the impact of ΔCB rate on loan growth to turn positive from setting the derivative of the estimated equation with respect to ΔCB rate equal to zero. Calculation yields a value approximately equal to 0.21, which is just over our panel's mean value of 0.20. This implies that banks in our panel with levels of market power only 1 percent higher than the panel's average are able to completely insulate the negative impact of a monetary policy contraction on bank lending. Similar quantitative results are found for the regressions presented in columns 7 and 8.

The results on the rest of the interaction terms show that liquidity, capitalization, provisions and, in some cases, profitability are also important bank characteristics in affecting bank loans. In particular, the negative effect of changes in monetary policy on loans is weaker for banks with higher liquidity and capitalization and stronger for banks with higher provisions. These findings suggest that banks with high capitalization and liquidity are also able to buffer the effect of a monetary policy change, in a way very similar to the one we discussed for market power. In contrast, given an increase in the monetary policy variable, banks with higher provisions will curtail loans by even more compared with the average bank in the sample. If we calculate the equivalent points for liquidity and capitalization where the impact of the ΔCB rate on loan growth turns positive, we will find, based on specification 6, values equal to 0.298 and

0.154, respectively. Considering that the mean values in our panel for these variables are 0.206 and 0.087, we can conclude that the negative effect of the monetary policy variable reverses for banks with only very high levels of liquidity and capitalization. Given these findings, the market power variable emerges as the most important bank characteristic affecting the impact of a change in monetary policy on bank loans, at least in our sample.

In column 8 we examine the sensitivity of our results to the inclusion of the Boone indicator as a measure of bank market power instead of the Lerner index. The results remain practically unaffected: A one-point increase in the CB rate is associated with a 7.2 percent decrease in bank loans. However, this effect becomes zero for banks with a value of 0.41 for the Boone indicator, which again is very close to the mean value of the Boone indicator in our panel (0.42). Thus, in a similar fashion with the results in the regressions involving the Lerner index, our findings show that for banks with even moderate levels of market power, the negative effect of the CB rate on bank loans disappears.

In table 4 we rerun specifications 5, 6, and 8 of table 3 separately for the euro area and the United States. The statistical significance of the results remains unaffected. The coefficient estimates show that the impact of the monetary policy variable in the United States is somewhat larger than it is in the euro area. Yet, the coefficients on the interaction terms of the monetary policy variable with the Lerner index show that euro-area banks with a Lerner index equal to 0.21 completely buffer the negative effect of monetary policy changes on bank loans (the result comes from column 2). The equivalent value for the U.S. banks is 0.28. This shows that somewhat lower levels of market power are required in the euro area to buffer monetary policy shocks compared with the United States, even though admittedly the difference is not very large. This finding also carries through when using the Boone indicator (see columns 3 and 7 for the euro area and the United States, respectively).

4.2 Credit Risk Equations

In table 5 we essentially replicate table 3 for equation (2). The dependent variable is the annual change in the ratio of non-performing loans (denoted as problem loans) to total loans. We favor the model

Table 4. Bank Loan Equations: Euro Area vs. United States

	Euro Area			United States		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ΔCB Rate	−0.045***	−0.043***	−0.042***	−0.060***	−0.068***	−0.065***
	(−3.008)	(−2.899)	(−2.854)	(−3.789)	(−3.864)	(−4.363)
ΔCB Rate * Lerner Index	0.213***	0.207***		0.230***	0.244***	
	(7.970)	(7.126)		(2.994)	(3.799)	
ΔCB Rate * Liquidity	0.289***	0.282***	0.292***	0.298***	0.212***	0.232***
	(5.423)	(5.331)	(4.924)	(6.270)	(5.149)	(4.993)
ΔCB Rate * Capitalization	0.363***	0.369***	0.311***	0.662***	0.747***	1.532***
	(7.723)	(7.385)	(7.436)	(6.850)	(5.599)	(7.834)
ΔCB Rate * Provisions		−0.516***	−0.711***		−0.565***	−0.559***
		(−5.289)	(−7.059)		(−4.745)	−(4.475)
ΔCB Rate * Profitability		0.873***	0.829***		0.807***	0.851***
		(10.167)	(10.202)		(10.386)	(10.953)
ΔCB Rate * Boone Indicator			0.109***			0.172***
			(3.695)			(2.825)
Constant Term	0.169***	0.168***	0.121***	0.260***	0.275***	0.333***
	(20.367)	(21.769)	(8.818)	(15.184)	(13.110)	(13.573)
Observations	25,001	22,129	22,203	22,831	19,915	19,915
UI Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00
WIT Test (p-value)	28.72	24.54	23.19	34.16	32.51	32.28
OIT Test (p-value)	0.177	0.163	0.188	0.206	0.244	0.230

Notes: The table reports estimated coefficients and t-statistics (in parentheses). The dependent variable is the annual loan growth. The explanatory variables are defined in table 1 and are all lagged one year. Δ in front of the CB rate denotes annual change. All regressions are estimated with LIML for dynamic panels and include country-specific time effects. Regressions 1–3 are estimated using the euro-area panel of banks and regressions 4–7 using the U.S. panel. UIT is the p-value of the under-identification LM test by Kleibergen and Paap, which requires a value lower than 0.05 to reject the null hypothesis at the 5 percent level. WIT is the Wald F-statistic of the weak identification test by Kleibergen and Paap, which must be higher than approximately 10 to reject the null hypothesis. OIT is the p-value of the over-identification test by Hansen, which requires a value higher than 0.05 to reject the null hypothesis at the 5 percent level. ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

Table 5. Credit Risk Equations: Full Sample

	GMM Results			LIML Results				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔCB Rate	−0.041***	−0.040***	−0.037***	−0.039*	−0.040**	−0.045***	−0.046***	−0.045***
	(−11.038)	(−8.937)	(−5.565)	(−11.746)	(−8.444)	(−8.624)	(−8.524)	(−8.416)
ΔCB Rate * Lerner Index	0.206***	0.230***	0.210***	0.108**	0.216***	0.211***	0.282***	
	(5.450)	(5.495)	(5.417)	(2.567)	(5.228)	(5.817)	(5.832)	
ΔCB Rate * Liquidity		0.134***	0.139***		0.165***	0.157***	0.170***	0.171***
		(4.814)	(5.129)		(7.687)	(6.653)	(6.149)	(5.662)
ΔCB Rate * Capitalization		0.253***	0.259***		0.208***	0.275***	0.248**	0.202***
		(3.358)	(3.326)		(4.995)	(3.553)	(2.247)	(4.117)
ΔCB Rate * Provisions			−0.525**			−0.516**	−0.503**	−0.491**
			(−2.51)			(−2.407)	(−2.281)	(−2.272)
ΔCB Rate * Profitability			0.919***			1.103***	1.132***	1.041***
			(3.048)			(4.344)	(4.170)	(3.335)
Growth							−0.010	−0.006
							(−1.372)	(−.858)
ΔCB Rate * Boone Indicator								0.118***
								(3.187)
Constant Term	−3.573***	−3.584***	−3.707***	−0.094***	−0.099***	−0.116***	−0.139***	−0.139***
	(−83.830)	(−82.358)	(−72.301)	(−9.299)	(−9.279)	(−12.036)	(−9.382)	(−9.070)
Observations	40,226	40,223	38,546	40,226	40,223	38,546	38,546	38,602
Sargan Test (p-value)	0.204	0.167	0.308					
UI Test (p-value)				0.00	0.00	0.00	0.00	0.00
WIT Test (p-value)				37.48	33.52	33.10	36.77	35.15
OIT Test (p-value)				0.407	0.554	0.550	0.628	0.500

Notes: The table reports estimated coefficients and t-statistics (in parentheses). The dependent variable is the annual change in the ratio of non-performing loans (problem loans) to total loans. The explanatory variables are defined in table 1 and are all lagged one year. Regressions 1–3 are estimated with GMM for dynamic panels and regressions 4–8 with LIML for dynamic panels. All regressions include country-specific time effects. Sargan is the p-value of the over-identification test by Sargan, which requires a value higher than 0.05 to reject the null hypothesis at the 5 percent level. UIT is the p-value of the under-identification LM test by Kleibergen and Paap, which requires a value lower than 0.05 to reject the null hypothesis at the 5 percent level. WIT is the Wald F-statistic of the weak identification test by Kleibergen and Paap, which must be higher than approximately 10 to reject the null hypothesis. OIT is the p-value of the over-identification test by Hansen, which requires a value higher than 0.05 to reject the null hypothesis at the 5 percent level. ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

in first differences because this reduces substantially the presence of serial correlation of second order, the presence of which yields inconsistent estimates in dynamic panel data models. Also, most of the mechanisms underlying the risk-taking channel concern new risk and thus are better given by the change in problem loans. In the credit risk equations, the choice of the estimation method (GMM in columns 1–3 and LIML in columns 4–8) affects the results less than in the bank loan equations. Overall, the results show that the impact of the monetary policy variable on problem loans is negative, and this is consistent with the presence of a risk-taking channel. In other words, a fall in the CB rate increases the problem loans for the average bank in the sample. However, quite similarly with the bank loan equations, this effect is less pronounced for banks with high market power, liquidity, capital, and profitability.

If we consider the results in column 6, we note that a 1 percent decrease in the CB rate increases our problem-loans variable by 4.5 percent, which is a sizable change for one year. However, this negative effect weakens for banks with high market power, capitalization, liquidity, and profitability. In contrast, this effect strengthens for banks with high levels of provisions. Calculating the points for the Lerner index, liquidity, capitalization, and profitability where the negative effect of the monetary policy variable becomes zero yields values equal to 0.21, 0.29, 0.16, and 0.04, respectively. From these values, only the one for the Lerner index is close to its mean value in the sample, while the rest are quite higher relative to their means (see table 1). Thus, we can conclude that bank market power again emerges as the most important of the bank characteristics considered here and in the previous literature, in that it buffers the negative impact of monetary policy changes on bank risk. This is the case because only moderate levels of bank market power are sufficient to make the risk-taking channel ineffective, while the equivalent levels for capitalization, liquidity, and profitability are very high.

In table 6 we split the sample between the euro-area and the U.S. banks and reestimate equation (2). The results are once more equivalent to those for the bank loan equations. The difference in the results between the two sub-samples is that the point at which the negative effect of the monetary policy rate goes to zero due to market power is lower in the euro area (0.21) than in the United States (0.26). This shows that the risk-taking channel is less operative in

Table 6. Credit Risk Equations: Euro Area vs. United States

	Euro Area			United States		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔCB Rate	−0.031***	−0.033***	−0.032***	−0.045***	−0.051***	−0.049***
	(−4.391)	(−4.376)	(−4.343)	(−8.586)	(−8.192)	(−8.153)
ΔCB Rate * Lerner Index	0.156***	0.158***		0.194***	0.198***	
	(3.003)	(3.163)		(3.753)	(4.007)	
ΔCB Rate * Liquidity	0.115***	0.118***	0.110***	0.146***	0.145***	0.149***
	(4.103)	(4.300)	(3.848)	(4.129)	(4.188)	(4.365)
ΔCB Rate * Capitalization	0.210***	0.206***	0.209***	0.220***	0.227***	0.207***
	(3.470)	(3.366)	(3.314)	(4.006)	(4.131)	(4.041)
ΔCB Rate * Provisions		−0.536***	−0.512***		−0.106	−0.107
		(−2.900)	(−2.811)		(−0.404)	(−0.737)
ΔCB Rate * Profitability		0.976***	0.935***		0.906***	0.907***
		(3.805)	(3.709)		(3.640)	(3.621)
ΔCB Rate * Boone Indicator			0.084***			0.140***
			(3.116)			(4.051)
Constant Term	−0.126***	−0.071***	−0.097***	−0.021**	−0.030**	−0.029***
	(−2.626)	(−5.650)	(−4.344)	(−2.371)	(−2.494)	(−2.625)
Observations	22,333	21,229	22,385	17,893	17,317	17,317
UI Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00
WIT Test (p-value)	32.47	33.30	32.60	38.22	33.59	34.70
OIT Test (p-value)	0.502	0.462	0.428	0.605	0.629	0.594

Notes: The table reports estimated coefficients and t-statistics (in parentheses). The dependent variable is the annual change in the ratio of non-performing loans (problem loans) to total loans. The explanatory variables are defined in table 1 and are all lagged one year. All regressions are estimated with LIML for dynamic panels and include country-specific time effects. Regressions 1–3 are estimated using the euro-area panel of banks and regressions 4–6 using the U.S. panel. UIT is the p-value of the under-identification LM test by Kleibergen and Paap, which requires a value lower than 0.05 to reject the null hypothesis at the 5 percent level. WIT is the Wald F-statistic of the weak identification test by Kleibergen and Paap, which must be higher than approximately 10 to reject the null hypothesis. OIT is the p-value of the over-identification test by Hansen, which requires a value higher than 0.05 to reject the null hypothesis at the 5 percent level. ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

the euro area for banks with even average levels of market power. The results for the Boone indicator (columns 3 and 7) confirm this finding. These results can be explained by the structural characteristics of the two banking sectors. In the euro-area member states, most banking sectors are characterized by a relatively small number of banks that probably have relatively equal opportunities in alternative sources of finance and in attracting short-term deposits. In the United States, the banking industry is characterized by a very large number of banks operating locally and a relatively small number of banks operating nationally and internationally. We confirm that the two groups have very large differences in their market power levels. Banks in our sample operating locally have an average Lerner index equal to 0.18, while banks operating nationally have an average Lerner index equal to 0.27. Thus, it is the local U.S. banks that are prone to larger fluctuations in their loans and credit risk following monetary policy changes.

4.3 Results from Taylor-Rule Residuals

As a further exercise, we consider Taylor-rule residuals as our measure of monetary policy changes. The new variable measures the unexpected component of fluctuations in central bank rates and is a measure of monetary policy shocks frequently used in the monetary literature (e.g., Maddaloni and Peydro 2011).

In table 7 we replicate the results of the regressions reported in column 6 of tables 3 and 5, using the Taylor-rule residuals instead of the CB rate. The results from both the bank loan and the credit risk equations show that the coefficients on the Taylor-rule residuals are slightly higher than in the equivalent equations in tables 3 and 5. Further, the values of the Lerner index for which the impact of monetary policy shocks becomes zero are 0.28 and 0.27 in columns 1 and 2, respectively. This shows that when monetary policy changes are purely unexpected, it takes somewhat higher market power to buffer the impact of these shocks on bank loans and credit risk. This is intuitive because purely unexpected shocks find banks less prepared to insulate their portfolios. However, we should note that the higher market power (by 0.07 points in the Lerner index) required to buffer these shocks, relative to the equivalent value of 0.21 when using the CB rate, does not make a very large difference in the results. The

Table 7. Taylor-Rule Residuals as a Measure of Monetary Policy Shocks

	Bank Loan Equation	**Credit Risk Equation**
	(1)	**(2)**
Taylor Residuals	−0.082***	−0.053***
	(−6.404)	(−9.628)
Taylor Residuals * Lerner Index	0.294***	0.195***
	(3.510)	(4.189)
Taylor Residuals * Liquidity	0.225***	0.141***
	(4.852)	(5.238)
Taylor Residuals * Capitalization	0.213***	0.262***
	(3.088)	(3.347)
Taylor Residuals * Provisions	−0.520**	−0.449**
	−(2.477)	(−2.033)
Taylor Residuals * Profitability	0.850***	0.948***
	(2.879)	(4.216)
Constant Term	0.307***	−0.249***
	(22.648)	(−20.036)
Observations	42,044	38,546
UI Test (p-value)	0.00	0.00
WIT Test (p-value)	26.53	30.22
OIT Test (p-value)	0.207	0.416

Notes: The table reports estimated coefficients and t-statistics (in parentheses). The dependent variable in column 1 is the annual loan growth and in column 2 the annual change in the ratio of non-performing loans (problem loans) to total loans. The explanatory variables are defined in table 1 and are all lagged one year. Estimation method is LIML for dynamic panels. Both regressions include bank fixed effects and country-specific time effects. UIT is the p-value of the under-identification LM test by Kleibergen and Paap, which requires a value lower than 0.05 to reject the null hypothesis at the 5 percent level. WIT is the Wald F-statistic of the weak identification test by Kleibergen and Paap, which must be higher than approximately 10 to reject the null hypothesis. OIT is the p-value of the over-identification test by Hansen, which requires a value higher than 0.05 to reject the null hypothesis at the 5 percent level. ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

interaction terms with the rest of the bank characteristics also show that the levels of liquidity, capitalization, and profitability required to buffer the shocks are also slightly larger than the levels obtained in the specifications with the CB rate.

4.4 The Effect of the Crisis

In this sub-section we consider whether the mechanism described above for the loan and credit risk equations changes following the eruption of the sub-prime crisis in 2007. We carry out this exercise by introducing in equations (1) and (2) a crisis dummy variable that takes the value 1 from 2007 onward, its interaction terms with the CB rate and the Lerner index, and a triple interaction term between the crisis dummy, the CB rate, and the Lerner index. Table 8 reports the estimation results. In regressions 1–4 the dependent variable is loan growth and in regressions 5–8 the change in the problem loans ratio. All regressions are estimated with LIML.

Column 1 is the equivalent of column 6 of table 3, augmented with the crisis dummy and the relevant interaction terms. The coefficient on the crisis dummy is negative and statistically significant, showing that loan growth rates deteriorated since 2007 for the average bank in the sample. The interaction term between the ΔCB rate and the crisis dummy is also negative and statistically significant, showing that following the sub-prime crisis, the negative impact of a monetary policy change on bank loans intensified. More interesting in our case are the coefficient estimates on the interaction term between the ΔCB rate and the Lerner index and the coefficient estimate on the triple interaction term. Both are positive and statistically significant at conventional levels, indicating that banks with market power are still able to buffer the impact of changes in central bank rates and more so after 2007. However, taking partial effects for the level of Lerner index required to completely buffer the effect of monetary policy on bank loans, we find that (according to equation (1)) the value on the Lerner index needs to be approximately 0.54.[7] The relevant values of the Lerner and the Boone indices are also quite high in the rest of the specifications for both the bank

[7] This result comes from column 1 by calculating the ratio $(0.064 + 0.072)/(0.150 + 0.100)$.

Table 8. The Effect of the Financial Crisis

	Bank Loan Equations				Credit Risk Equations			
	Full Sample	Full Sample	Euro Area	United States	Full Sample	Full Sample	Euro Area	United States
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔCB Rate	−0.064***	−0.058***	−0.046***	−0.061***	−0.040***	−0.042***	−0.031***	−0.045***
	(−5.162)	(−4.241)	(−3.002)	(−4.355)	(−8.933)	(−8.417)	(−4.390)	(−8.575)
Crisis Dummy	−0.331***	−0.335***	−0.329***	−0.402***	0.699***	0.710***	0.507***	0.605***
	(−49.910)	(−50.103)	(−50.104)	(−55.121)	(37.240)	(37.855)	(25.140)	(33.140)
ΔCB Rate * Crisis Dummy	−0.072***	−0.064***	−0.060***	−0.073***	−0.057***	−0.057***	−0.052***	−0.058***
	(−5.501)	(−4.207)	(−4.004)	(−5.744)	(−3.840)	(−3.902)	(−3.508)	(−3.922)
ΔCB Rate * Lerner Index	0.150**		0.141**	0.126**	0.151**		0.142**	0.168***
	(2.448)		(2.205)	(2.194)	(2.305)		(2.361)	(3.014)
ΔCB Rate * Lerner Index * Crisis Dummy	0.100***		0.076**	0.099***	0.022		0.019	0.046*
	(3.990)		(2.407)	(3.125)	(0.507)		(0.304)	(1.738)
ΔCB Rate * Boone Indicator		0.093***				0.103**		
		(3.002)				(2.498)		
ΔCB Rate * Boone Indicator * Crisis Dummy		0.072**				0.010		
		(2.375)				(0.207)		
Constant Term	0.096***	0.029***	0.017***	0.042***	−0.020***	−0.072***	−0.032***	−0.032***
	(27.722)	(9.830)	(6.569)	(10.877)	(−5.284)	(−24.422)	(−8.672)	(−3.837)
Observations	47,832	47,888	25,001	22,831	40,223	40,279	23,333	17,893
UI Test (p-value)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WIT Test (p-value)	23.58	24.18	31.10	21.09	32.14	37.02	29.28	23.07
OIT Test (p-value)	0.245	0.329	0.186	0.318	0.124	0.119	0.173	0.203

Notes: The table reports estimated coefficients and t-statistics (in parentheses). In regressions 1–4 the dependent variable is the annual loan growth and the CB rate variable is measured as the annual change. In columns 5–8 the dependent variable is the annual change in the ratio of non-performing loans (problem loans) to total loans and the CB rate variable is measured in changes. The explanatory variables are defined in table 1 and are all lagged one year. All regressions are estimated with LIML for dynamic panels and include country-specific time effects. UIT is the p-value of the under-identification LM test by Kleibergen and Paap, which requires a value lower than 0.05 to reject the null hypothesis at the 5 percent level. WIT is the Wald F-statistic of the weak identification test by Kleibergen and Paap, which must be higher than approximately 10 to reject the null hypothesis. OIT is the p-value of the over-identification test by Hansen, which requires a value higher than 0.05 to reject the null hypothesis at the 5 percent level. ***, **, and * denote statistical significance at the 1 percent, 5 percent, and 10 percent level, respectively.

loan and the credit risk equations (see column 5 for the credit risk equations when using the Lerner index and columns 2 and 6 for the bank loan and credit risk equations when using the Boone indicator). Finally, the results are also similar when splitting the sample between euro-area and U.S. banks (see columns 3 and 4 for the bank loan equations and columns 7 and 8 for the credit risk equations).

Overall, the results from table 8 provide evidence that the sub-prime mortgage crisis enhanced the potency of the bank lending and risk-taking channels. This result is essentially in line with the finding of Gambacorta and Marques-Ibanez (2011), who also document that the sub-prime crisis enhanced the potency of the bank lending channel in the euro area and the United States. Here we suggest that although before the crisis even moderate levels of bank market power were able to buffer the negative impact of a monetary policy change on bank loans and credit risk, this is not the case after 2007, where very high levels of market power are needed to buffer this negative effect. An interpretation for this result is that during periods of distress, even banks with relatively high market power cannot find alternative sources of finance, which are very limited due to overall liquidity constraints in the financial sector. Naturally, these banks resort to central bank financing, and therefore their marginal cost is affected by fluctuations in central bank policy rates more severely.

4.5 Additional Analysis

In an effort to further identify the sources of our main result that market power of banks lowers the impact of monetary policy on bank loans and credit risk, we first consider estimating our baseline specification (the equivalent of column 6 of tables 3 and 5) separately for each euro-area country in our sample. Due to space considerations, we do not report the results, which are available on request. These results show that the main conclusion carries through to all countries except for Austria. The finding for Austria could stem from the fact that the variation of market power among Austrian banks is quite small relative to the within-country variation in the market power of other euro-area countries. The higher coefficient estimates on the interaction terms between the monetary policy variable and the Lerner index are identified for Greece, Portugal, and Belgium. In line with the argument for the Austrian case, these are banking systems characterized by high variation in the market power of banks.

A second set of additional tests considers the impact of bank size. From a macroeconomic and regulatory perspective, the main interest could be on the risk-taking and lending behavior of the large systemic banks, and one could argue that the interaction term including bank size (i.e., an analysis at the mean of the sample) might be insufficient to capture potential differences between large and small banks. Thus, we reestimate our baseline specifications using two separate sub-samples: the first including only the largest 10 percent of banks of each country in terms of total assets and the second including the rest of the banks. The results from the two sub-samples are essentially equivalent among each other and to those presented in tables 3 and 5. This implies that bank size is not the main driving force in our results, essentially confirming the analysis on the interaction terms in the bank loan and credit risk equations.

5. Conclusions

The present study seeks to identify whether bank market power plays an important role in the bank lending and risk-taking channels of monetary policy. The analysis is carried out for the euro-area countries and the United States over the period 1997–2010. We first estimate market power of banks for each bank observation in our sample, using a method that essentially allows each bank to have its own production technology in each year. Subsequently, we estimate loan and credit risk equations and find that bank market power is more important for the potency of the bank lending and risk-taking channels, compared with other bank characteristics, like liquidity and capitalization, employed in the previous literature. This finding is robust to a number of alternative specifications, measures of monetary policy and bank market power, and estimation methodologies.

Given the importance of bank market power in the monetary policy transmission mechanism, we also compare the potency of the bank lending and risk-taking channels in the period 2007–10 with the period before 2007. We find that the market power required to completely insulate bank portfolios from monetary policy impulses in the period 2007–10 increased substantially compared with the period before the crisis. Given that prior to 2007 even moderate levels of market power would completely buffer the negative effect of monetary policy impulses, we suggest that the potency of the bank lending and risk-taking channels has increased substantially since 2007 in both the euro area and the United States.

The analysis of this paper has already covered a lot of ground, and therefore we have chosen to leave some interesting extensions for future research. An obvious immediate extension would be to explore the role of market power in assessing the effect of monetary policy on real output in empirical models similar to the ones proposed by Driscoll (2004) or Ashcraft (2006). If, in addition, more disaggregate bank-level data on loans is available, an interesting study may involve the effect of bank market power on the maturity of loans and the term structure of interest rates.

Appendix 1. Basic Analytical Derivations for the Boone Indicator

The Boone indicator allows capturing the link between competition and efficiency in a direct manner. In particular, it is based on the efficient-structure hypothesis in the sense that more efficient firms are more profitable (or attain higher market shares), and this relation increases with the degree of market power. More formally (and following closely Boone, Griffith, and Harrison 2005), assume that each bank i produces one symmetrically differentiated product q at time t and faces a demand curve of the form

$$p(q_i, q_{-i}) = a - bq_i - d\sum\nolimits_{j \neq i} q_j, \tag{6}$$

where p is the price of the product q, a corresponds to the size of the market, b corresponds to the market elasticity of demand, d captures the extent to which consumers view the different products in a market as close substitutes, and j is a competitor. Each bank chooses q to solve

$$\max_{q \geq 0}\{(a - bq - d\sum\nolimits_{j \neq i} q_j)q - mc_i q\}, \tag{7}$$

where $a > mc > 0$ and $0 < d \leq b$. For a Cournot-Nash game, the first-order condition is

$$a - 2bq_i - d\sum\nolimits_{j \neq i} q_j - mc_i = 0. \tag{8}$$

If N banks are present in the banking system, one obtains N first-order conditions of the form

$$q(mc_i) = [(2b/d - 1)a - (2b/d + N - 2)mc_i + \sum_{j=1}^{N} mc_j]/[(2b + d(N-1))(2b/d - 1)]. \tag{9}$$

A bank's variable profits are defined as

$$\pi(mc_i) = (a - bq(mc_i) - d\sum\nolimits_{j\neq i} q(mc_j))q(mc_i) - mc_i q(mc_i) = 0. \tag{10}$$

These profits are variable in the sense that they do not include the entry cost γ of a bank in the market. In other words, a bank with marginal cost mc_i enters the industry if and only if $\pi(mc_i) \geq \gamma$. Given the above equations, Boone, Griffith, and Harrison (2005) verify that variable profits can be written as

$$\pi(mc_i) = b[q(mc_i)]^2. \tag{11}$$

Two ways can be considered in which competition can change within this model. Competition increases (i) when goods become more substitutable (that is, d increases) and (ii) when entry costs γ are lower. Now define the relative profits measure of market power as

$$RP(mc_i, mc_j) = \pi(mc_i)/\pi(mc_j). \tag{12}$$

The following lemma shows the output reallocation effect that is important in understanding why this measure is a robust indicator of competition.

LEMMA 1. *The effect of an increase in d on relative variable costs with $c_i < c_j$ is*

$$\frac{\partial\left(\frac{c_i q(c_i)}{c_j q(c_j)}\right)}{\partial d} > 0.$$

The effect of a fall in γ, which allows bank $N + 1$ to enter the industry on relative variable costs with $c_i < c_j$, is

$$\frac{\partial\left(\frac{c_i q(c_i)}{c_j q(c_j)}\right)}{\partial N} > 0.$$

The lemma shows that an increase in competition, either through a rise in d or a fall in γ, reallocates output from relatively inefficient to more efficient banks. Because of equation (11), the lemma also implies that an increase in competition raises profits of relatively more efficient banks (or reduces the profits of the relatively more efficient banks by less). Hence, relative profits is a robust measure of competition, because any change in competition intensity that reallocates output from less efficient to more efficient banks increases the profits of the more efficient banks relative to the less efficient. So if, for example, a bank wants to keep its inputs higher than its efficient level of employment, output will be reallocated to other banks in the industry. This holds as long as there exists one bank in the industry that maximizes profits. In the empirical analysis, we are using a world sample of banks with all banks pooled together under a technique that allows this (i.e., pooling together all banks) irrespective of the different technologies faced by banks. Thus, clearly profit-maximizing banks are present in our sample. The only way this would not hold would have been if a banking industry is completely fragmented—as, for example, in previously centrally planned economies. However, our samples on these countries start after the initiation of reforms (e.g., competition from foreign-owned banks has started).

Now how can the relative profits measure of market power, as represented by equation (12), be approximated empirically? Instead of investigating the relation between relative profits of bank i and some reference bank π_i/π_1 and marginal costs, one can estimate log profits as a function of marginal cost (i.e., as in equation (2)).[8] This is equivalent to estimating the relation using the log of profits relative to some reference profit π_1(e.g., the profits of the most efficient bank), since $\ln(\pi_i/\pi_1) = \ln \pi_i - \ln \pi_1$. In practice it can be problematic to specify this reference profit, and so in equation (2) the parameter $\ln \pi_1$ is absorbed into the constant term a. Therefore, the

[8]Boone, Griffith, and Harrison (2005) suggest using average cost instead of marginal costs, since the latter is usually not available. Below we show that estimating marginal cost for the individual bank is not an issue.

relative profits measure of competition is captured by the estimated coefficient β of equation (2), which measures the extent to which less efficient banks are punished with lower relative profits.

Appendix 2. Practical Issues in the Estimation of Bank Market Power

A thorough discussion of the smooth-coefficient model can be found in Li et al. (2002) and Mamuneas, Savvides, and Stengos (2006). Delis (2012), and Delis, Iosifidi, and Tsionas (2012) use this model to estimate marginal cost for each observation in their sample. We use exactly the same approach here and provide below a summary of the discussion from Delis, Iosifidi, and Tsionas (2012) for convenience.

We can write the econometric form of the total cost equation as

$$Y_i = E(Y_i|W_i) + e_i = X_i\beta_1 + V_i\beta_2(Z_i) + e_i. \tag{13}$$

In this equation, β_2 is a function of one or more variables with dimension k added to the vector Z, which is an important element of the analysis and will be discussed below. The presence of a linear part in equation (13) is in line with the idea of the semi-parametric model as opposed to a fully non-parametric model. The coefficients of this part are estimated in a first step as averages of the polynomial fitting by using an initial bandwidth chosen by cross-validation. In the second step we use these average estimates to redefine the dependent variable as

$$Y_i^* = V_i\beta_2(z) + e_i^*, \tag{14}$$

where the stars denote the redefined dependent variable and error term.

The coefficient $\beta_2(z)$ that is evaluated at a z point of Z is a smooth but unknown function of z. Here, we estimate $\beta_2(z)$ using a local least-squares approach.[9] In equation (14), $K(z, \lambda)$ is a kernel function and λ is the smoothing parameter for sample size n.

[9] Mamuneas, Savvides, and Stengos (2006) discuss in detail how this function can take specific parametric formulations (such as linear) that can be tested against the general unknown specification. They also provide formulas for the local least-squares criterion.

A critical issue in the estimation process is the choice of the variable(s) to comprise Z. The best candidates are variables that are highly correlated with β_2 but that also allow variation for β_2 across firms and time. In a cost function, the natural candidates to use as Z are the input prices. The advantage of this choice is that input prices most certainly affect β_2 significantly. This has been shown many times when researchers employ a translog specification, which includes multiplicative terms of output with input prices, to estimate the cost function parametrically. Delis, Iosifidi, and Tsionas (2102) show that a linear combination of input prices is the best candidate. Thus, we primarily use the linear combination of w_1, w_2, and w_3 as Z.

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