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Conference Paper

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Beiträge zur Jahrestagung des Vereins für Socialpolitik 2016: Demographischer Wandel -
Session: Business Cycles: Firms and Banks, No. A08-V3

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Kreiser, Swetlana; Kick, Thomas; Merkl, Christian; Ruprecht, Benedikt (2016) :
Banking and the Macroeconomy: A Micro-Macro Linkage, Beiträge zur Jahrestagung des Vereins für
Socialpolitik 2016: Demographischer Wandel - Session: Business Cycles: Firms and Banks, No. A08-
V3, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften, Leibniz-Informationszentrum
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This Version is available at:

<https://hdl.handle.net/10419/145921>

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Banking and the Macroeconomy: A Micro-Macro Linkage

March 1, 2016

Abstract

In this paper, we modify the model by Gertler and Karadi (2011) such that it can be calibrated to the empirical elasticity of bank loan supply with respect to bank capital changes. We estimate this elasticity based on microeconomic data for all German banks. Their business model resembles that of the banks in the model. We find that the estimated elasticity is 0.3, which is substantially lower than the implied elasticity of 1 in the baseline model. Nevertheless, even when calibrating the model to the significantly lower partial equilibrium elasticity, the banking sector remains an important source and amplifier for the macroeconomy. This is due to general equilibrium effects, which play an important role in the transmission of the shocks. We show that the lower elasticity has a dampening effect but the precise quantitative implications depend on the responsiveness of the banks' loan supply to different aggregate shocks.

1 Introduction

The banking sector can be important for the macroeconomy in at least two ways. First, it may amplify aggregate shocks and thereby lead to larger business cycle fluctuations. Second, it may originate shocks (e.g. due to bank capital losses) that have important feedback effects on the macroeconomy. In both cases, financial frictions are the driving force for the transmission of the effects to the real economy. Gertler and Karadi (2011, GK henceforth) have proposed an important workhorse model that acts in these two dimensions. In the GK model, bankers can divert a certain fraction of assets and thereby only receive a certain amount of funding to prevent bankruptcy in equilibrium. This limits the loan volume they can hand out to production firms and generates an external finance premium between the interest rates on bank loans and the central bank interest rate. The ability to lend in the GK model is constrained by banks' equity position, which can only be increased by retained earnings. Thus, the connection between bank capital and loan supply is crucial for the effects of the banking sector on the macroeconomy.

Interestingly, so far there is no evidence whether the GK model can be calibrated to the actual microeconomic bank behavior. However, it is important to test whether the model suffers from potential micro-macro puzzles.¹ For instance, if banks' reaction to capital losses in the model is a lot larger than in the data, the model may gauge a too important role of the banking sector for the macroeconomy (or vice versa).

This paper shows how the estimated co-movement between bank capital and loan supply on the microeconomic level can be connected to the dynamic stochastic general equilibrium model by GK. We show that the original GK model has a partial equilibrium elasticity of loan supply with respect to capital of one, i.e. a bank capital loss of one individual bank of 1 per cent is associated with reduction of lending of 1 per cent for this bank. We propose a convenient way of modifying the GK model in order to obtain partial equilibrium elasticities that are different from one. Then, we estimate the partial equilibrium elasticity with real microeconomic data. For this purpose, we use supervisory micro data provided by the Deutsche Bundesbank (i.e. portfolio-level data from the Bundesbank's Borrowers' Statistics, bank distress data from the Distress Data Base, as well as bank balance sheet data from the prudential database BAKIS) for all German banks and employ regional area fixed effects regressions and a local matching approach. We find that the actual long-run elasticity of banks' loan supply with respect to bank capital is around 0.3. We calibrate the modified GK model to this elasticity and find that despite this lower partial equilibrium elasticity, the banking system is still highly relevant for the macroeconomy, in

¹Micro-macro puzzles are present in many other areas of macroeconomics. Aggregate models require for example a larger Frisch elasticity of labor supply to obtain sufficiently large labor fluctuations, while microeconomic estimation deliver rather moderate labor supply elasticities. Alternatively, small scale New Keynesian models would ask for relatively rigid prices to be in line with aggregate price dynamics (Chari et al. 2000), while the microeconomic evidence seems to point to smaller price durations (e.g. Bilal and Klenow 2004).

particular with regard to the amplification of shocks and for the effects of shocks that originate in the banking sector. What is the intuition for this surprising result? The model has powerful general equilibrium effects. If one bank is hit by a bank capital shock, it takes a long time until the bank returns to its steady state level of capital by retaining earnings. If all banks are hit by a bank capital shock, market prices react and monetary policy adjusts. We show that the partial equilibrium elasticity is a lot larger than the general equilibrium elasticity. In our simulations, the responses of the aggregate effects of a net worth shock in the GK model and in our modified model are fairly similar.

Why do we perform our estimations using German data? Very importantly, we have high quality balance sheet information on a yearly basis for the entire universe of German universal banks (which are around 1700 institutions in the cross-section in 2013). The majority of German banks has a business model which largely resembles that of the banks in the GK model. These banks have a regional business model that focuses on lending activities (instead of investment banking or fee income-driven activities). In addition, as in GK these banks cannot issue equity (but have to absorb losses and grow by retaining earnings).² The German banking system is not only very much in line with theory, in addition, it allows us to identify the co-movement of bank capital and lending supply. Obviously, changes in lending may either be driven by demand or supply. In order to isolate supply effects, we use the matching method by Carlson et al. (2013). The regional principle of most German banks allows us to identify these effects appropriately.

Our paper provides a valuable contribution concerning the role of the German banking system for the macroeconomy. However, our results reach beyond the German case. Both our proposition of how to modify the GK model, and the insights on the effects lower partial equilibrium elasticities have on aggregate outcomes are relevant for other economies as well.

The remainder of this paper proceeds as follows. In Section 2 we describe the empirical strategy and provide empirical results. Section 3 contains the core banking part of the GK model, the analytical results and the modification of the model. In Section 4, we calibrate the modified model, show numerical results and demonstrate their implications. Section 4 concludes.

2 Empirical Analysis

2.1 The Effect of Bank Capital on Lending

Our empirical analysis aims at computing an elasticity of loan supply with respect to changes in capital for German banks, which we then use to calibrate

²The majority of German universal banks consists of either cooperative banks (which are owned by their customers) and their central cooperative banks (as money-center banks), or local savings banks (which are owned by local governments) and their Landesbanks (as money-center banks). Both types of banks usually do not issue equity as an instrument to increase their capital stock. The third pillar represents private commercial banks which are much more heterogeneous and exposed to the national and international markets for bank capital.

the model in Section 3.

The existence of a relation between bank capital and lending has been widely examined in empirical studies. The main issue when trying to estimate the effect of capital on lending is endogeneity.³ Factors that affect loan supply could also affect loan demand. Firms' demand for credit could therefore be driven not solely by the supply side of credit. It is thus necessary to separate supply from demand effects in order to estimate an exogenously driven change in the amount of loans resulting from a change in the capital position. The empirical literature deals with this issue in various ways. Gambacorta and Mistrulli (2004) directly include control variables for credit demand in their regression. Jiménez et al. (2012) disentangle the supply of credit from its demand by proxying credit demand by loan applications. Similarly, Bassett et al. (2014) use survey data to construct a credit supply indicator which is adjusted for bank specific and macroeconomic factors that affect loan demand.

Another approach can be found in Carlson et al. (2013). The authors examine commercial banks in the United States. Their basic assumption is that banks operating in the same geographical area face the same economic environment and therefore the same demand for credit.

They create a set of matched banks based on the banks' geographical vicinity and on the banks' business models.⁴ Then, each bank is compared to its matched set regarding its capital position. Changes in lending between each bank and its matched set can therefore be attributed to differences between the banks. The advantage of this approach is that the supply side of credit can be isolated while differencing out the demand side of credit.

This advantage is even more evident for the German banking system, which we investigate. German savings and cooperative banks, which constitute the majority of German banks, operate according to the regional principle ("Regionalprinzip"). The savings banks' statutes lay down that their day-to-day business has to be conducted primarily within a limited regional area. Moreover, as pointed out by Berger et al. (2014), the regional principle is also de facto enforced for cooperative banks. Stolz and Wedow (2012) further state that the German economy is mainly dominated by small and medium-sized firms that borrow primarily from local savings and cooperative banks. Therefore, the assumption made by the authors regarding the local environment should hold with greater certainty for Germany. The approach is thus particularly well suited for analyzing the relationship between capital and lending for German banks and, as stressed by Carlson et al. (2013), theoretically controls better for local demand conditions in contrast to proxy variables. We apply the matching algorithm to German data as a complementary method to the more general fixed effects approach.

Using German data has also some other advantages. First, the Deutsche Bundesbank provides high quality bank-level data including balance sheet and profit and loss statistics, borrowers' statistics and bank distress data. Second,

³A discussion of the endogeneity issue can be found in Peek and Rosengren (2000).

⁴A bank is either matched to another single bank (1-1 matched set) or to several banks (1-N matched set).

unlike the banks in many other (European) countries most of the banks in the German three-pillar banking system have a business model which is dominated by regional lending and generating interest income, which is a prerequisite for properly estimating and clearly identifying the effects in our model. Third, Germany is the largest economy in Europe.

2.2 Methodology and Data

We estimate two empirical models in which we isolate the effect of bank capital on credit supply. First, a conventional fixed effects model with interacted regional and time fixed effects to control for time-varying local demand effects, and second the matching model by Carlson et al. (2013) described above. To make the estimates comparable in both models, we use the same set of control variables which we consider adequate to control for a banks' business model.

The fixed effects estimation equation for bank i and year t including an interaction term of regional and time fixed effects has following form:

$$\begin{aligned} \Delta \ln L_{it} = & \alpha + \beta CR_{it-1} + \sum_{j=1}^2 \delta_j \Delta \ln L_{it-j} + \theta LLP_{it-1} \\ & + \nu NPL_{it-1} + \rho_{it} Reg_i * Year_t + \epsilon_{it} \end{aligned} \quad (1)$$

L denote loans to domestic enterprises and households.⁵ CR is a capital ratio defined as total capital over total assets. The corresponding β is the coefficient of interest as it captures the effect of credit supply due to a variation in the equity capital positions on banks' balance sheets. We refrain from scaling capital with risk-weighted assets for three reasons: First, the definition of risk-weighted assets has changed several times over the sample period. Second, in the literature and politics, there is a controversial discussion on the adequacy of risk weights in banking regulation.⁶ Third, both the GK model and our modified model are calibrated on total lending (instead of lending in different risk categories) in the macroeconomy.

In addition, we include two lags of the dependent variable to capture the extent to which loan supply can be explained by past values. LLP is the ratio of loan loss provisions over total loans and NPL is the non-performing loans to total loans ratio. Banks set aside provisions for loans that are expected to generate losses or to become delinquent, which is reflected in the banks' profit and loss accounts. In addition, non-performing loans contain banks' claims that are overdue by more than 90 days. Both the LLP and the NPL ratios are therefore assumed to be negatively associated with the bank's credit supply.

⁵Given that lending is not stationary in our data set, we specify our model in growth rates instead of levels in order to avoid spurious regressions.

⁶See, for example, Behn et al. (2014) or Behn et al. (2015) for a critical discussion on the limits of model-based regulation, as well as several statements by President Weidmann (Deutsche Bundesbank) on the inappropriateness of zero risk weights for sovereign exposures.

As described above, in order to control for local economic conditions, we include an interaction term consisting of *Reg*, a regional district dummy, and *Year*, a time dummy. It captures the differential effect of economic conditions in the regional districts, including local demand for credit, for each year. The intercept α is the mean for the baseline categories of *Reg* and *Year*.

Next, we apply the two-step matching algorithm, proposed by Carlson et al. (2013) to our data. In a first step, banks are matched according to their geographic coordinates. Thereby, the matching procedure is repeated for each bank in each year and solely relies on distance. In a second step, the business model of each bank is compared to the business models of the matched set of neighboring banks. For this purpose, we select a range of business model indicators, and exclude banks from the matched set, whose business model greatly diverges from the reference bank's business model.⁷

Consequently, our matched sets include banks that have a similar balance sheet composition, size and profitability, and that are located in the vicinity of their reference banks. This is crucial for making the assumption that demand for credit is identical in the vicinity of the reference bank.

In a second step, we modify the estimation equation above by calculating for each variable the differences between the reference bank's observation and the average observations of its matched set. Since we eliminate the effect of economic conditions and loan demand via the averages of neighboring banks, interaction terms are no longer needed in our regression model. The modified estimation equation for reference bank i , year t and the average of the bank's matched set m has following form:

$$\begin{aligned} \Delta \ln L_{it} - \Delta \ln L_{mt} &= \beta (CR_{it-1} - CR_{mt-1}) \\ &+ \sum_{j=1}^2 \delta_j (\Delta \ln L_{it-j} - \Delta \ln L_{mt-j}) \\ &+ \theta (LLP_{it-1} - LLP_{mt-1}) \\ &+ \nu (NPL_{it-1} - NPL_{mt-1}) + (\epsilon_{it} - \epsilon_{mt}) \end{aligned} \quad (2)$$

The parameter β now has a slightly different interpretation because it measures the effect on loan supply of bank i in comparison to the matched set of banks m .⁸

However, both estimation techniques are equivalent in that they yield a coefficient β that shows the initial or short-run impact of capital changes on loans measured in percentage points. In the modified GK model presented in Section 3, there are no meaningful adjustment dynamics, i.e. the partial equilibrium short-run elasticity for a single bank would be equal to the bank's long-run elasticity. In the data, we explicitly control for dynamic adjustment.

⁷Details regarding the comparison of the banks' business models are provided in Appendix A.

⁸Note that including capital growth as an additional explanatory variable as proposed by Carlson et al. (2013) yields similar estimation results.

Thus, we decide to use the long-run coefficient as our benchmark for the macro model. Therefore, we calculate the long run (or steady state) coefficient using following equation:

$$\beta_{SS} = \frac{\beta}{1 - \delta_1 - \delta_2} \quad (3)$$

The long-run elasticity of $\Delta \ln L$ with respect to CR is then computed for the regional and time fixed effects regression by evaluating the expression above at the regressors' means and for the matching regression at the peer group's means only. We obtain the standard errors for the long-run coefficient and the elasticity using the delta method. Appendix A contains a detailed derivation of the standard errors following Greene (2012).

We use data on an individual bank level for all German banks for the period from 1998 to 2013 provided by the Deutsche Bundesbank. A description of the data, the data preparation procedure and descriptive statistics are shown in Appendix A.

2.3 Results

Table 1 shows that variation in banks' capital position significantly affects loan supply. Depending on the estimation procedure, the short-run coefficients of the total capital ratio vary from 0.07 to 0.1. Therefore, an immediate increase in the capital ratio by 1 percentage point increases loan growth on average by 0.07 to 0.1 percentage points. The estimate in the fixed effects regression is higher than those in the matching regressions which may be associated with the business model adjustment that we performed additionally in the matching regressions.⁹

Although equally statistically significant, the long-run parameters are in general considerably larger than the short-run parameters, which is due to the persistence of loan growth. The basis for the calibration of the macro model in Section 4 is the long-run elasticity of loan supply with respect to capital changes, which is displayed in the last row of Table 1. Evaluated at the means of the loan growth and capital ratio variables and having the same statistical significance as the long-run coefficients, the estimates range from 0.4 to 0.6. Our numerical simulations in Section 5 are performed using a lower bound elasticity of 0.3, which we get by estimating the 1:N matching specification without the insignificant second lag of the dependent variable as explanatory variable (regression output see Appendix A). Therefore, if a bank has a 1 per cent lower capital ratio than its peer group, its loan growth would be lower by 0.3 per cent compared to its peer group. For details regarding the calibration of the macro model refer to Section 4.

Note that, consistent with our theoretical model from Section 3, the estimates for the long-run elasticity do not specify whether the reduction in loan

⁹Compared to Carlson et al. (2013), who report estimates of 0.13 to 0.15, our regression coefficients are smaller in magnitude. Naturally, this reflects the difference between the U.S. and the German banking systems.

supply is driven by a capital decline or by a reduction in assets (see discussion in Section 3.1).

As for the other explanatory variables, last year's loan growth helps explain a considerable share of this year's loan growth, while the effect of loan growth two years ago is only significant in the 1:1-matching regression. As expected, both indicators of loan quality, loan loss provisions and non-performing loans, negatively affect loan supply as expected. Both are highly significant, but the impact of loan loss provisions substantially exceeds that of non-performing loans, although the share of the former to total loans is with a mean of 0.50 to 0.68 % on average higher than the share of the latter (mean of 4.55 to 4.60 %).

Summarizing, a single bank's growth of loan supply decreases on average at the lower bound by 0.3 % when the bank faces a decline in its total capital ratio of 1 %. In the following, we use this elasticity to investigate how the banking system as a whole behaves when it suffers a capital shortage, and which feedback effects any such capital shortage has on the real economy.

Coefficients	Fixed Effects	Matching 1:N	Matching 1:1
β	0.095*** (0.023)	0.069*** (0.018)	0.092*** (0.019)
δ_1	0.504*** (0.030)	0.463*** (0.006)	0.500*** (0.007)
δ_2	-0.009 (0.007)	-0.008 (0.005)	-0.014** (0.006)
θ	-0.014*** (0.001)	-0.016*** (0.001)	-0.017*** (0.001)
ν	-0.001*** (0.000)	-0.001*** (0.000)	-0.001*** (0.000)
α	0.042*** (0.005)	-	-
R^2	0.437	0.286	0.323
N	32,226	21,748	18,778
β_{SS}	0.189*** (0.040)	0.126*** (0.033)	0.179*** (0.037)
$Elasticity_{SS}$	0.537*** (0.114)	0.375** (0.100)	0.583*** (0.121)

*Note: The table shows results for the fixed effects and the matching regressions for all banks where long-run coefficients and elasticities are evaluated at means. The dependent variable for the fixed effects regression is $\Delta \ln L_{it}$ and for the matching regressions $\Delta \ln L_{it} - \Delta \ln L_{mt}$ with L denoting total loans. The fixed effects regression includes an interaction term of regional and time fixed effects and standard errors are clustered at the regional district level. The standard errors for the long-run coefficients and elasticities are computed using the delta method. The parameters for the interaction terms are not reported for the fixed effects regression, but they are jointly significant when performing a regular Wald test. Note that we keep two lags of the dependent variable as explanatory variables since they are jointly significant for all three specifications. Clustered standard errors are reported in parentheses. Coefficients with *, **, *** are significant at the 10 %, 5 %, and 1 % level respectively using standard t-distribution.*

Table 1: Results for the fixed effects and the matching regressions for all banks

3 Banks' Reaction to Capital Shocks

3.1 The Baseline Banking Model

Banks in the Gertler and Karadi (2011) model borrow funds at the riskless rate R (set by the central bank) and lend to firms at rate R_k , where $R_k - R$ is defined as the external finance premium. Thus, the dynamic equation for the equity/net worth (N_j) of a particular bank j is

$$N_{jt+1} = (R_{kt} - R_t) Q_t S_{jt} + R_{t+1} N_{jt}, \quad (4)$$

where S_j is the quantity of loans and Q is the market price for loans. Note that bankers in GK hold the capital stock of the economy. Thus, the market price of loans is equal to the market price of capital.

Bankers maximize the discounted present value V_j by choosing an optimal quantity of loans. They take into account that they will only survive with probability θ :

$$V_{jt} = \sum_{i=0}^{\infty} (1 - \theta) \theta^i \beta^{i+1} \Lambda_{t,t+i} [(R_{kt+1+i} - R_{t+1+i}) Q_{t+i} S_{jt+i} + R_{t+1+i} N_{jt+i}]. \quad (5)$$

As long as $R_k > R$, the bank would like to increase its loan volume indefinitely. In order to prevent banks from doing so, GK embed a moral hazard/costly enforcement problem. They assume that banks can divert a certain fraction of assets λ and households cannot recover this fraction in the event of default. According to the incentive compatibility constraint households are only willing to supply funds to the bank if

$$V_{jt} \geq \lambda Q_t S_{jt-1}, \quad (6)$$

i.e. when the gain from diverting funds is smaller than the value of the bank because this will prevent diversion of funds in equilibrium.

Thus, in equilibrium bankers will extend lending up to the maximum possible amount:

$$V_{jt} = \lambda Q_t S_{jt-1}. \quad (7)$$

Substituting (7) into (5), we obtain:

$$(1 - \theta) \sum_{i=0}^{\infty} \theta^i \beta^{i+1} \Lambda_{t,t+i} [(R_{kt+1+i} - R_{t+1+i}) Q_{t+i} S_{jt+i} + R_{t+1+i} N_{jt+i}] = \lambda Q_t S_{jt-1}. \quad (8)$$

In order to express this equation in steady state, we have to take into account that assets and net worth of surviving banks grow at gross rate z in steady

state. Intuitively, (surviving) banks retain their profits, increase their equity and thereby their ability to borrow.

Thus, in steady state:

$$\lambda QS_j = \frac{(1 - \theta) \beta [(R_k - R) QS_j + RN_j]}{1 - \theta z \beta}. \quad (9)$$

Reformulating this term:

$$QS_j = \frac{(1 - \theta) \beta R}{\lambda (1 - \theta z \beta) - (1 - \theta) \beta [(R_k - R)]} N_j. \quad (10)$$

This equation pins down the asset to capital ratio (leverage ratio) for the bank. Note that the leverage ratio only depends on aggregate variables (not on bank-specific ones). This expression allows us to calculate a partial equilibrium elasticity of a particular bank's lending with respect to its net worth (i.e. what is the connection between these two variables at given market prices, as measured in the empirical analysis):

$$\frac{\partial \ln S_j}{\partial \ln N_j} = 1. \quad (11)$$

A 1% lower net worth (equity stock) is always associated with a 1% lower loan supply to firms. The intuition for the partial equilibrium elasticity of 1 is straightforward: The incentive compatibility constraint pins down a fixed leverage ratio, which does not depend on any bank-specific variables. Thus, in partial equilibrium (i.e. without adjustments of aggregate price variables such as R_k , R and Q), net worth and the balance sheet size always move together at this fixed ratio. Note that this is not a causal relation but a correlation that applies irrespective of its cause, i.e. whether the change was triggered by the asset or the liability side. This is in line with our empirical identification strategy in Section 2.

3.2 The Modified Banking Model

In order to make the model more flexible (and to be in line with the empirical elasticity), let's assume that diversion of assets is a function of the balance sheet size, which either be concave or convex, i.e. $\lambda(S_j)$ with $\frac{\partial \lambda(S_j)}{\partial S_j} > < 0$. It may be easier for bankers to divert funds if banks are smaller or larger (e.g. due to a different corporate governance structure).

Replacing λ by $\lambda(S_j)$ in equation 7 we get in steady state:

$$\lambda(S_j) QS_j = \frac{(1 - \theta) \beta [(R_k - R) QS_j + RN_j]}{1 - \theta z \beta} \quad (12)$$

We define an implicit function

$$f := (\lambda(S_j) (1 - \theta z \beta) - (1 - \theta) \beta (R_k - R)) QS_j - (1 - \theta) \beta RN_j \quad (13)$$

and use the implicit functions theorem:

$$\begin{aligned} \frac{\partial S_j}{\partial N_j} &= -\frac{\frac{\partial f}{\partial N_j}}{\frac{\partial f}{\partial S_j}} \\ &= \frac{(1-\theta)\beta R}{(\lambda(S_j)(1-\theta z\beta) - (1-\theta)\beta(R_k - R))Q + \frac{\partial \lambda(S_j)}{\partial S_j}(1-\theta z\beta)QS_j} \end{aligned} \quad (14)$$

Thus:

$$\frac{\partial \ln S_j}{\partial \ln N_j} = \frac{\lambda(S_j)(1-\theta z\beta) - (1-\theta)\beta(R_k - R)}{\lambda(S_j)(1-\theta z\beta) - (1-\theta)\beta(R_k - R) + \frac{\partial \lambda(S_j)}{\partial S_j}(1-\theta z\beta)S_j} \quad (15)$$

Note that for $\frac{\partial \lambda(S_j)}{\partial S_j} = 0$ we get the special case $\frac{\partial \ln S_j}{\partial \ln N_j} = 1$. For a convex function ($\frac{\partial \lambda(S_j)}{\partial S_j} > 0$), the elasticity becomes smaller than one. For a concave function ($\frac{\partial \lambda(S_j)}{\partial S_j} < 0$), the elasticity becomes larger than one.

In a nutshell, our simple model modification provides enough flexibility to calibrate the model according to microeconomic estimation results. Our empirical estimation has shown that the partial equilibrium elasticity is significantly smaller than one, and therefore $\frac{\partial \lambda(S_j)}{\partial S_j} > 0$. Intuitively, this means that for a larger bank it is easier to divert a larger share of funds. As emphasized by GK, funds diversion should not be interpreted literally. Instead, we interpret the bankers as managers who grant extensive bonuses or implement inefficient organizational structures. Thus, it appears realistic that this type of inefficiency gets more severe with the organizational complexity and therefore, with the size of the bank.

In our numerical analysis, we use the following functional form, which is consistent with the convex shape:

$$\lambda(S_{tj}) = cS_{tj}^\psi, \text{ with } \psi > 0. \quad (16)$$

4 Calibration

For our calibration, we attempt to be as close as possible to GK for comparability reasons. At the same time, we adjust some parameter values due to the modified model structure and due to German specificities. Table 2 shows the choice of model parameters. As described by GK, 15 parameters are pretty standard in the DSGE literature. For comparability reasons, we do not change any of the parameters of households, intermediate goods firms, capital producing firms, retail firms and the government.

Only some of the parameters/functions for financial intermediaries are different. We pick the same survival rate of bankers (θ) as GK. While the fraction

of assets that can be diverted (λ) is exogenous in GK, it is replaced by the function $\lambda(S_{tj}) = cS_{tj}^\Psi$ in our model. We choose the remaining three parameters (c, Ψ, ω) to hit three targets, namely, the steady state leverage ratio (ϕ), the steady state spread (external finance premium) between banks' loans and the riskless interest rate ($R_k - R$) and a partial equilibrium elasticity of bank loans with respect to bank capital changes of 0.3. We are interested in assessing how the economy behaves when the partial equilibrium elasticity of loan supply with respect to changes in a bank's capital position is calibrated to the estimated elasticity. Given that the implied elasticity in the original GK model is one, we take the most conservative estimate of 0.3 for our numerical simulation.

We target the same external finance premium as GK, namely 100 basis points on an annual basis. However, we choose a steady state leverage ratio of 7 (instead of 4). Analogously to the balance sheet composition of banks in the model, the leverage ratio of 7 is calculated by the ratio of bank loans to capital.¹⁰

How do we determine the partial equilibrium elasticity of bank loans with respect to bank capital in the model? It is important that this elasticity corresponds to our empirical analysis, which measures the loan supply effects of bank capital changes on the bank level. To replicate this in our model, we switch off all general equilibrium effects. In particular, we simulate the partial equilibrium banking model where market prices are not affected by a policy shock. In addition, there is no adjustment of firms' capital stock, aggregate employment or monetary policy. Intuitively, if a bank is atomistic, a bank-specific capital shock does not affect any of the economy-wide variables. Thus, the bank has to adjust by its own means (e.g. by having a different leverage ratio according to the incentive constraint and by retaining earnings). The model equations of the partial equilibrium banking model can be found in Appendix B.

We solve our model with a log-linearization (i.e. with a first order Taylor approximation). The bank leverage ϕ (in log-linearized form) is

$$\eta\hat{\phi}_t = \phi v\hat{v}_t + \eta\hat{\eta}_t - \Psi^2\phi c^2 S^{2\Psi-1}\hat{s}_t, \quad (17)$$

where v is the expected discounted marginal gain of a bank of increasing assets and η is the ceteris paribus gain from having an extra unit of net worth (see Appendix B and GK).

In the GK model, the last term on the right hand side is not present. This term allows us to calibrate the partial equilibrium elasticity to 0.3. For this purpose, we require $\Psi = 3$. While this implies a rather strong convexity of $\lambda = cS^\Psi$ (in terms of the underlying nonlinear function), it has to be kept in mind that we identify the partial equilibrium elasticity based on a log-linearization. Ignoring partial equilibrium adjustments of \hat{v}_t and $\hat{\eta}_t$, the direct reaction of the leverage ratio to changes in the balance sheet size would be $\Psi^2\phi c^2 S^{2\Psi-1}/\eta =$

¹⁰We use aggregate data provided by the Deutsche Bundesbank that corresponds to the definition in our empirical analysis. Therefore, we take total bank loans to domestic firms and households and total bank capital. Results for a leverage ratio of 4 are available on request. The key findings of the paper are not affected by the choice of the leverage ratio of 7.

0.5894. 1% lower assets would allow the firm to increase its leverage ratio by roughly 0.6% (corresponding to a 0.4% lower capital base instead of a 1% lower capital base as in GK). Remember that we calibrated an elasticity of 0.3 and not 0.4. The difference can be explained by endogenous adjustments of \hat{v}_t and $\hat{\eta}_t$ (i.e. the endogenous adjustment of the value of changing assets and net worth).

Households		
β	0.99	Discount rate
h	0.815	Habit parameter
χ	3.409	Utility weight
φ	0.276	Labor supply parameter
Financial intermediaries		
c	0.002	Scaling parameter in diversion function
Ψ	3.000	Convexity in diversion function
ω	0.002	Transfer to entering bankers
θ	0.972	Survival rate of bankers
Intermediate goods firms		
α	0.330	Effective capital share
U	1.000	Steady state utilization rate
$\delta(U)$	0.025	Steady state depreciation rate
ς	7.200	Elasticity of depreciation rate wrt utilization
Capital producing firm		
η_i	1.728	Inverse elasticity of net investment to capital price
Retail firms		
ε	4.167	Elasticity of substitution on the goods market
γ	0.779	Calvo parameter (fixed prices)
γ_p	0.241	Price indexation
Government		
κ_π	1.500	Weight on inflation in Taylor rule
κ_y	0.250	Weight on output gap in Taylor rule
ρ	0.8	Smoothing parameter
G/Y	0.2	Steady state share of government spending

Table 2: Parametrization of the Model

5 Simulation Results

Figures 1 to 4 show the reaction of the model economy to a net worth shock, to an aggregate productivity shock, to an interest rate shock and to a capital quality shock for our modified model, for the baseline Gertler and Karadi model, and for a frictionless economy without a banking sector. The persistence of all

shocks is set as in GK.¹¹ The shock size is normalized to 1 percent for the aggregate productivity, the interest rate shock and the capital shock. For the net worth shock, the exogenous shock size is 25 percent. Figure 1 shows that the endogenous fall of the net worth is even larger due to an endogenous decline of market prices and, hence, a depreciation of assets.

In all four cases, our model economy, which is calibrated to the estimated microeconomic elasticity, generates a somewhat milder recession than the GK baseline model (see the responses of GDP, investment and net worth in the first row of the figures). The intuition is straightforward. Banks face a decline of their net capital because of the negative aggregate shocks. They reduce their loan supply since they are able to attract a smaller quantity of deposits (resulting from their asset diversion constraint). With our modified asset diversion constraint, the fraction of assets that can be diverted falls when the loan supply falls. Therefore, banks can leverage themselves more than in the GK model immediately after the respective aggregate shock hits the economy. Thus, the loan supply decreases by less in our model than in the GK model. Given that banks have to deleverage to a greater extent in our model when the shock disappears, the external finance premium increases by more after the shock. This allows banks in our model to recapitalize and to return to the steady state.

While aggregate variables react qualitatively by less in our model than in the GK economy, in three of four exercises (namely, net worth, aggregate productivity and interest rate shock) the quantitative reaction is fairly similar. In different words: Although the microeconomic elasticity is substantially smaller in our model than in GK, the macroeconomic differences remain very moderate for three shocks. Why is this the case? Under these three shocks, the leverage ratio in the GK model shows a strong response while the loan volume movements are relatively moderate. As a consequence, the extra effects due to a relaxed asset diversion constraint are moderate. This can be understood by looking at the relevant log-linearized equation. When $\hat{\phi}_t$ already moves a lot due to changes of \hat{v}_t and $\hat{\eta}_t$, the extra effects due to changes in the balance sheet volume are small:

$$\eta\hat{\phi}_t = \phi v\hat{v}_t + \eta\hat{\eta}_t - \Psi^2\phi c^2 S^{2\Psi-1}\hat{s}_t. \quad (18)$$

By contrast, under a capital quality shock to firms' assets, larger quantitative differences between the GK model and our model arise. The reason can be seen in Figure 4. In contrast to the other shocks, the capital quality shock has a substantial effect on the loan volume.

Intuitively, a capital quality shock acts both as a negative loan supply and negative loan demand shock. Similar to a net worth shock, it affects the loan supply. Given that the capital becomes less productive, assets/loans lose value and banks' net worth is reduced. But at the same time, the decline of the marginal product of capital leads to a decline of the demand for productive

¹¹The net worth shock has no past dependence, the productivity shock has an autocorrelation of 0.9, the interest rate shock an autocorrelation of 0.8 and the asset quality shock an autocorrelation of 0.66.

capital and thereby loans. Both mechanisms lead to a fall of the loan volume. This reduces banks' ability to divert assets (i.e. the moral hazard problem) and thereby their ability to attract external funding falls by less. This explains why we obtain a substantial difference between our model and the GK model for the capital quality shock.

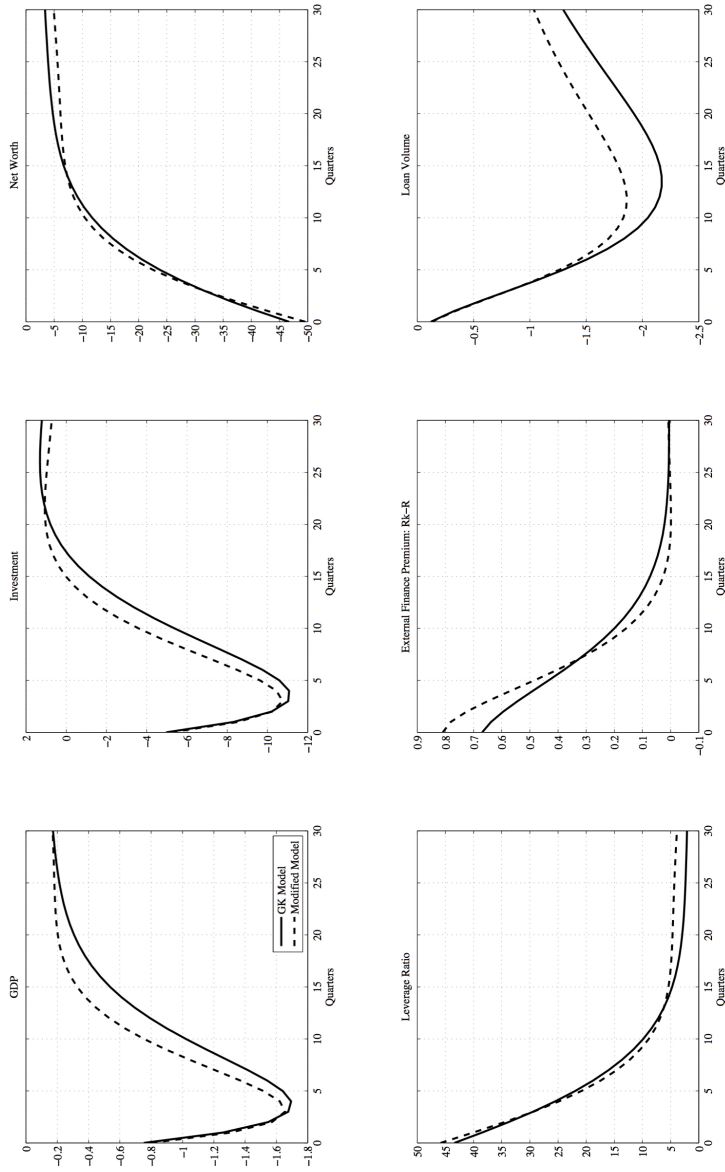


Figure 1: Net Worth Shock

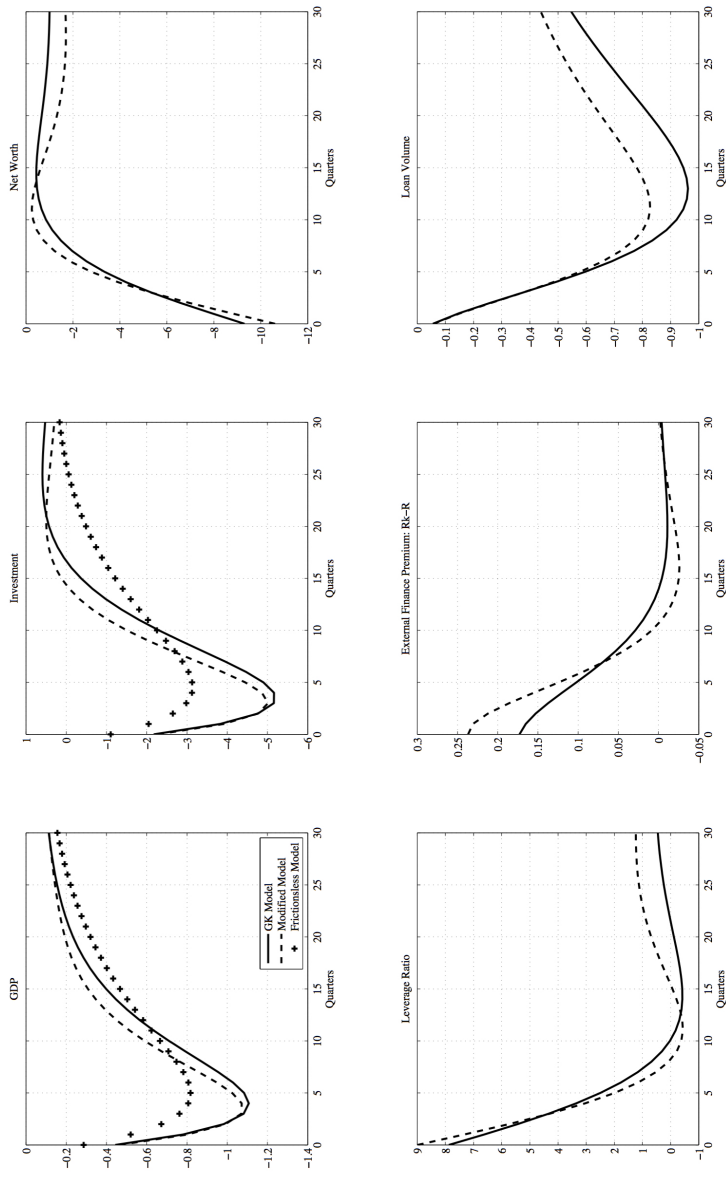


Figure 2: Aggregate Productivity Shock

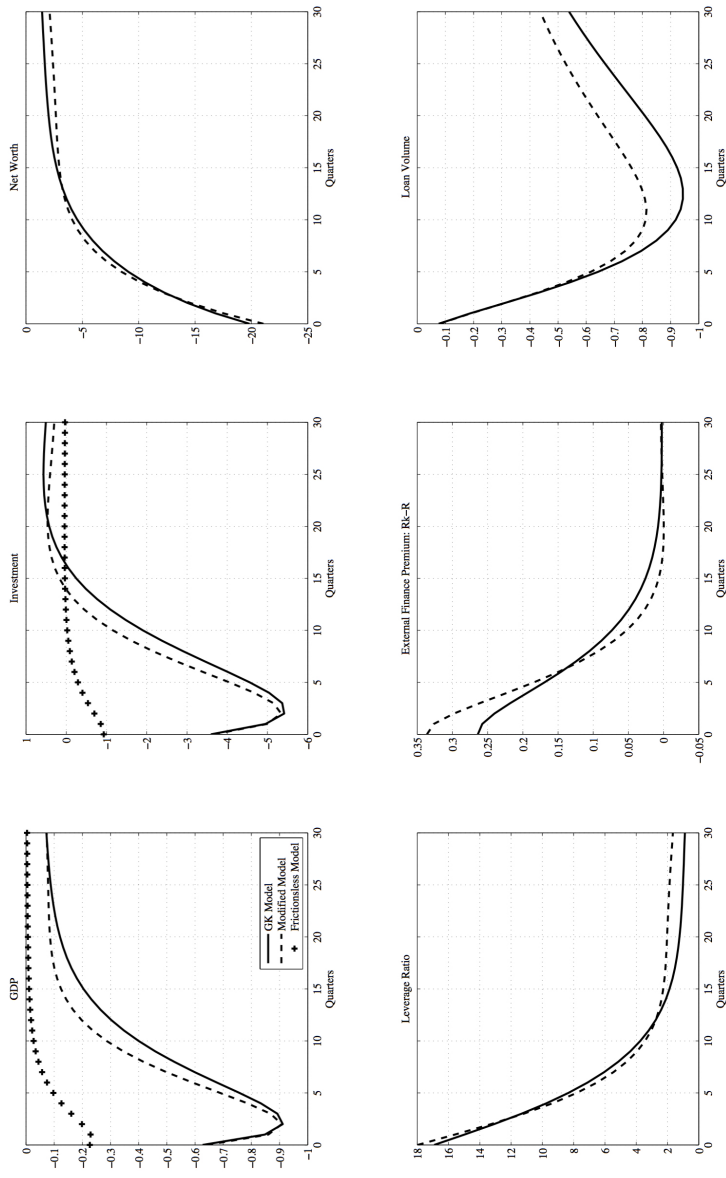


Figure 3: Interest Rate Shock

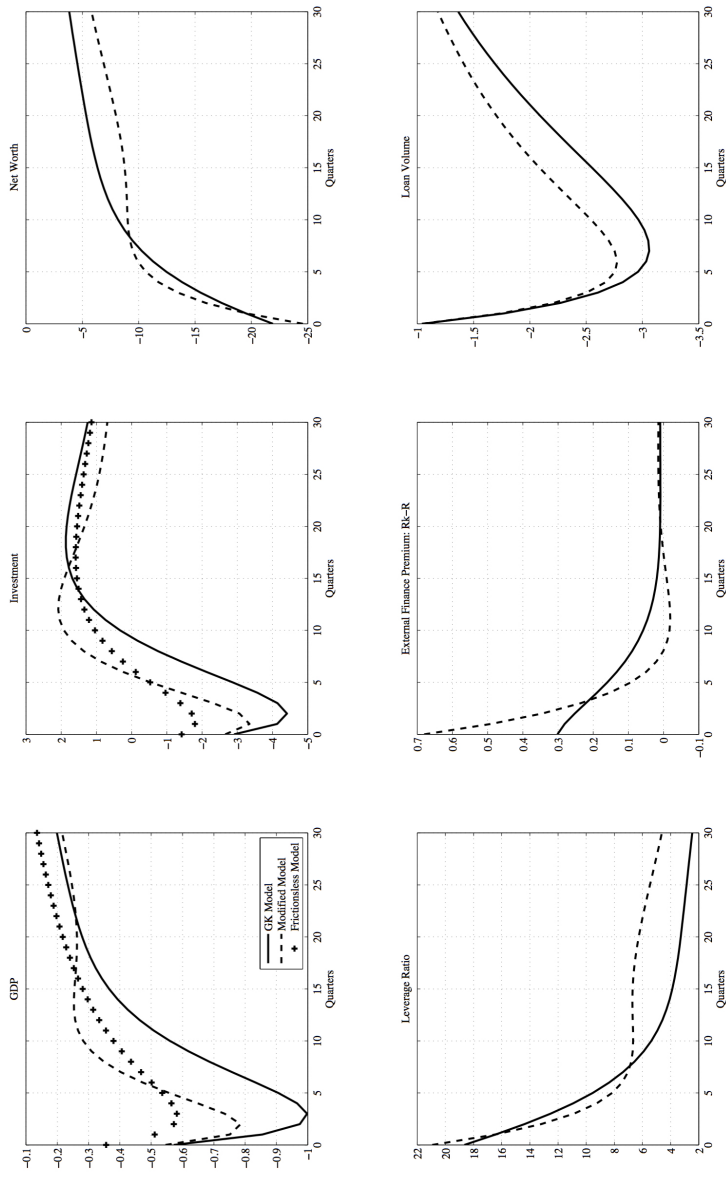


Figure 4: Capital Quality Shock

It is also interesting to compare the IRFs in our model to the frictionless economy (i.e. without a banking sector and thereby with an external finance premium of zero). Interest rate shocks show much more of an effect under financial frictions than in the frictionless economy. By contrast, the differences under productivity shocks are smaller. The reason is that productivity shocks affect the leverage ratio by less than interest rate shocks.

For the capital quality shock, our model comes closer to the frictionless economy. However, in the short run, the drop in investment is twice as large as in the frictionless economy. In the medium run, when the value of assets returns to its old value, this implies a positive loan supply shock (which is absent in the frictionless model) and thereby investment recovers more quickly.

Overall, the banking sector remains a substantial source of disturbance and amplification for the real economy. While we have reduced the microeconomic elasticity by factor 3, the feedback effects on the macroeconomy remain strong. The main reason is that general equilibrium effects are very powerful in the model. In a partial equilibrium framework, the capital drop of an atomistic bank does not lead to any price adjustments. In the full general equilibrium model, there are various adjustment mechanisms that lead to a larger difference between the partial equilibrium and the general equilibrium elasticity. This can most easily be illustrated for the net worth shock. When an individual bank is hit by a negative 1% capital shock, lending goes down by 0.3%. However, in the general equilibrium model (see Figure 1), the co-movement between net worth and the capital shock is quantitatively a lot smaller. One of the key reasons is the endogenous adjustment of the external finance premium. When all banks are hit by a net worth shock, the reduced supply for loans increases their price R_k . This higher return on loans leads to larger (expected) future profits and thereby allows banks to collect more deposits (due to a relaxed asset diversion constraint).

6 Conclusion

This paper shows an application of how to connect microeconomic behavior of the banking sector to macroeconomic modeling. Specifically, we estimate an empirical elasticity of bank loan supply with respect to capital changes of 0.3 at the lower bound using supervisory data provided by the Deutsche Bundesbank. Given, that the implied partial equilibrium elasticity in the model by Gertler and Karadi (2011) equals 1, we modify their model in order to be able to calibrate it to the estimated elasticity. By simulating different aggregate shocks, we assess the model behavior in light of its ability to generate amplification. The simulated results suggest that the lower microeconomic elasticity generally has a dampening effect on the shocks. Nevertheless, the banking sector is still of great importance as source and amplifier of business cycle fluctuations. We attribute this to the powerful general equilibrium effects in the model, i.e. the much lower partial equilibrium elasticity is not translated into a proportionally lower general equilibrium elasticity.

Although the outcomes of our modification approach are certainly model dependent, we regard our study an important contribution to the financial frictions literature. To our knowledge, this study is the first attempting to link microeconomic evidence to a dynamic general equilibrium (DSGE) model with a banking sector. We leave it to future research whether other banking DSGE models are similarly robust with respect to different microeconomic elasticities.

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A Empirical Model

A.1 Data, Data Processing and Descriptive Statistics

All supervisory micro data are provided by the Deutsche Bundesbank. In particular, we use portfolio-level data from the Bundesbank's Borrowers' Statistics, bank distress data from the Distress Data Base, as well as bank balance sheet data from the Bundesbank's prudential database BAKIS (including the auditor reports, "Sonderdatenkatalog", with information on the profit and loss accounts. The data set is available from 1998 to 2013. Our dependent variable, loan growth, is calculated on an annual basis using total long-term loans to domestic households and enterprises including mortgage loans. In the case of bank mergers we artificially create a third bank from the year of the merger in the dataset. By the merger treatment procedure the total number of banks in the data set is increased (i.e. the merger treatment causes the number of banks to exceed the maximum number of banks in a given year).

For the matching regressions, we match banks based on their geographic coordinates. Therefore, we convert street addresses of banks to longitude and latitude coordinates using "Google geocoding".¹² Then, for each bank, we perform distance matching by finding 10 banks that have minimum distance to the reference bank.¹³ Of these 10 banks only those are kept in the matched set that have a similar business model as the reference bank, whereby similarity is evaluated with balance sheet, off balance sheet and profit and loss data. First, analogous to Carlson et al. (2013), we keep only those banks in the matched set, whose total assets are within the range of one third to three times the total assets of the reference bank. Second, we compare several ratios defining a bank's business model: the ratio of corporate loans to total loans, the share of fee income to the sum of interest income and fee income, the ratio of total off-balance sheet activities to total assets, the ratio of deposits to total assets, the net interest margin to total assets, and the ratio of interbank liabilities to total interest bearing liabilities. We then compute the sum of the standardized squared differences between the ratios of each bank and the reference bank, whereby the variance of each ratio is standardized to 0.01. Hence, the sum of squared differences indicates the discrepancy between the reference bank's and the matched bank's business models. Due to the normalization of the ratios' variance, the threshold for the sum of standardized squared differences in order for the bank to be kept in the matched set is 0.06. The reference bank is compared either to a single bank (1:1-matching), i.e. the bank's best match, or to a group of banks, i.e. those banks that remained in the matched set (1:N-matching). Since the matching procedure is performed for each year and each bank, the number of banks N in the match varies over time and between banks. Summary statistics for the fixed effects and the matching regressions are presented in Table 2.

¹²The geocoding is performed in Stata using the command *geocode3*.

¹³We use Roy Wada's *distmatch* command in Stata.

Variable	Units	Fixed Effects			Matching 1:N			Matching 1:1		
		Mean	Std. Dev.	Median	Mean	Std. Dev.	Median	Mean	Std. Dev.	Median
Number of matched banks	-	-	-	-	1.57	0.86	1	1	0	0
Distance between reference bank and matched banks	km	-	-	-	14.96	9.96	13.30	15.53	10.52	13.89
Growth rate of total loans	%	2.72	5.50	2.47	2.80	4.01	2.56	2.66	4.08	2.43
Total capital ratio	%	7.95	2.37	7.52	7.85	1.71	7.59	7.84	1.72	7.57
Ratio of loan-loss provisions to total loans	%	0.51	0.46	0.39	0.50	0.34	0.43	0.68	0.51	0.57
Ratio of non-performing loans to total loans	%	4.55	3.62	3.68	4.60	2.75	4.06	4.59	2.91	4.00
Total assets	million euros	1,060	3,530	271	754	2,480	267	679	2,170	248
Ratio of corporate loans to total loans	%	46.88	15.24	46.30	46.12	11.74	45.69	45.90	11.52	45.59
Ratio of deposits to total assets	%	39.54	11.42	38.36	39.10	9.26	38.3	39.12	9.35	38.27
Ratio of fee income to interest income and fee income	%	12.78	6.99	11.88	12.53	4.67	12.11	12.53	4.68	12.15
Ratio of off-balance sheet activities to total assets	%	5.82	4.08	4.81	5.47	3.13	4.78	5.40	3.11	4.75
Net interest margin to total assets	%	2.56	0.55	2.56	2.60	0.44	2.60	2.61	0.43	2.60
Ratio of interbank liabilities to total interest bearing liabilities	%	15.83	11.73	14.31	14.22	10.00	13.67	14.25	9.66	13.75
Number of observations			32,226			21,748			18,778	

Table 3: Summary Statistics

A.2 Alternative Empirical Specification without second Lag of Loan Growth

We estimate the analogous specification of Carlson et al. (2013) in which we include total capital C as an additional explanatory variable. It is included in order to account for changes in the supply of funds due to the natural growth of the bank. The fixed effects estimation equation for bank i and year t including an interaction term of regional and time fixed effects has following form:

$$\begin{aligned} \Delta \ln L_{it} = & \alpha + \beta CR_{it-1} + \delta \Delta \ln L_{it-1} \\ & + \theta LLP_{it-1} + \nu NPL_{it-1} + \rho_{it} Reg_i * Year_t + \epsilon_{it} \end{aligned} \quad (19)$$

The matching estimation equation for year t , reference bank i and the average of the bank's matched set m has following form:

$$\begin{aligned} \Delta \ln L_{it} - \Delta \ln L_{mt} = & \beta (CR_{it-1} - CR_{mt-1}) \\ & + \delta (\Delta \ln L_{it-1} - \Delta \ln L_{mt-1}) \\ & + \theta (LLP_{it-1} - LLP_{mt-1}) \\ & + \nu (NPL_{it-1} - NPL_{mt-1}) + (\epsilon_{it} - \epsilon_{mt}) \end{aligned} \quad (20)$$

Table 4 shows the regression results.

Coefficients	Fixed Effects	Matching 1:N	Matching 1:1
β	0.098*** (0.027)	0.055*** (0.018)	0.092*** (0.019)
δ_1	0.384*** (0.014)	0.334*** (0.006)	0.500*** (0.007)
δ_2	-	-	-0.014** (0.006)
θ	-0.014*** (0.001)	-0.016*** (0.001)	-0.017*** (0.001)
ν	-0.002*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)
α	0.052*** (0.002)	-	-
R^2	0.387	0.231	0.323
N	33,644	23,351	18,778
β_{SS}	0.159*** (0.043)	0.082*** (0.028)	0.179*** (0.037)
$Elasticity_{SS}$	0.458*** (0.124)	0.250** (0.084)	0.583*** (0.121)

*Note: The table shows results for the fixed effects and the matching regressions for all banks where long-run coefficients and elasticities are evaluated at means. The dependent variable for the fixed effects regression is $\Delta \ln L_{it}$ and for the matching regressions $\Delta \ln L_{it} - \Delta \ln L_{mt}$ with L denoting total loans. The fixed effects regression includes an interaction term of regional and time fixed effects and standard errors are clustered at the regional district level. The standard errors for the long-run coefficients and elasticities are computed using the delta method. The parameters for the interaction terms are not reported for the fixed effects regression, but they are jointly significant when performing a regular Wald test. Note that we keep two lags of the dependent variable as explanatory variables since they are jointly significant for all three specifications. Clustered standard errors are reported in parentheses. Coefficients with *, **, *** are significant at the 10 %, 5 %, and 1 % level respectively using standard t-distribution.*

Table 4: Results for the fixed effects and the matching regressions for all banks

A.3 Delta Method

If a sequence of $K \times 1$ random vectors \mathbf{z}_n is root- n asymptotically normally distributed with

$$\sqrt{n}(\bar{\mathbf{z}}_n - \boldsymbol{\mu}) \xrightarrow{d} N(\mathbf{0}, \boldsymbol{\Sigma}), \quad (21)$$

where n is the total number of observations, $\boldsymbol{\mu}$ is a vector of population means and $\boldsymbol{\Sigma}$ is the variance-covariance matrix, and if $\mathbf{g}(\mathbf{z}_n)$ is a set of continuous differentiable functions, then $\mathbf{g}(\mathbf{z}_n)$ is root- n asymptotically normally distributed with

$$\sqrt{n}[\mathbf{g}(\bar{\mathbf{z}}_n) - \mathbf{g}(\boldsymbol{\mu})] \xrightarrow{d} N[\mathbf{0}, \mathbf{G}(\boldsymbol{\mu}) \boldsymbol{\Sigma} \mathbf{G}(\boldsymbol{\mu})'], \quad (22)$$

where $\mathbf{G}(\boldsymbol{\mu})$ is the matrix of partial derivatives $\frac{\partial \mathbf{g}(\boldsymbol{\mu})}{\partial \boldsymbol{\mu}'}$ (Greene(2012)). In order to compute the standard errors for the long-run coefficients in our regressions, we take the partial derivatives of the estimated long-run coefficient

$$\hat{\beta}_{SS} = \frac{\hat{\beta}}{1 - \hat{\delta}_1 - \hat{\delta}_2} \quad (23)$$

with respect to the parameters of the regression equation. The derivatives are combined in the vector \mathbf{g} . For the fixed effects regression, the vector of partial derivatives is

$$\mathbf{g}' = \frac{\partial \hat{\beta}_{SS}}{\partial \mathbf{b}'} = \left[0, \frac{1}{1 - \hat{\delta}_1 - \hat{\delta}_2}, 0, \frac{\hat{\beta}}{(1 - \hat{\delta}_1 - \hat{\delta}_2)^2}, \frac{\hat{\beta}}{(1 - \hat{\delta}_1 - \hat{\delta}_2)^2}, 0, 0, \mathbf{0} \right] \quad (24)$$

where $\mathbf{b} = [\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\delta}_1, \hat{\delta}_1, \hat{\theta}, \hat{\nu}, \hat{\rho}_{it}]$. For the matching regressions, the vector of partial derivatives is

$$\mathbf{g}' = \frac{\partial \hat{\beta}_{SS}}{\partial \mathbf{b}'} = \left[\frac{1}{1 - \hat{\delta}_1 - \hat{\delta}_2}, 0, \frac{\hat{\beta}}{(1 - \hat{\delta}_1 - \hat{\delta}_2)^2}, \frac{\hat{\beta}}{(1 - \hat{\delta}_1 - \hat{\delta}_2)^2}, 0, 0 \right] \quad (25)$$

where $\mathbf{b} = [\hat{\beta}, \hat{\gamma}, \hat{\delta}_1, \hat{\delta}_1, \hat{\theta}, \hat{\nu}]$. Using (??), we can compute the asymptotic variance for the estimated long-run coefficient as

$$\mathbf{g}' \left[s^2 (\mathbf{X}' \mathbf{X})^{-1} \right] \mathbf{g}, \quad (26)$$

where scalar s^2 is the estimated error variance, $\mathbf{X}_{(nT \times K)}$ is the data matrix, nT is the number of observations and K is the number of variables in the regression. s^2 is computed as follows:

$$s^2 = \frac{\mathbf{e}' \mathbf{e}}{n - K},$$

where $\mathbf{e}_{(nT \times 1)}$ is the vector of least squares residuals from equation: $\mathbf{e} = \mathbf{y} - \mathbf{X}\mathbf{b}$. Therefore, the dimension of the asymptotic variance estimator of the long-run coefficient is a scalar.

B Theoretical Model

We take the model by Gertler and Karadi (2011) and modify it to make it flexible enough to integrate the partial equilibrium elasticity from the microeconomic estimations.

B.1 Households

Households maximize intertemporal utility subject to their budget constraint. As in GK, they face habit formation. Thus, the optimal labor supply equation is

$$\varrho_t W_t = \chi L_t^\varphi, \quad (27)$$

where W_t is the real wage, L_t is the labor input, χ is a weight in the utility function and ϱ_t is defined as follows:

$$\varrho_t = (C_t - hC_{t-1})^{-1} - \beta h E_t (C_{t+1} - hC_t)^{-1}. \quad (28)$$

The Euler consumption equation is

$$E_t \beta \Lambda_{t,t+1} R_{t+1} = 1. \quad (29)$$

with the stochastic discount factor

$$\Lambda_{t,t+1} = \frac{\varrho_{t+1}}{\varrho_t}. \quad (30)$$

B.2 Financial Intermediaries

We modify the financial intermediary's problem in order to be flexible enough for our calibration. Gertler and Karadi's baseline model is nested. A banker's net worth is

$$N_t = \theta [(R_{kt} - R_t) \phi_{t-1} + R_t] N_{t-1} + \omega Q_t S_{t-1}, \quad (31)$$

where R_{kt} is return on the intermediary's assets, R_t is the interest rate paid on the intermediary's debt, $Q_t S_{t-1}$ total quantity of assets (with Q_t being the market price and S_{t-1} the real quantity of assets). θ is the exogenous probability that a banker remains in business. $\phi_{t-1} = \frac{\eta_t}{\lambda(S_t) - v_t}$ is the ratio of privately intermediated assets to equity (private leverage ratio). In contrast to GK, we assume that the fraction of assets that a banker can divert ($\lambda(S_t)$) is a function of its balance sheet size. GK's model is nested by setting $\lambda'(S_t) = 0$.

As in Gertler and Karadi, we define

$$v_t = E_t [(1 - \theta) \beta \Lambda_{t,t+1} (R_{kt} - R_t) + \beta \Lambda_{t,t+1} \beta \theta \varkappa_{t,t+1} v_{t+1}], \quad (32)$$

and

$$z_{t,t+1} = \frac{\phi_{t+1}}{\phi_t} z_{t,t+1}. \quad (33)$$

The growth rate of assets between t and $t + i$ is

$$\eta_t = E_t [(1 - \theta) + \beta \Lambda_{t,t+1} \beta \theta z_{t,t+1} \eta_{t+1}], \quad (34)$$

with

$$z_{t,t+1} = (R_{kt} - R_t) \phi_t + R_{t+1}. \quad (35)$$

The overall aggregate net worth in the economy is

$$N_t = (N_{et} + N_{nt}) \exp^{\varepsilon_t^N}, \quad (36)$$

where N_{et} is the existing net worth, N_{nt} is the newly injected net worth and ε_t^N is an i.i.d. shock to net worth.

The existing net worth is equal to the survival probability multiplied with the past net worth and retained profits.

$$N_{et} = \theta [(R_{kt} - R_t) \phi_{t-1} + R_t] N_{t-1}. \quad (37)$$

As GK, we assume that the net worth for new bankers is

$$N_{nt} = \omega Q_t S_{t-1}. \quad (38)$$

B.3 Intermediate Goods Firms

Intermediate goods producing firms use capital (K_t) and labor to produce goods (Y_t). In addition, they choose an optimal capital utilization rate (U_t):

$$Y_t = A_t (U_t \xi_t K_t)^\alpha L_t^{1-\alpha}, \quad (39)$$

where A_t is total factor productivity. And ξ_t is the capital quality shock. Note that aggregate productivity is subject to aggregate shocks:

$$A_t = A_{t-1}^{\rho^a} \exp^{\varepsilon_t^a}, \quad (40)$$

where ε_t^a is an i.i.d. shock.

The aggregate production function is subject to two types of aggregate shocks. First, aggregate total factor productivity (A_t) may vary. Second, there is a capital quality shock ξ_t .

$$\xi_t = \xi_{t-1}^{\rho^\xi} \exp^{\varepsilon_t^\xi}, \quad (41)$$

where ε_t^ξ is an i.i.d. shock.

Firms' profit maximization yields the following optimal utilization rate:

$$P_{mt} \alpha \frac{Y_t}{U_t} = \delta' (U_t) \xi_t K_t \quad (42)$$

where P_{mt+1} is the price of the intermediate good and $\delta'(U_t)$ is the first derivative of the depreciation rate of capital with respect to the intensity of capital utilization.

The optimal labor demand is

$$P_{mt}(1 - \alpha) \frac{Y_t}{L_t} = W_t, \quad (43)$$

where the marginal product of labor is equal to the wage.

The optimal capital demand is

$$R_{kt+1} = \frac{\left[P_{mt+1} \alpha \frac{Y_{t+1}}{\xi_{t+1} K_{t+1}} + Q_{t+1} - \delta U_{t+1} \right] \xi_{t+1}}{Q_t}, \quad (44)$$

where the rental price of capital R_{kt+1} is equal to the return on capital.

B.4 Capital Producing Firms

GK assume flow adjustment costs of investment, which depend on the net investment flow. The capital price is

$$Q_t = 1 + f(\cdot) + \frac{I_{nt} + I_{ss}}{I_{nt-1} + I_{ss}} f'(\cdot) - E_t \beta \Lambda_{t,t+1} \left(\frac{I_{nt} + I_{ss}}{I_{nt-1} + I_{ss}} \right)^2 f'(\cdot), \quad (45)$$

with $f(1) = f'(1) = 0$ and $f''(1) > 0$.

B.5 Retail Firms

Retail firms pick an optimal price level P_t^* subject to the Calvo mechanism and indexation. The first order condition is

$$\sum_{i=0}^{\infty} \gamma^i \beta^i \Lambda_{t,t+i} \left[\frac{P_t^*}{P_{t+i}} \prod_{k=1}^i (1 + \pi_{t+k-1})^{\gamma_p} - \mu P_{mt+1} \right] Y_{ft+i} = 0, \quad (46)$$

where γ is the Calvo probability that prices cannot be adjusted, γ_p is the degree of indexation and $\mu = \varepsilon / (\varepsilon - 1)$ is the mark-up.

Aggregate prices can then be expressed as

$$P_t = \left[(1 - \gamma) (P_t^*)^{1-\varepsilon} + \gamma (\pi_{t-1}^{\gamma_p} P_{t-1})^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}. \quad (47)$$

B.6 Resource Constraints and Policy

The aggregate resource constraint is

$$Y_t = C_t + I_t + f \left(\frac{I_{nt} + I_{ss}}{I_{nt-1} + I_{ss}} \right) (I_{nt} + I_{ss}) + G_t, \quad (48)$$

i.e. aggregate output consists of consumption, investment and investment adjustment costs.

Capital is the remaining past capital plus the new investment. The past capital is multiplied with one minus the depreciation rate and the capital quality shock.

$$K_{t+1} = (1 - \delta(U_t)) \xi_t K_t + I_t \quad (49)$$

The government finances its spending by lump-sum taxation.

Monetary policy follows a Taylor rule with interest rate smoothing:

$$\left(\frac{1 + i_t}{1 + \bar{i}} \right) = \left(\frac{\pi_t}{\pi_t^*} \right)^{\kappa_\pi(1-\rho)} \left(\frac{Y_t}{Y_t^*} \right)^{\kappa_y(1-\rho)} i_{t-1}^\rho \exp^{\varepsilon_t^i}, \quad (50)$$

where κ_π is the weight on inflation in the Taylor rule, κ_y is the weight on output, ρ is the smoothing parameter, π_t^* is the natural level of inflation and Y_t^* is the flex-price level of output and ε_t^i is the interest rate shock.

In contrast to GK, we do not model any unconventional policy.

Real and nominal interest rates are linked via the Fisher equation:

$$1 + i_t = R_{t+1} E_t \pi_{t+1} \quad (51)$$

C The Loglinearized Leverage Equation

We assume that the diversion of funds depends on the asset size:

$$\lambda(S_{jt}) = c S_{jt}^\Psi \quad (52)$$

Thus, the new leverage equation is

$$Q_t S_{jt} = \frac{\eta_t}{\lambda(S_{jt}) - v_t} N_{jt}, \quad (53)$$

i.e.:

$$\phi_t = \frac{\eta_t}{\lambda(S_{jt}) - v_t}. \quad (54)$$

Loglinearizing the last equation, we obtain:

$$\hat{\phi}_t = \hat{\eta}_t - \frac{\lambda'(S) \lambda(S)}{\lambda(S) - v} \hat{\lambda}(s_{jt}) + \frac{v}{\lambda(S) - v} \hat{v}_t. \quad (55)$$

Now let's do the log-linearization for a specific functional form:

$$\lambda(S_{jt}) = c S_{jt}^\Psi \quad (56)$$

Log-linearized:

$$\hat{\lambda}(S_{jt}) = \Psi \hat{s}_{jt} \quad (57)$$