

Hampered Monetary Policy Transmission – a Supply Side Story?*

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Abstract

This paper shows that the supply side of credit is a major factor for the phenomenon of hampered monetary policy transmission in monopolistic banking markets. Using results from stress tests conducted within the *Low-interest-rate Survey 2017*, we analyse the effect of individual and regional level market power on the pass-through of exogenous monetary policy shocks to retail rates. Our data which covers all 1,555 small and medium sized banks in Germany provides a clear way to partial out demand shocks: we are thus able to show that while banks with more market power charge on average higher loan rates, they spare their borrowers a part of monetary policy contractions and at the same time withhold a substantial part of rising market rates from their depositors. Because high-market-power banks in the sample are relatively more profitable, we argue that these banks seem to have the capacity to build lending-relationships with their customers and subsequently insure them against adverse shocks.

Keywords: bank lending channel, monetary policy transmission, bank competition

JEL classification: E43, E51, E52, G21.

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1 Introduction

The Great Recession has stressed the importance of credit markets for real business cycles. A vast empirical evidence concurs that contractions in credit supply contributed substantially to the recent economic downturn.¹ In order to counteract the drying-up of credit, central banks in the U.S. as well as the EU have intervened heavily in order to boost banks' loan provision. Targeting the supply side of credit in the transmission of monetary policy to the real economy hinges not only on the assumption that borrowers cannot perfectly substitute between bank loans and other types of funds (e.g. issued bonds) but also that monetary policy has a strong direct effect on the real economy via credit supply (apart from its effect through real interest rates). This independent effect of monetary policy on credit supply is referred to as the bank lending channel.² The recent financial crisis is furthermore likely to have shaped banking markets in a way that requires a re-evaluation of monetary policy transmission to both financial and real variables.³

In this article, we make use of a unique supervisory data set on the entire population of small and medium-sized banks in Germany, the *Low-interest-rate Survey 2017*, and determine whether imperfectly competitive banking markets impede monetary policy transmission through the supply side of credit markets. In spring 2017, the German Federal Financial Authority (henceforth *BaFin*) and Deutsche Bundesbank (henceforth *Bundesbank*) conducted a supervisory measure according to which all small and medium-sized banks in Germany were required to report interest rates for loans and deposits. In particular, end-of-2017 projected retail rates for two different predefined scenarios taking

¹Chodorow-Reich (2013); Di Maggio and Kermani (2017) for the U.S., Bentolila, Jansen, and Jiménez (2017) for Spain, and Buera and Karmakar, 2016 for Portugal.

²Bernanke and Blinder (1988) and Bernanke and Blinder (1992) motivate the *credit view* as a contrast to the *money view*. According to the latter, banks have no role transmitting monetary policy to real variables while they can be crucial under the former. The credit channel is commonly divided into balance sheet and bank lending channel. The balance sheet channel establishes that (productivity or monetary policy) shocks are amplified through *borrowers'* balance sheets, a mechanism also known as the *financial accelerator* (Bernanke and Gertler, 1989, 1995; Bernanke, Gertler, and Gilchrist, 1999). The bank lending channel on the other hand focuses on how monetary policy affects the external finance premium through the credit supply side, i.e. banks in their role as *lenders*, and real variables (Bernanke and Blinder, 1992; Kashyap and Stein, 1994, 2000).

³See Agarwal, Chomsisengphet, Mahoney, and Stroebel (2017), Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao (2017), Drechsler, Savov, and Schnabl (2017).

place over the same time horizon were to be disclosed: 1) a hypothetical exogenous and permanent monetary policy contraction and 2) the absence thereof, meaning no change in monetary policy as opposed to end of 2016. This data set is exceptional for two reasons: because of its coverage (88 percent of all credit institutions in Germany⁴) and because it delivers two data points per bank, one for each scenario, which we can use as treatment and counterfactual outcome, respectively. By taking the difference between the retail rates in the shock and the constant scenario, we can thus partial out any factors banks expect to change over the course of 2017 which influence interest rates apart from monetary policy. Consequently, expected shifts in credit demand unrelated to the monetary policy change are controlled for. We are therefore able to assess the supply-sided effect of imperfect competition among banks on the pass-through of monetary policy to loan and deposit rates. Our results suggest that following a contraction in the policy rate, a bank's pass-through to loan rates is on average smaller by 4–5 percentage points when the bank belongs to the 90th percentile of the pricing power distribution or when operating in a highly concentrated market. Banks also exert market power in the deposit market to a substantial degree: in a highly concentrated deposit market, banks have a lower average pass-through by almost 10 percentage points as opposed to a mildly concentrated market where monetary policy transmission is on average only 3 percentage points lower.

Results are confounded if banks – despite the instructions – assume credit demand to shift differently in the two scenarios. Because bankers understand the first scenario as an adverse scenario⁵, they might assume credit demand to contract only in the shock scenario. If they do so, they are likely to base their expectations on past events. Following increases in the policy rate, demand in the EU generally falls to a larger extent at riskier banks (Altavilla, Boucinha, Holton, and Ongena, 2018) and riskier banks tend to be those with less market power (Kick and Prieto, 2014). Therefore, predicted demand shifts should be

⁴The only other data source available containing interest rates at the individual level (MFI interest rate statistic) is a substantially smaller subset of all German banks (Weth, 2002).

⁵In stress testing exercises, the shock scenario is the one that challenges banks' balance sheets. Often, the adverse scenario also entails a macroeconomic scenario with a predefined decline in GDP. See e.g. https://www.esrb.europa.eu/mppa/stress/shared/pdf/esrb.20180131_EBA_stress_test_scenario__macrofinancial.en.pdf?43a5f3c6c04f2daa03bd950b55d8897b.

larger at banks with less market power. In the event that these differential (predicted) changes in demand mostly drive our results, we should therefore observe a relatively *smaller* pass-through at banks with *less* market power. This is because a drop in demand counteracts the upward pressure on the price after an exogenous increase in banks' funding costs. The fact that we find the opposite, suggests that we are identifying a pure credit supply shift. Due to the fact that German banks operate locally and because we find that banks in imperfectly competitive markets have higher profits and return on assets, our results indicate that these banks are likely to have the capacity to build relationships with their borrowers and subsequently insure them against adverse shocks.

Our findings speak to various strands of the literature. Both the theoretical and empirical literature debate about the effect of imperfect competition on loan and deposit pricing. Furthermore, from a theoretical point of view a hampered pass-through in a monopolistic banking market can be a result of frictions on the supply or demand side of credit.⁶ The more closely related banking literature formulates that under the structure-conduct-performance paradigm banks extract monopolistic rents in concentrated markets by setting lower deposit rates and higher loan rates (Berger, 1995). Thus, after a monetary contraction, banks in imperfectly competitive markets could raise loan rates relatively more (and deposit rates relatively less) than in a competitive environment. However, under the efficient-structure hypothesis, efficiency and concentration are positively correlated and therefore banks might as well set lower loan rates in relatively more concentrated markets (Berger, 1995). On a similar note, information asymmetries can be reduced by relationship lending which may lead to more favourable outcomes for some borrowers while market power can promote relationship lending (Rajan, 1992; Petersen and Rajan, 1995). According to Rajan (1992), this is because only in monopolistic markets banks can share the future surplus of a match which may imply lower loan rates at

⁶Macroeconomic models know both situations in which monopolistic competition leads to amplified and mitigated responses in retail rates. For amplification, see e.g. Gerali, Neri, Sessa, and Signoretti (2010) or Duffie and Krishnamurthy (2016). Models for a hampered pass-through via the supply side are provided by Martinez-Miera and Repullo (2018) and Corbae and Levine (2018). However the same outcome in monopolistic banking markets can occur due to constraints on the demand side (Güntner, 2011).

the beginning of a match for certain borrowers. Banks in perfectly competitive markets which need to break even every period cannot do so.

This paper confirms that in the German context monetary policy transmission and market power are negatively related which is in line with previous literature on the U.S. and the EU.⁷ The question about the underlying channel remains largely unanswered though. This is because research on monetary policy transmission so far has only worked with realised retail rates over time where monetary policy shocks are likely to coincide with shifts in credit demand which so far have not (sufficiently) been controlled for. Reasons for a hampered pass-through may lie *within* financial institutions such as their portfolio or cost structures that make it optimal for banks with more market power to transmit smaller fractions of positive interest rate shocks to retail rates. For instance, banks might exert market power on their liability side (e.g. in the market for deposits) and therefore have the potential to smooth interest rates on their asset side. On the other hand, it may also be the case that over the business cycle credit demand shifts systematically differently *across* banks with different degrees of market power. The former mechanism identifies frictions on the credit supply side; the latter instead tells a credit demand story.

Our contribution to the above literature is therefore to show that supply side effects dominate. As a result, we prove the existence of a bank lending channel which has not yet been pinned down in relation to imperfect competition for Europe.⁸ To our knowledge, only [Drechsler et al. \(2017\)](#) establish a direct, impeding effect of deposit market

⁷[Van Leuvensteijn, Sorensen, Bikker, and van Rixtel \(2013\)](#) and [Gropp, Kok, and Lichtenberger \(2014\)](#) conclude an impaired pass-trough of monetary policy to realised loan and deposit rates with respect to within-banking sector competition in Europe. [Schlueter, Busch, Sievers, and Hartmann-Wendels \(2016\)](#) identify the same pattern for Germany. See [Adams and Amel \(2011\)](#); [Fungáčová, Solanko, and Weill \(2014\)](#); [Leroy \(2014\)](#); [Sääskilahti \(2016\)](#) for the U.S., and [De Graeve, De Jonghe, and Vander Vennet \(2007\)](#) for Belgium.

⁸While various papers tend to find a bank lending channel in the EU, other characteristics than competition measures are typically examined. Testing several European countries, [De Bondt et al. \(1998\)](#) find a bank lending channel for Germany. [Altunbaş, Fazylov, and Molyneux \(2002\)](#), however, only identify one for Italy and Spain (but not for Germany). [Weth \(2002\)](#) examines the pass-through from market rates to German bank lending rates with respect bank size and refinancing conditions with results in favour of a lending channel. According to [Kakes and Sturm \(2002\)](#), bank lending in Germany reacts differently to monetary policy across different banking groups and e.g. liquidity buffers. Their finding confirms previous work by [Worms \(2001\)](#).

concentration on monetary policy transmission to bank lending.⁹ This result is, however, specific to the U.S. case. Inherent structural differences across the two banking markets as well as effects that the recent financial crisis and different extraordinary monetary policy measures had on them raise doubts on whether findings for the U.S. can be translated to Europe. For instance, the sovereign debt crisis in 2011/12 posed a particular challenge to Europe's unintegrated banking market and lead the European Central Bank (ECB) to target sovereign spreads of particular countries in the EU, a phenomenon which was absent in the U.S. We show that, in contrast to the U.S. (Drechsler et al., 2017), counties with high banking market concentration in Germany are on average smaller and populated by a lower share of people over the age of 65. Furthermore, while – similar to the U.S. – high-concentration banks' exposures in the respective product market are on average higher than those of low-concentration banks in Germany in 2016, this has not always been the case in Germany.

The paper proceeds as follows. Section 2 motivates our empirical part theoretically, section 3 introduces the data sets, section 4 our measures of imperfect competition and section 5 specifies our empirical approach. Results are presented in section 6 and section 7 concludes.

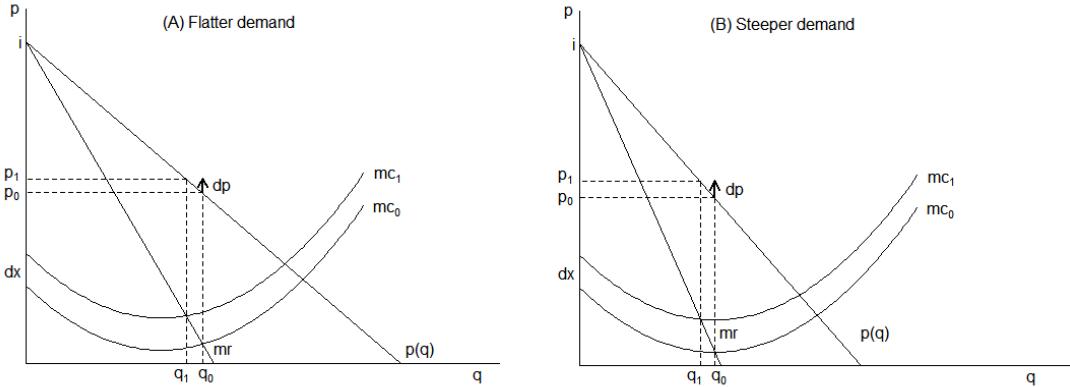
2 Conceptual framework

In theoretical models, banking markets are commonly characterised by some sort of imperfect competition (e.g. Gerali et al., 2010; Martinez-Miera and Repullo, 2018). In the context of monetary policy transmission, the central bank's policy rate can furthermore be interpreted as a bank's marginal costs since banks consider it as the reference rate for their funding (Agarwal et al., 2017; Martinez-Miera and Repullo, 2018; Corbae and Levine, 2018). The standard textbook model of monopolistic competition therefore pro-

⁹Using geographical variation in the degree of concentration, they find that bank branches in more concentrated markets widen the spread between deposit rates and the Fed funds rate in response to a monetary policy contraction relative to a branch of the same bank but operating in a less concentrated market (Drechsler et al., 2017).

vides a useful and simple framework to formalise changes in prices for loans where p is to be interpreted as the rate which a bank charges for one unit of loan, q . Accordingly, a change in the equilibrium price can be the result of cost and/or demand shifts (see [Figure 1](#) which displays an exogenous cost shock).

Figure 1: Monopolistic competition



Note: The figure shows the pass-through of a cost shock to prices in two markets with monopolistic competition. Panel A considers a case with a relatively flat demand curve, i.e. a market in which a monopolist can exert relatively less market power; Panel B considers a case with a relatively steep demand curve, i.e. a market with relatively more market power. (Inverse) demand is denoted by $p(q)$, marginal revenues by mr and marginal costs by mc . A demand shock would shift $p(q)$, and accordingly mr .

A change in the equilibrium price, dp , can therefore be expressed as a function of the two shocks:

$$dp = \frac{\partial p}{\partial x} dx + \frac{\partial p}{\partial i} di \quad (1)$$

where dx denotes an exogenous parallel cost shift (i.e. x denotes the intercept of the marginal cost curve) and di a demand shift (i.e. i is the intercept of the inverse demand curve). The intercept of the demand curve can be interpreted as the maximum price a (marginal) borrower would be willing to pay (in the limit when $q \rightarrow 0$). Thus, the first term on the right-hand side of equation (1) captures the equilibrium price change after a cost shock in the absence of demand shifts, and the second term the corresponding change after a demand shift when no funding costs shock is present. In the event that

both shocks occur at the same time, equation (1) formalises the full adjustment of the price from the old to the new equilibrium.

This can be expressed in more detail. Considering that in the presented model the equilibrium price p is a function of q and i while q is in turn a function of x and i , $p(q(x, i), i)$, for any functional form of demand and marginal cost curve, the analytical solution to dp is given by (see [Section A.1](#) for proof)

$$dp = \frac{\partial p}{\partial q} \frac{\partial q}{\partial x} dx + \left(\frac{\partial p}{\partial i} + \frac{\partial p}{\partial q} \frac{\partial q}{\partial i} \right) di \quad (2)$$

where $\frac{\partial q}{\partial x}$ is the change in the equilibrium quantity in response to a change in costs, $\frac{\partial p}{\partial i}$ is the partial derivative of demand with respect to its intercept and $\frac{\partial q}{\partial i}$ reflects the dependence of the equilibrium quantity on the intercept of the demand curve (see [Section A.1](#) for further details). Equation (2) shows that the equilibrium price adjustment to any of the shocks depends on the slope of the demand curve, $\frac{\partial p}{\partial q}$. Hence, the steepness of demand (or the elasticity of demand) determines not only the extent to which a monopolist can exert market power¹⁰, but also the adjustment of the equilibrium price in response to shocks.

If for every loan quantity, borrowers are suddenly willing to pay a different price, then demand shifts. Here, a productivity shock or a shock to agent's expectations about the evolution of the business cycle may be one reason. Alternatively, a monetary policy shock which induces a change in the cost of funds, affects marginal costs: a monetary policy contraction increases the cost of funds and therefore shifts the marginal cost curve up, leading to a higher equilibrium loan rate (see [Figure 1](#)). Equation (2) demonstrates that the size of the price adjustment always depends on the slope of demand and the according degree of the monopolist's pricing power.

¹⁰Solving $\max_q \pi = p(q)q - c(q)$ gives $\frac{dp(q)}{dq}q + p(q) - \frac{dc(q)}{dq} = 0$. Rewriting leads to $p(q)[\frac{dp}{dq}q - 1] = mc$ with $\frac{dc(q)}{dq}$ denoting marginal costs, mc . The elasticity of demand, ϵ , is $\epsilon = \frac{dq}{dp} \frac{p}{q}$. Rewriting once more gives $\frac{1}{|\epsilon|} = \frac{p - mc}{mc}$ which is the definition of the Lerner Index. Therefore, the less elastic demand in the old equilibrium point, the more market power a bank can exert. Note, maximising over p instead of q leads to the same results.

Papers examining realised interest rates and their response to changes in the reference rate observe rates over the monetary and business cycle where dp is the change in the price over time, $dp = p_{t+1} - p_t$, (Van Leuvenstein et al., 2013; Schlueter et al., 2016). According to equations (1) and (2) heterogeneities in dp can either stem from different supply side adjustments or from credit demand shifts unrelated to monetary policy changes. It is furthermore plausible that demand behaves systematically differently across different types of banks where bank typologies are related to their degree of market power; in that event, resulting heterogeneities in the transmission of monetary policy are not a result of frictions on the credit supply side. Therefore, without a credible control for demand shifts, or ensuring that di in equation (1) is zero, a lower transmission of monetary policy among banks with more market power cannot serve as evidence for a bank lending channel without a reasonable doubt.

Instead, we can disentangle the supply from the demand side in the price setting to a large extent. This is because the underlying dataset of this paper is of special nature. Banks are required to assume two scenarios, one in which a hypothetical monetary policy shock, dx , is zero and one in which it is equal to 200 BP. The instructions ensure that in the second scenario banks assume an *exogenous* monetary policy shock (BaFin/Bundesbank, 2017). Then banks report consequent interest rates for the year which follows the shock giving us two data points per bank for (the end of) 2017. The difference between the two then represents our dp which is calculated per bank j :

$$dp_j = p_{j,\text{shock},t+1} - p_{j,\text{constant},t+1}$$

where $p_{j,\text{shock},t+1}$ denotes the predicted loan rate in the shock scenario and $p_{j,\text{constant},t+1}$ the one in the scenario where no monetary policy shock occurs, both for the same point in time. Provided that banks (correctly) assume $di = 0$, we observe price changes *conditional on* an exogenous monetary policy shock:

$$dp_j = p_{j,t+1}|_{dx=200BP} - p_{j,t+1}|_{dx=0} \quad (3)$$

Furthermore, the effect of any demand shocks which, despite the instructions, banks may potentially assume over the course of 2017 is differenced out when calculating dp_j – as long as those demand shocks are unrelated to monetary policy. Similarly, any change in other factors, which matter for the pass-through (apart from monetary policy or demand shocks), that banks might expect cancels out. In other words, we partial out any predicted (demand) shifts over the year 2017 at the bank level, as long as the bank assumes them to be the same in both scenarios. Therefore, only the effect of the shock which affects the supply side is left (as in equation (3) and displayed in [Figure 1](#)).

In the presented model, demand falls as a result of higher loan rates following the shock, represented by a movement *along* the demand curve. Yet, because a monetary policy contraction may affect borrowers' balance sheets, the change in credit demand could be amplified. According to the financial accelerator mechanism, a monetary contraction typically results in declining asset prices, shrinking collateral and thus a drop in capital or credit demand ([Bernanke and Gertler, 1989](#); [Bernanke et al., 1999](#)). As a result, it is plausible that banks might assume an inward shift in credit demand in the shock scenario as opposed to the constant scenario. This would not be cancelled out by our empirical approach. There is, however, strong evidence that borrowers do not assign randomly to lenders ([Schwert, 2018](#)). Therefore, demand shifts are likely to vary systematically across banks. Indeed, [Altavilla et al. \(2018\)](#) find that in response to a contractionary monetary policy shock, demand contracts relatively more at riskier banks. According to the *competition-stability* nexus, banks with more market power can be considered as less risky since they realise profits from monopoly rents while in competitive markets banks search for yield in riskier investments.¹¹ Therefore, in the event that banks expect a negative demand shift in the shock scenario, those with more market power are likely to predict this shift to be relatively smaller. If that is the case, reported price changes are *ceteris paribus* larger at more monopolistic banks. This is because for banks with less market power a relatively larger drop in demand mitigates the upward pressure on the

¹¹See [Kick and Prieto \(2014\)](#) for an overview of the literature and evidence for a negative relationship between market power and bank risk taking.

price from the positive cost shock to a relatively larger extent. Thus, if that drives the results, we should find a *larger* pass-through among banks with more market power.

Summing up, we are likely to observe pure supply-side adjustments in prices in response to an exogenous monetary policy contraction. That is, we are able to estimate the direction of

$$\frac{d(dp/dx)}{d\text{market power}} >< 0. \quad (4)$$

Note that even in the simple model presented above, when market power is measured by the slope of demand, the direction is ambiguous; when marginal costs are convex and the slope of demand passes a certain threshold, the pass-through of monetary policy falls in market power, hence the relationship in equation (4) is negative. The analytical solution to the threshold is derived in [Section A.2](#). Otherwise, the model predicts that banks with more market power change prices relatively more, giving equation (4) a positive sign. However, the model does not capture many potential frictions affecting the credit supply side; sticky relationships between borrower and lender or imperfect competition in the market for deposits are potential sources of distortion for the way banks pass cost shocks on to loan rates. We therefore turn to the empirical analysis.

3 Data

For our analyses, we merge bank-level supervisory data of all banks in Germany with a unique data set that contains interest rates for various product categories on banks' asset and liability sides: the *Low-interest-rate survey 2017*.

3.1 Low-interest-rate Survey 2017

Between April and June 2017, BaFin and Bundesbank conducted a supervisory measure on all 1,555 small and medium-sized German credit institutions on their profitability and

resilience in the low-interest rate environment in a bottom-up exercise.¹² Supervisory stress tests in the context of banking supervision are generally conducted in *top-down* and *bottom-up* exercises. Top-down refers to tests which supervisory institutions run based on the bank-by-bank reporting data they have on the supervised banks; in bottom-up exercises, banks are obliged to run simulations or calculations themselves using their individual risk management assumptions and parameters while complying with constraints given by the authorities. Results need to be reported to the supervisors which in turn conduct quality assurance to ensure comparable results. While the exact modelling of banks is unknown, the bottom-up approach allows a more individual and thus more meaningful reflection of the banks' vulnerabilities under a certain scenario when taking into account data that the authorities do not have at hand.

Data collected under the *Low-interest-rate Survey 2017* contains outcomes from various stress tests on interest rate risk, credit risk and market risk. For our purpose, we work with the stress test data on interest rate risk. In particular, banks had to report retail rates for e.g. loans, subcategories therein, and deposits which they would set in response to two hypothetical scenarios taking place as of 01.01.2017.

The two scenarios are phrased specifically as follows:

1. “Constant yield curve (static balance sheet assumption¹³): the yield curve as of 31.12.2016 remains unchanged for the whole time horizon. The static balance sheet assumption holds.” ([BaFin/Bundesbank, 2017](#))
2. “+200 BP shock (static balance sheet assumption): the yield curve ad hoc (parallelly) shifts by 200 BP as of 01.01.2017 compared to 31.12.2016 and remains unchanged for the whole time horizon. The static balance sheet assumption holds.” ([BaFin/Bundesbank, 2017](#))

¹²The supervisory measure was conducted on all small and medium-sized banks which are supervised by BaFin and Bundesbank according to § 6b **KWG**. Significant institutions (*SIs*) under direct European Central Bank (*ECB*) supervision are excluded.

¹³For comparability reasons and to prevent implausible portfolio enhancements, banks were required to replace maturing business with equivalent new business at prevailing standards regarding e.g. probabilities of default of borrowers and contracted volumes.

Because the upward shift in the yield curve is defined to be permanent ([BaFin/Bundesbank, 2017](#)), the shock scenario per definition implies a contractionary monetary policy shock. It is verified that banks understand the shock to be permanent.¹⁴ A bank's reported interest rate in the first scenario therefore serves as the second part of the right-hand-side of equation (3), and the one reported for the second scenario as the first part of the right-hand-side of equation (3). To avoid that old contracts confound our results, we focus exclusively on new business which for loans is further divided into fixed and adjustable rate contracts (deposit rates are adjustable only). To take into account that banks with relatively larger shares of fixed rate contracts are likely to change loan rates to a smaller extent, for each scenario and bank, we calculate the (new business) loan rate as a volume-weighted average over fixed and adjustable rates.

In a quality assurance process, stress test submissions were continuously quality-checked to ensure that all reporting banks submit meaningful data. Cross-checks with reporting data (e.g. interest income and expenses or loan volumes) and peer group comparisons¹⁵ ensure that numbers reported are plausible and fulfil quality standards. Furthermore, banks were advised to submit revised versions in case of poor or insufficient data. Data quality is of high importance because results provide the basis for individual (Pillar 2) capital guidances in the supervisory review and evaluation process (*SREP*) framework.¹⁶

The question whether banks may have an incentive to consistently bias projected interest rates in a certain way could arise. First, from a macroeconomic perspective it is plausible that banks want to avoid a (drastic) increase in the policy rate because that would raise the cost of refinancing immediately while fixed-term contracts on bank's asset sides can not be adjusted accordingly. This is likely to cause cuts in profits for each bank. Because soaring loan rates would depress the real economy, whose stability is one

¹⁴Due to the permanent nature of the shock, all current and fixed assets have to be written down.

¹⁵For instance, the maturing portion of a certain balance sheet position is compared across banks with a similar average maturity in that portfolio.

¹⁶For more information, see https://www.bafin.de/SharedDocs/Veroeffentlichungen/EN/Fachartikel/2018/fa_bj_1807_Risikotragfaehigkeit_en.html

of the main goals of the ECB, banks, if they had any room for giving strategic answers, could have an incentive to utilise the stress test answers and overstate the severity of consequences from the shock scenario. Second, the difference between the interest incomes in the two scenarios (called stress effect) is the basis on which subsequent capital guidances are derived. Because the size of the stress effect and that of the derived capital buffers are positively correlated, all banks could have an incentive to overstate (understate) the pass-through to loan (deposit) rates. Thus, banks generally have an incentive to pass on 100 percent of the shock to loan rates and none of it to deposit rates. This, however, holds true irrespectively of the level of market power. Even if no systematic bias is expected in the present data¹⁷, we can conclude that because we are interested in the interaction effect of the pass-through and imperfect competition, the incentive structure is unlikely to influence our results in a systematic way.

3.2 Panel data

We select and estimate explanatory variables from annual balances and profit and loss accounts reported to the Bundesbank on a yearly basis. From this dataset, we take control variables and, most importantly, compute measures for market power. Because here, we work on the entire population of financial institutions in Germany, we explicitly take the “big banks”, i.e. SIs supervised by the ECB, in the pool of competitors into account. We keep a long time horizon (from 1994 to 2016) in order to make sure we achieve plausible results of estimated measures and their evolution over time. Due to mergers and acquisitions we work with an unbalanced panel. In the final analyses we only use the 2016, i.e. ex-ante, values of explanatory variables from that dataset. A shortcoming of this dataset is that we cannot see where exactly the big banks conduct their business but assign all of it to the location (county) of their respective headquarters. This will be further discussed below.

¹⁷§ 6b [KWG](#) and [EU-Regulation\(1093/2010\)](#) apply.

3.3 Data cleansing

Before merging the panel and the stress test data, we clean the two data sets separately. To exclude implausible bank-year observations in the panel data, we drop observations with negative or zero total assets, equity and total loans (i.e. sum of financial and non-financial loans) and impose the following conditions: Loans-to-assets ratio and deposits-to-assets ratio must not exceed 1 and 0.98, respectively, and the equity-to-assets ratio must lie between 0.009 and 0.5. The personnel expenses- and other administrative expenses-to-assets ratio must be in a range of 0.0005 and 0.05 ([Van Leuvenstein et al., 2013](#)). Before we impose the latter two conditions, we winzorize the expense variables at the upper and lower percentile ([Kick, Pausch, and Ruprecht, 2015](#)). That leaves us with more than 54,200 bank-year observations.

From the stress test data, building societies (*Bausparkassen*) are excluded as they are highly specialized. We furthermore exclude some few banks which despite the elaborated quality assurance process still appear to have provided data of insufficient quality. To deal with outliers, we winzorise interest rate levels and pass-through variables (the difference between the rates in the shock and the constant scenario normalized by the size of the shock) at the upper and lower percentile. Finally, we only keep those banks that pass the quality requirements imposed on both datasets.

4 Measures of competition and concentration

In order to empirically determine whether interest rate levels vary with imperfect competition and whether monetary policy transmission falls or rises with it, we alternatively use an individual pricing power and a market concentration index.¹⁸ The Lerner Index is widely applied in the banking literature which provides guidance on how to estimate it

¹⁸It has been established in the literature that various competition measures may be only weakly interrelated (e.g. [Claessens and Laeven, 2004](#); [Bikker, Shaffer, and Spierdijk, 2012](#) and citations therein for empirical evidence, and [Lapteacru \(2014\)](#) for theoretical work).

from micro data.¹⁹ To our best knowledge, it is moreover the only well-known measure one can compute *at the bank-level*, thereby enabling us to study heterogeneities across banks very closely. Because the banks in our sample operate locally, we also apply an aggregate concentration measure, the Herfindahl-Hirschman Index.²⁰

4.1 Individual pricing power: Lerner Index

The Lerner Index (LI) measures a firm's difference between price and marginal cost, and therefore its monopolistic power (Elzinga and Mills, 2011). In the absence of market power, under perfect competition, the LI is zero. Because the LI sets the price in relation to marginal costs, the maximum value of the LI should be below, but close to 1 (perfect monopoly). The LI for bank j at time t is defined as

$$LI_{jt} = \frac{\frac{TOR_{jt}}{Y_{jt}} - MC_{jt}}{\frac{TOR_{jt}}{Y_{jt}}} \quad (5)$$

with average revenues calculated as a fraction of total revenues TOR_{jt} , and total output, Y_{jt} , and marginal costs are denoted by MC_{jt} .²¹ We define total revenues as revenues that can be attributed to loan provision in the wider sense, excluding revenues from financial transactions such as trading derivatives.²² Total revenues therefore consist of interest income from credit and money market operations, and revenues from fee-based business. Total output is commonly defined as the sum of loans to non-financial customers (i.e. households and private firms), inter-bank loans and securities (Mester, 1996).

Marginal costs are the derivative of total costs with respect to output. We therefore

¹⁹See e.g. Valverde and Fernandez (2007) for the determinants of bank margins, Berger, Klapper, and Turk-Ariis (2009) and Kick and Prieto (2014) for assessing the relationship between competition and financial stability and Sääskilahti (2016) on competition and lending volumes in the recent crisis.

²⁰Alternative measures would be the Boone Indicator (Kick and Prieto, 2014), or the Panzaar-Rosse H-Statistic. The latter has drawn much criticism in determining competition (Bikker et al., 2012 and Shaffer and Spierdijk, 2015).

²¹Under imperfect competition: $P(Q) = AR$, because $AR = avg.Profit + AC = \frac{profit}{Y} + \frac{TOC}{Y} = \frac{TOR_{jt}}{Y_{jt}}$ with TOR_{jt} denoting total revenues of bank j in year t , and TOC total costs.

²²In a robustness check, we verified that including financial transactions does not make a substantial difference in the results.

estimate total costs for each bank in our sample using a translog cost function (Christensen, Jorgenson, and Lau, 1973). A detailed derivation of a bank's cost function can be found in Appendix B.

As stressed by Koetter, Kolari, and Spierdijk (2012), cost inefficiencies should be accounted for since the LI may be biased downwards if perfect efficiency is assumed. That is, we allow for e.g. suboptimal use of input factors. We do not impose an assumption on why banks might operate inefficiently but we explicitly allow them to act according to the *quiet life hypothesis* which states that market power is negatively correlated with cost efficiency (Koetter and Vins, 2008).²³ Total costs are therefore estimated with maximum likelihood, in a stochastic frontier model (Aigner, Lovell, and Schmidt, 1977; Meeusen and van Den Broeck, 1977; Greene, 2005). Intuitively, when estimating total costs in that way, the model allows for inefficiencies that make the optimizing agent (here banks) deviate from the optimal cost-minimum.

Taking it to the data, we impose linear homogeneity of the total cost function w.r.t input prices. Our functional form for the cost function follows Koetter et al. (2012) and Kick et al. (2015) and is

$$\begin{aligned} \ln \frac{TOC_{jt}}{w_{1jt}} = & \alpha + \beta_1 \ln Y_{jt} + \frac{\beta_2}{2} (\ln Y_{jt})^2 + \sum_{h=2}^3 \gamma_h \ln \frac{w_{hjt}}{w_{1jt}} + \frac{\gamma_{22}}{2} \left(\ln \frac{w_{2jt}}{w_{1jt}} \right)^2 + \\ & \frac{\gamma_{33}}{2} \left(\ln \frac{w_{3jt}}{w_{1jt}} \right)^2 + \frac{\gamma_{23}}{2} \ln \frac{w_{2jt}}{w_{1jt}} \ln \frac{w_{3jt}}{w_{1jt}} + \sum_{h=2}^3 \frac{\delta_h}{2} \ln \frac{w_{hjt}}{w_{1jt}} \ln Y_{jt} + \zeta_1 \ln z_{jt} + \\ & \frac{\zeta_2}{2} (\ln z_{jt})^2 + \sum_{h=2}^3 \frac{\eta_h}{2} \ln \frac{w_{hjt}}{w_{1jt}} \ln z_{jt} + \theta \ln Y_{it} \ln z_{it} + \sum_{h=1}^2 \kappa_h tr^h + \\ & \kappa_3 tr \ln Y_{it} + \kappa_4 tr \ln z_{jt} + \sum_{h=1}^2 \kappa_{h+4} tr \ln \frac{w_{h+1,it}}{w_{1jt}} + v_j + u_j \end{aligned} \quad (6)$$

where w_{1jt} , w_{2jt} and w_{3jt} denote bank j 's input prices for loanable funds, labour and fixed capital, respectively. Very similar to Kick et al. (2015), we calculate the input price

²³That is, as Koetter (2013) we abstain from estimating profits before taxes taking into consideration profit inefficiencies but rather take total revenues and output directly from the data. See e.g. Kick et al. (2015) for an estimation of the LI with profit inefficiencies.

for loanable funds as interest expenses divided by interest-paying liabilities and for labour as the ratio of personnel expenses and the number of full-time employee equivalents.²⁴ Finally, we approximate capital expenses by other administrative expenses to fixed assets. Y_{jt} is as defined above. We include a bank's equity, z_{jt} , to control for heterogeneity in total costs across different bank sizes. Cross products between input prices and output with equity, respectively (η_2, η_3, θ) , allow the effect of prices and output on total costs to vary between smaller and bigger banks. We also include a linear trend, tr , single and squared, as well as interacted with input prices, output, and equity. The error term of the cost function estimation consists of two components, v_j , a random, i.i.d. term ($v_j \sim \mathcal{N}(0, \sigma_v)$), and an inefficiency term u_j for which we assume an exponential distribution. Assuming that the two components are independent, the above reduced-form model is estimated with maximum-likelihood.

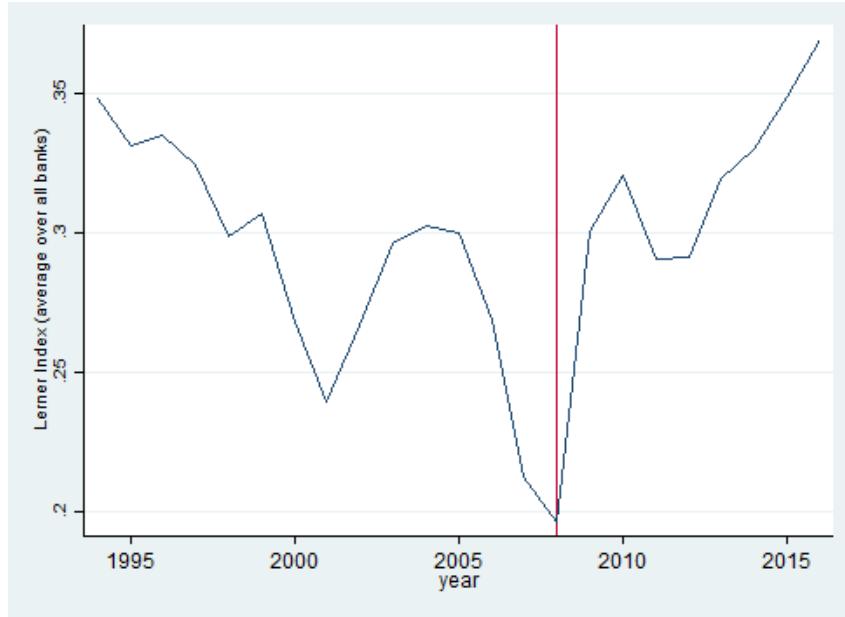
Having estimated a bank's total cost, its marginal costs are derived as follows:

$$\begin{aligned} MC_{jt} &= \frac{\partial \ln TOC_{jt}}{\partial \ln Y_{jt}} \frac{TOC_{jt}}{Y_{jt}} \\ &= \left(\beta_1 + \beta_2 \ln Y_{jt} + \sum_{h=2}^3 \frac{\delta_h}{2} \ln \frac{w_{hjt}}{w_{1jt}} + \theta \ln z_{jt} + \kappa_3 tr \right) \frac{TOC_{jt}}{Y_{jt}} \end{aligned} \quad (7)$$

Finally, one LI per bank and year can be calculated based on equation (5). Summary statistics of all variables used or estimated in this section can be found in [Table 8](#) in [Appendix B](#). [Figure 2](#) depicts the evolution of the mean LI (i.e. the unweighted average over all banks) over time. While in the final analyses we only use the 2016 values, the graph serves as a plausibility check of our measure and helps to understand the historic evolution of aggregate competition in Germany. Dynamics are in line with other results for Germany ([Koetter, 2013](#)). [Weill \(2013\)](#) shows that bank competition in the EU did not increase during the 2000's; instead, average pricing power of banks clearly rose in Germany until 2004. According to other studies, banks generally compete most severely for prices

²⁴[Van Leuvenstijn et al. \(2013\)](#) for example divide these expenses by total assets due to lack of data on staff numbers.

Figure 2: Evolution of average competition (pricing power) over time



Note: The figure shows the unweighted mean of pricing power of all German banks over time. Vertical red line in (i.e. at the end of) 2008.

during expansions (Ruckes, 2004) and competition in various EMU states increased until 2008 before trends reverted (Brämer, Gischer, Richter, and Weiß, 2013). Confirming previous research, our calculations show that in Germany (price) competition rose in the boom years leading up to the financial crash and reached its peak at the end of 2008 (red line in Figure 2). During that time, average revenues dropped while marginal costs rose on average, a trend that reversed for both variables from 2009 onwards (see Figure F1 in the Appendix). Potential reasons for the turnaround could be found in the extraordinary monetary policy measures undertaken in response to the crisis (Koetter, 2013). Lately, pricing power has been on the rise again, with average pricing power reaching an unprecedented level on our scale from 1994 – 2016.

4.2 Market concentration: Herfindahl-Hirschman Index

Structural indicators seek to derive the degree of competition from market characteristics, the underlying idea being that in highly concentrated markets, firms can exert some market power (Mason, 1939; Bain, 1956). The structure-conduct-performance paradigm

formulates that margins such as loan spreads are positively related to concentration. However, few firms in a market might also operate in strong competition to each other; thus, the relationship between individual pricing power and concentration is not trivial. Therefore, unlike Adams and Amel (2011) or Sääskilahti (2016) we distinguish clearly between *individual* price setting power and the market *environment* and include both as separate measures for imperfect competition (i.e. market power) into our analysis.

The Herfindhal-Hirschman Index which assigns a single value of concentration to a market is calculated as

$$HHI_d^p = \sum_i (LMS_{jd}^p)^2 \quad (8)$$

where the sum of bank-level (j) local market shares (LMS_j) goes over all i banks that have their head quarter in administrative district or urban district, d .²⁵ In a highly concentrated market, the HHI_d^p approaches a value of 1. A bank j 's local market share is the share of a specific portfolio p in the aggregate per county d :

$$LMS_{jd}^p = \frac{X_{jd}^p}{\sum_i X_{jd}^p} \quad (9)$$

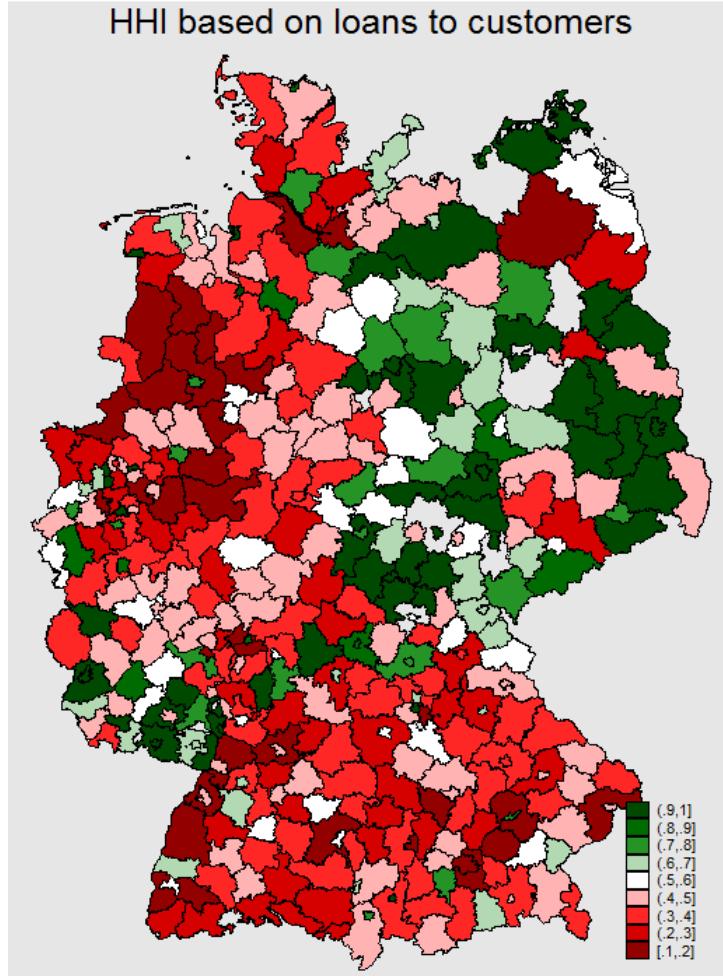
where the sum goes again over all i banks in a district; for X_{jd}^p we alternatively use deposits, loans to non-financial private customers and interbank loans.

Figure 3 shows the geographical variation in loan market concentration across Germany in 2016. Markets tend to be more concentrated in the north-east of Germany, meaning that there it occurs that one single bank is located in a county (darkest green)²⁶. Our approach suffers from shortcomings. When seeking to determine market concentration in a bank's relevant market, we assign the total value of deposits and loans to a bank's head-quarter which reports balance sheet information to the Bundesbank. This implies that we assume that a bank conducts all business in the county of its head-quarter. This

²⁵In 2016, Germany consists of 294 administrative districts and 107 urban districts, leading to a total of 401.

²⁶Concentration in the loan and deposit market has been on a steady rise up until 2008 after which it stagnated (but never fell). See Figure F2 in the Appendix.

Figure 3: Geographical variation of loan market concentration



Note: The figure shows the HHI's in the market for loans to private customers across the 401 counties (i.e. administrative (“Landkreise”) and urban districts (“Kreisfreie Städte”)) in Germany in 2016.

should not lead to a bias for savings and cooperative banks because they mostly report as separate entities (i.e. head-quarters) and due to the *regional principle* are bound to operate locally (Stolz and Wedow, 2011).²⁷ However, it significantly biases results for big banks. The majority is located in Frankfurt or other large cities but operates country-wide. If, for instance, a big private bank conducts business in the same region and market segment as a local savings bank outside of Frankfurt, then our measure of concentration for the county in which that savings bank is located is biased upwards. If on the other

²⁷Because banks are only bound to operate locally when providing credit, the regional principle does not necessarily hold for deposits. Due to the housebank-principle in Germany and because the HHI for deposits is highly correlated with the HHI for loans, we still believe the measure to be informative.

hand the big banks compete with the 1,482 banks in our sample only on specific, limited markets, then the bias of our HHI is limited, too. Many papers work with information on branch locations (e.g. Kick and Prieto, 2014, or Drechsler et al., 2017) to infer a clearer picture on market concentration. Information on branches in Germany is, however, only reliably available until 2004. Furthermore, because data are not available at the branch level, assumptions would have to be made to assign shares of exposure to the various branches, leading to a different level of insecurity and lack of precision. We therefore desist from hand-collecting all bank branches and instead run some additional robustness tests.

4.3 Competition and concentration

Panel A, B and C of Table 1 present summary statistics of county and bank characteristics in 2016 for our stress-tested banks. Panel D looks at bank characteristics of all banks over the whole time period 1994–2016. In panels A and B, we look at low-LI versus high-LI counties, and low-HHI_{loans} versus high-HHI_{loans} counties with at least one bank in 2016, respectively. Because the LI is bank-specific, we first calculate county-level averages of the LI. Note that the HHI is already calculated at the county level. We then divide the sample at the respective median of the (county-level) LI and the HHI distribution. Column (I) furthermore only presents data for banks for which a meaningful LI could be estimated²⁸.

High-LI and high-HHI counties respectively have on average a smaller population in absolute terms and are characterised by a somewhat lower share of individuals over the age of 65 (Panel A). High-HHI counties are furthermore smaller while high-LI counties are on average larger. When averaging bank characteristics at the county level, both high-LI and HHI counties are populated by banks with on average higher return on assets and profits (Panel B). Similarly, high-LI and HHI banks are more profitable (Panel C).

²⁸In some occasions, the LI was negative or above one, we replaced these data entries by *missings* in the analysis and exclude them for this section.

Differences across the two measures of imperfect competition arise when looking at the banks' average exposure in the loan market: high-LI banks and counties appear to have on average lower loan volumes while high HHI banks and counties have higher loan volumes (Panels B and C). Over the full time period, when taking into account all banks, both high LI and HHI banks have smaller loan volumes (Panel D).²⁹ Regarding volumes and market concentration, respectively, the pattern seems to be similar to the banking market in the U.S. There, high HHI institutions have larger portfolios regarding deposits ([Drechsler et al., 2017](#)).³⁰ However, high HHI counties in the U.S. are larger and have a higher population share that is older than 65.

Summing up, county-level pricing power and market concentration are related in opposite ways to county size, and county-average and bank-level size of the loan portfolio, respectively (in 2016). However, both higher market concentration and higher pricing power seem to indicate higher profitability while the discrepancy in profitability.

²⁹Results are qualitatively similar when applying the HHI in the deposit market and splitting the samples analogously.

³⁰Patterns in our data do not change when applying the HHI for deposits and relating that to deposit volumes. Because the regional principle does not need to hold in the deposit market in Germany, we focus on loan volumes and corresponding market concentration.

Table 1: Descriptive statistics

	(I) Lerner Index			(II) Herfindahl Index		
	All	Low LI	High LI	All	Low HHI	High HHI
<i>Panel A: County characteristics (2016)</i>						
Population (in 1000)	210	235	185	210	265	156
Area (sq. km)	891	786	1000	891	995	791
Over 65 (%)	19.2	19.8	18.5	19.2	19.4	18.9
Obs. (counties)	385	192	192	385	192	192
<i>Panel B: Bank characteristics by county (2016)</i>						
Profits (millions)	2085	1859	2294	2011	1683	2343
ROA (%)	0.77	0.67	0.87	0.74	0.72	0.76
Loans (millions)	921	1151	685	910	859	961
LI/HHI	0.37	0.32	0.42	0.547	0.36	0.74
Obs. (counties)	385	192	192	385	192	192
<i>Panel C: Bank characteristics (2016)</i>						
Profits (millions)	1,964	1,531	2,397	1,854	1,527	2,181
ROA (%)	0.77	0.60	0.94	0.72	0.0070	0.75
Loans (millions)	961	1307	615	960	886	1034
Deposits (millions)	669	815	523	661	611	711
LI/HHI	0.37	0.29	0.45	0.43	0.28	0.58
Obs. (bank)	1,442	721	721	1,482	741	741
<i>Panel D: Bank characteristics (all banks, 1994-2016)</i>						
Profits (millions)	444	379	509	425	330	520
ROA (%)	1.0	0.68	1.3	0.86	0.91	0.81
Loans (millions)	1116	1865	367	1261	1479	1042
LI/HHI	0.30	0.23	0.37	0.36	0.22	0.5
Obs. (bank x year)	51,565	25,782	25,782	54,228	27,114	27,114

Notes: Summary statistics at the county and bank x year level. Panels break the sample into the median of the LI (I) and the HHI (II) distribution, respectively. All banks for which a plausible LI (i.e. a number between 0 and 1) could be calculated are considered for exercise (I) and only counties with at least one bank are considered for exercise (II). The HHI is concentration in the market for loans to private customers. Return on assets (ROA) is calculated as profits (i.e. the difference between total revenues and total costs) over total assets. Loans are the yearly reported volumes for loans to private customers in banks' balance sheets. Sources: Bundesbank supervisory data. Statistisches Bundesamt.

5 Econometric analysis

The main advantage of the data set at hand is that it provides both, a treatment outcome, which are retail rates after a monetary policy shock, *and* the otherwise counterfactual outcome. We furthermore analyse deposit rates in addition to loan rates. In doing so, we examine not only heterogeneities across banks but also within.

5.1 Methodology

First, we test whether banks in more concentrated markets set higher loan rates and lower deposit rates. Because the LI measures bank-level price setting power, it is implied by a bank's interest rate *level*. Hence, to avoid endogeneity issues we drop it from this estimation.³¹

$$ir_j^p = \alpha_0 + \alpha_1 HHI_c^p + \sum_{m=2}^M \alpha_m X_{jm} + \epsilon_j \quad (I)$$

where ir_j^p consists of 2017 interest rate levels (in percent) for the constant scenario, $ir_{j,const}^p$ for different product categories p . As previously elaborated, all interest rates are rates for new business and are volume-weighted averages over fixed and adjustable rate contracts. Pre-shock (i.e. 2016) values of explanatory variables are used; HHI is concentration in the respective product market p in county c in which the bank operates.³² To test the quality of the survey data, we run the same regression with $ir_{j,shock}^p$ as a dependent variable. In all specifications, we control for several additional bank characteristics apart from competition, X_{jm} , listed in the following subsection. Results of specification (I) show whether concentration along with other control variables are significantly related to interest rate levels for different bank products where α_1 measures the general effect of market concentration on levels of interest rates.

We then move on to the main analyses where the dependent variable is the pass-

³¹As market power is generally quite persistent, including the LI with a time lag would not solve the problem.

³²To be precise, it is market concentration in the county in which a bank has its head-quarter.

through of monetary policy, defined by the difference between the treatment and the counterfactual outcome, i.e. $ir_{j,\text{shock}}^p$ and $ir_{j,\text{const}}^p$, respectively. Because the additional control variables ($\sum_{m=2}^M X_{jm}$) should affect interest rate levels in both scenarios in a similar way, their effects should cancel out in the pass-through regression. In other words, we expect the only interaction effect to be between the pass-through and imperfect competition.

We examine whether banks' pass-through is on average more or less complete the higher their individually exerted market power or the more concentrated the market environment is by estimating:

$$PT ir_j^p = \alpha_0 + \alpha_1 LI_j + \epsilon_j \quad (II)$$

$$PT ir_j^p = \alpha_0 + \alpha_1 HHI_c^p + \epsilon_j \quad (III)$$

where $PT ir_j^p = (ir_{j,\text{shock}}^p - ir_{j,\text{const}}^p)/200\text{ BP}$ for product category p and explanatory variables are as above. That is, we normalise price changes by the size of the shock. Coefficients are hence to be interpreted in percentage points (henceforth *p.p.*), where in both regressions α_1 is our coefficients of interest, telling us the direction of equation (4). In (II), the coefficient gives by how many percentage points the pass-through changes with a marginal unit-increase in individual pricing power. In (III) we assess the analogous relationship between monetary policy transmission and market concentration.

5.2 Control variables

We control for several bank characteristics that might affect interest rate levels and/or the pass-through of monetary policy. Equity financing is associated with higher costs as opposed to external financing (Maudos and De Guevara, 2004). Hence, we expect a bank to set lower loan rates the higher its share of external funding; thus, we control for a bank's *leverage* defined as the fraction of total assets over equity (Barattieri, Moretti, and Quadrini, 2016). On a similar note, De Graeve et al. (2007) find a positive relationship

between loan spreads and capital buffers since holding equity is associated with costs e.g. in the form of forgone profit; hence, we control for excess capital over risk-weighted assets, *excess capital*. We also control for *liquidity* by including securities over total liabilities, a variable which is important for the pass-through of monetary policy shocks to credit volumes by banks ([Kashyap and Stein, 2000](#)). Monetary policy tightening aggravates liquidity constraints and therefore banks with lower levels of liquidity tighten lending by more. [De Graeve et al. \(2007\)](#) furthermore find that liquid banks have a lower pass-through. A bank's *funding* structure has been found to matter for its pass-trough of monetary policy (e.g. [De Graeve et al., 2007](#); [Weth, 2002](#)). In our analyses we also test whether the ratio of deposits to interest paying liabilities has an effect on the level of bank's interest rates. On the one hand, given the low interest environment and mostly negative EURIBOR rates in 2016, it is plausible that our funding variable is positively associated with interest rate levels for loans. On the other hand, deposits are a more stable source of funding [Hanson, Shleifer, Stein, and Vishny \(2015\)](#) and banks relying more on deposit funding are found to be less vulnerable to financial shocks ([Jensen and Johannesen, 2017](#)). Therefore, a negative relationship between loan rates and deposit funding could also occur. We explicitly do not control for bank size in the pass-through estimation as it has been shown that (in contrast to the U.S.) this is likely not to be adequate for the European and, in particular, the German banking market ([Ehrmann and Worms, 2001](#); [Worms, 2001](#)). Due to the institutional structure of the German banking system, bank size is not a good predictor for access to funds via e.g. the interbank market. Small and medium sized banks mostly belong to the savings cooperative banks sector and are well interconnected within the respective sector via their central institutions ([Worms, 2001](#)). Therefore, small banks may be able to substitute between different sorts of funds and thus smooth interest rates in response to monetary contractions. Note that we, however, take bank size into account when estimating bank-level marginal costs in order to assess individual pricing power.

6 Results

This section discusses results for interest rate levels and the pass-through of a monetary policy shock to loan and deposit rates, followed by robustness checks.

6.1 Summary statistics

[Table 2](#) highlights asymmetries within banks across the pricing of their products. Column (1) displays averages and standard deviations for interest rates in the constant scenario; thus, they represent retail rates for noted categories which reporting banks would set in 2017 in the absence of a sudden change in monetary policy. In that occasion, average loan rates would lie at 3.2 percent and rates for interbank loans would be slightly negative. The average rate for deposits would be virtually zero. Column (2) provides average retail rates for the shock scenario and column (3) the pass-through of the shock in percent. Following a 200 BP shock, banks would on average pass on 78 percent of the shock corresponding to an increase in loan rates by 157 BP. At the same time, banks would on average only offer higher deposit rates by 64 BP which implies a pass-through of 32 percent. Interest rates for interbank loans are closest to market rates with a pass-through of 90 percent.

Table 2: Summary statistics

	(1) ir _{constant}		(2) ir _{shock}		(3) PT ir _p		Obs.
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
<i>Loans</i>	3.20	0.95	4.77	0.94	78.42	15.5	1,466
<i>Bank loans</i>	-0.025	0.30	1.79	0.46	90.24	19.56	1,433
<i>Deposits</i>	0.01	0.05	0.65	0.40	31.76	20.06	1,478

Notes: Summary statistics for interest rate levels and the pass-through for noted categories. Interest rate levels are volume-weighted interest rates, weighted with a banks' volume in fixed and adjustable rate contracts. Interest rate levels and the pass-through are winzorised at the upper and lower percentile of the distribution, respectively. All variables to be interpreted in percent. Source: Low-interest-rate survey 2017.

Table 3: Interest rates for loans to non-financials, financials and deposits

Scenario	(1) ir _{loans} constant	(2) ir _{bankloans} constant	(3) ir _{deposits} constant	(4) ir _{loans} shock	(5) ir _{bankloans} shock	(6) ir _{deposits} shock
HHI _{loans}	0.548** (2.53)			0.411** (1.98)		
HHI _{bank loans}		-0.0552 (-0.88)			-0.0466 (-0.62)	
HHI _{deposits}			0.0079 (0.85)			-0.252*** (-3.18)
funding	-0.283 (-1.04)	-0.249* (-1.91)	-0.032 (-1.62)	-0.242 (-1.05)	-0.115 (-0.65)	0.274** (2.07)
excess capital	2.344* (1.65)	0.060 (0.28)	-0.100 (-1.37)	3.206** (2.44)	0.080 (0.23)	-1.285*** (-3.40)
liquidity	0.064 (0.12)	-0.0001*** (-4.20)	-0.000 (-0.57)	-0.033 (-0.06)	-0.000 (-0.99)	-0.0001* (-1.85)
leverage	-0.032*** (-5.06)	-0.000 (-0.02)	-0.001 (-1.53)	-0.029*** (-4.69)	-0.000 (-0.12)	-0.012*** (-2.99)
Constant	3.482*** (17.01)	0.118 (0.86)	0.051** (2.23)	5.015*** (28.03)	1.868*** (9.36)	0.875*** (5.92)
N	1466	1433	1478	1466	1433	1478
R ²	0.0591	0.0181	0.0270	0.0569	0.0023	0.0514

Notes: Results from estimating specification (I). The dependent variables are interest rates for noted categories and scenarios in percent, winzorised at the upper and lower percentile. *t* statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the county level Sources: Bundesbank supervisory data & Low-interest-rate survey 2017.

6.2 Interest rate levels

Turning to specification (I), in Table 3, we find that loan rates in both the constant and the shock scenario are on average higher in more concentrated markets (columns 1 and 4). Probably due to the long period of the low interest rate environment, deposit rates do not vary significantly across different levels of concentration in the absence of a policy contraction but would on average be significantly lower in more concentrated markets after the hypothetical shock (columns 3 and 6). Note that because we do not control for borrower characteristics, our results for loans to non-banks do not rule out the relationship lending story as formulated by Rajan (1992) and Petersen and Rajan

(1995). Accordingly, only for young firms with the lowest quality, credit is expected to be comparably cheaper in more concentrated markets as a result of relationship lending. Provided that, for instance, borrowing firms in our sample are on average rather old than young (or more generally speaking, ongoing relationships as opposed to new ones prevail), higher loan rates in more concentrated markets are in line with that theory. This is because banks in imperfectly competitive markets can back-load interest payments.

Turning to the additional bank controls, despite low interbank lending rates, the fraction of stable deposit funding (*funding*) is associated with lower loan rates, as are lower shares of costly equity financing (*leverage*). As expected, capital buffers (*excess capital*) translate into on average higher loan and lower deposit rates (columns 1 and 3, [Table 3](#)). Effects of bank controls are furthermore largely consistent across both scenarios. This can serve as an additional plausibility check for reported rates in response to the hypothetical monetary policy shock.

6.3 Pass-through of monetary policy shocks

[Table 4](#) provides estimation results according to specifications (II) and (III) for loans to non-financial customers and for deposits.³³ Columns (1) and (2) consistently show that monetary policy transmission to loan rates significantly falls in market power.

On average, a one-standard-deviation increase in the LI is associated with a lower pass-through to loan rates by 1.06 p.p. or 0.068 standard deviations. Furthermore, after an increase in banks' marginal cost of funds, banks in more concentrated markets *ceteris paribus* (henceforth *c.p.*) pass a smaller share of the shock on (column (2)): A one-standard-deviation increase in concentration on average leads to a lower pass-through by 1.17 p.p. or 0.075 standard deviations.

Even after partialling out banks' expectations of credit demand shifts that are orthogonal to the two scenarios our results corroborate a relatively more incomplete pass-through

³³Neither bank-level pricing power nor market concentration matter significantly for the pass-through of the monetary policy shock to interbank loan rates (see [Table C2](#)) and we therefore focus on loan and deposit rates.

Table 4: Pass-through to rates for loans to non-financial customers and deposits

	(1) PT ir _{loans}	(2) PT ir _{loans}	(3) PT ir _{deposits}	(4) PT ir _{deposits}
LI	-9.861** (-2.04)		4.448 (0.66)	
HHI _{loans}		-5.848*** (-2.78)		
HHI _{deposits}				-13.57*** (-3.14)
Constant	81.91*** (45.73)	80.92*** (80.42)	29.83*** (11.78)	37.63*** (14.73)
N	1427	1466	1438	1478
R ²	0.0047	0.0057	0.0006	0.0177

Notes: Results from estimating specification (II) and (III). The dependent variable is the pass-through of the monetary policy shock to interest rates for noted categories in percent, winzorised at the upper and lower percentile. *t* statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust for columns (1) and (3), and clustered at the county level for columns (2) and (4), respectively. Sources: Bundesbank supervisory data & Low-interest-rate survey.

with rising levels of market power. If different bank-level predictions of demand shifts between the baseline and the shock scenario entirely drove our results, we would observe the opposite, namely a larger pass-through with more market power. As discussed in [Section 2](#), in the shock scenario credit demand should, if anything, be expected to contract more at banks with less market power, c.p. making the pass-through relatively larger at more monopolistic banks. Thus, to the extent that banks do make those different demand predictions, our results are likely to be a lower bound for the hampering effect of market power on monetary policy transmission. Consequently, reasons for the negative effect of imperfect banking market competition on monetary policy transmission are to be found on the credit supply side. Doubts may furthermore arise because according to the instructions, all banks have to replace maturing business with identical new business (static balance sheet assumption). This inter alia implies that quantities are not allowed to adjust. Hence, if high-market power banks consistently have higher loan exposures, our results could be driven by the mere fact that these banks simply cannot raise rates by as much in order to keep up their high loan volumes. The positive relationship between

exposure and market concentration is indeed prevalent in our data. However, we have shown that high-LI banks on average have *lower* loan exposures. The fact that both indices imply the same direction of imperfect competition on the pass-through of the shock to loan rates should mitigate that concern.

An analysis of within-bank heterogeneities can provide further insights on the underlying mechanism by helping to understand potential strategic bank behaviour. In particular, distorted competition in the deposit market has been proven to be crucial for monetary policy transmission (Drechsler et al., 2017).³⁴ The possibility to save expenses on their liability sides may thus enable banks to smooth loan rates for their borrowers. While individual pricing power does not affect the sensitivity of deposit rates to a monetary policy contraction, market concentration plays a substantial role (column (3) and (4) of [Table 4](#)). On average, a one-standard-deviation increase in concentration leads to a lower pass-through by 0.13 p.p or 0.133 standard deviations.³⁵

To get a deeper understanding of the heterogeneities and magnitudes of the coefficients, we calculate c.p. effects from specifications (II) and (III) at two different percentiles of the LI and HHI for loans to non-financial customers and deposits, respectively. That is, $\alpha_1 * LI_{10th}$ gives the c.p. effect of individual pricing power on the pass-through for a bank with a LI at the 10th percentile of its distribution in 2016, $\alpha_1 * LI_{90th}$ analogously the effect of a bank with a price setting power at the 90th percentile. The logic carries through for the HHI. In response to a contractionary monetary policy shock, a bank with a low price setting power c.p. passes on 2.4 p.p. less to loan rates while a bank with a high LI passes on 4.8 p.p. less, respectively compared to a bank operating under perfect competition (first row of [Table 5](#)). If a market is moderately concentrated, banks on average withhold 2.7 p.p. and 1.2 p.p. in the pass-through to deposit rates and loan rates, respectively,

³⁴See also Sopp (2018) who builds a model where banks strategically use deposit rates to smooth overall profits. In that set-up, deposit rates depend on a bank's return on its loan portfolio.

³⁵In [Table C3](#) in the Appendix we include the additional bank control variables into the pass-through regression. Results indicate that the effect of imperfect competition is robust throughout. It furthermore tests whether additional controls have an interaction effect with monetary policy on our pass-through variable. Additional bank controls have no effect on the pass-through to loan rates but remain significant for monetary policy transmission to deposit rates; nevertheless, the effect of deposit market concentration is statistically and economically unchanged.

while this amounts to 9.6 p.p. and 4.2 p.p. in highly concentrated markets (second row of Table 5). Given an average pass-through to deposit rates of 30 percent, the effect on that market is of substantial magnitude.

Table 5: Ceteris paribus effects for different percentiles of LI and HHI

(1)		(2)	
PT ir _{loans}	LI10	PT ir _{deposits}	LI90
- 2.4	- 4.8	-	-
HHI10_{loans}	HHI90_{loans}	HHI10_{deposits}	HHI90_{deposits}
- 1.2	- 4.2	- 2.7	- 9.6

Notes: Results from estimating specifications (II) and (III). LI10 is the value of the LI at the 10th percentile of the sample distribution (in 2016), HHI10_{loans} is the value of the HHI in the loan market at the 10th percentile, that logic carries through for the rest of the table. Source: Bundesbank supervisory data & Low-interest-rate survey. Statistisches Bundesamt.

Presented results consistently corroborate that the pass-through of monetary policy is hampered by imperfect competition (Van Leuvensteijn et al., 2013; Gropp et al., 2014; Schlueter et al., 2016). We help understanding previous work by showing that this phenomenon is a supply-side story.

We can furthermore provide suggestions for the driving mechanism. The reason could lie in the shape of banks' marginal cost curves (see section 2). It, however, seems more likely that strategic bank behaviour motivates banks. That is, banks operating in more concentrated markets withhold part of the increase in interest rates from those who deposit savings with them and in turn spare their borrowers a part of the general rise in funding costs. Sticky relationships could promote that objective. Because interest payments of new matches can be back-loaded in concentrated markets (Rajan, 1992), banks can more easily form long-term relationships with their borrowers the more concentrated the market. Our analysis shows that while the two measures of imperfect competition seem to be related in opposite ways to several county and bank characteristics, both indicate that banks with higher market power have higher profits (in absolute terms and measured as return on assets) and results are largely consistent across the two measures. Because

banks with market power furthermore on average charge higher than competitive loan rates and subsequently do not pass positive interest rate shocks on to depositors, they are likely to have the ability absorb potential downside shocks to profits and thus insure their borrowers against such movements in the policy rate. In doing so, they also smooth their profits (Sopp, 2018). Together with the housebank (or regional) principle in Germany, this indicates that strong ties between credit institutions and their customers could be the driving mechanism for our results.

6.4 Robustness tests

Analyses regarding market concentration have hinged on the peculiarity of the German banking market, that is, the *regional principle* or the fact that banks mainly conduct business in the county in which they have their head quarter. While this is likely to hold for loans provided by small and medium-sized banks, it is problematic for the large banks and for the deposit market in general. To mitigate concerns related to that and to challenge our results further, we run two types of robustness tests in this section.

First, we introduce a different and very simple proxy for the competitive pressure in a bank’s surrounding area. That is, we move away from bank data and exploit the fact that cities are usually both more densely populated and characterised by higher bank penetration as well as better access to financial services in a wider sense. For instance, outdoor advertising by online banks promising “easy” access to credit are likely to be more present in cities as opposed to more suburban areas. Thus, we promote that population density and competitive pressure on a bank in an area are positively correlated. We therefore include population density (in 2016) instead of the previous competition/concentration measures into (II)/(III). Note that we move to an even more granular level and include population density at the municipality-level into our estimation.³⁶

³⁶We also test the dependence of interest rate levels on population density and find that loan rates in both scenarios are lower in more competitive markets as measured by higher population density (Table C1).

Table 6: Pass-through to interest rates for loans to non-financial customers and deposits

	(1) PT ir _{loans}	(2) PT ir _{deposits}
population density	2.326*** (6.07)	3.241* (1.79)
Constant	76.71*** (156.39)	29.35*** (31.45)
<i>N</i>	1455	1467
<i>R</i> ²	0.0183	0.0217

Notes: Results from estimating (II) with municipality-level population density as only competition/concentration measure. The dependent variable is the pass-through of the monetary policy shock to interest rates for credit to non-financial customers in percent, winzorised at the upper and lower percentile. Population density is municipality-level population density in 1000's of population per square kilometre. *t* statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the municipality level. Sources: Bundesbank supervisory data & Low-interest-rate survey. Statistisches Bundesamt.

Our previous results are confirmed by [Table 6](#); more competitive pressure as measured by higher population density increases monetary policy transmission to both loan and deposit rates. A higher density by 1000 people per square kilometre in a municipality c.p. means a higher pass-through by 2.3 p.p. to loan rates and 3.2 p.p. to deposit rates. Coefficients are highly significant for loan rates but only marginally significant for deposit rates.³⁷ The latter could underline that the regional principle does not necessarily hold for the German deposit market.³⁸ Second, [Table 7](#) indicates that our results are robust to measuring concentration based on loans for the pass-through to deposit rates (column 1). Furthermore, when using population density at the county level, results do not change either (columns 2 and 3).

³⁷When we also include the additional bank controls, results are unchanged ([Table C4](#)).

³⁸Just as the LI and the HHI are no determinants of the pass-through to interbank loan rates, population density has barely any influence (columns 5 and 6 of [Table C2](#)).

Table 7: Pass-through for loans to non-financial customers and deposits

	(1) PT ir _{deposits}	(2) PT ir _{loans}	(3) PT ir _{deposits}
HHI _{loans}	-14.75*** (-2.97)		
popul. density (county)		2.168*** (5.87)	3.395* (1.76)
Constant	38.06*** (13.60)	77.06*** (159.82)	29.56*** (32.99)
<i>N</i>	1478	1457	1469
<i>R</i> ²	0.0216	0.0153	0.0231

Notes: Results from estimating specification (III). The dependent variable is the pass-through of the monetary policy shock to interest rates for noted categories in percent, winzorised at the upper and lower percentile. Column 1 uses concentration in the loan market for the pass-through to deposit rates. Columns 2 and 3 use population density at the county instead of the municipality level in 2016. Population density is county-level population density in 1000's of population per square kilometre. *t* statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the county level. Sources: Bundesbank supervisory data & Low-interest-rate survey 2017. Statistisches Bundesamt.

7 Conclusion

The stress test on interest rate risk which was conducted on all small and medium sized banks in Germany in 2017 provides us with an exceptional data set on interest rates for loans and deposits in response to a hypothetical exogenous monetary policy shock. Because the data delivers two data points per bank for the same point in time, rates for after the policy shock and in the absence thereof, we can control for potential demand shifts. We use that data to show that banks in imperfectly competitive markets charge higher loan rates but pass on smaller fractions of monetary policy contractions on to their borrowers. At the same time, banks with market power raise deposit rates to a smaller extent. Because supply side effects mainly drive our results, we can to some extent close the gap between research on the existence of a bank lending channel and that focusing on the effect of imperfect competition in banking markets on monetary policy transmission. Market power seems to be associated with higher profits in our data. Furthermore, the strategic behaviour of banks regarding the pass-through to loan and deposit rates, respectively, coupled with the housebank-principle that is a dominant

characteristic of the German credit market, leads us to conclude that banks with market power have the capacity to build long-term relationships and insure their borrowers against adverse shocks – at the expense of their depositors.

A Appendix: Derivations for conceptual framework

A.1 Proof of equation (2)

For convenience, we repeat equation (2):

$$dp = \frac{\partial p}{\partial q} \frac{\partial q}{\partial x} dx + \left(\frac{\partial p}{\partial i} + \frac{\partial p}{\partial q} \frac{\partial q}{\partial i} \right) di$$

Consider the following functional forms for the curves in a standard IO model with monopolistic competition, using common textbook notation:

inverse demand is $p(q) = i - bq$ with $i, b > 0$, marginal revenues are $mr = i - 2bq$ and marginal costs are $mc = zq^2 - yq + x$ with $x, y, z > 0$ and $i > x$. Note, in a simpler version where marginal costs are linear, $z = 0$, $x > 0$, $y < 0$ or where marginal costs are constant, $z = 0$, $x > 0$, $y = 0$. Three parameters are of particular interest here. First, the higher b , the steeper inverse demand and the more market power a monopolist can exert by applying a mark-up on marginal costs when setting the optimal price. The slope of demand is the partial derivative of the demand function with respect to (henceforth w.r.t.) q :

$$\frac{\partial p}{\partial q} = -b. \quad (10)$$

Second, the value of i determines the intercept of the inverse demand curve with $q = 0$. An exogenous demand shock thus changes i and can be interpreted as the maximum price a (marginal) customer would be willing to pay (in the limit when $q \rightarrow 0$). The partial derivative of the demand function w.r.t. i is:

$$\frac{\partial p}{\partial i} = 1. \quad (11)$$

Third, x is the intercept of the marginal cost curve and therefore a shock to marginal costs changes x .

Profit maximisation leads to the equilibrium condition of $mr = mc$. As a result, the

equilibrium quantity, q^* , and price, p^* , are:

$$q^* = \frac{y - 2b + \sqrt{(2b - y)^2 + 4z(i - x)}}{2z} > 0 \quad (12)$$

$$p^* = i - \frac{b(y - 2b + \sqrt{(2b - y)^2 + 4z(i - x)})}{2z} > 0 \quad (13)$$

When $z = 0$, $y < 0$

$$p^* = i - \frac{b(i - x)}{2b + y} > 0$$

and $p^* = i - \frac{i-x}{2}$ when marginal costs are constant. The corresponding equilibrium quantities are

$$q^* = \frac{i - x}{2b + y}$$

and $q^* = \frac{i-x}{2b}$, respectively.

The pass-trough of a cost shock to the price is derived as the change in the price in response to a parallel shift in the marginal cost curve, i.e. a change in x . The total derivative of (13) w.r.t. x gives:

$$\frac{dp^*}{dx} = \frac{b}{\sqrt{(2b + y)^2 + 4z(i - x)}} > 0 \quad (14)$$

An increase in marginal costs results in an increase in the price. With $z = 0$, $y < 0$

$$\frac{dp^*}{dx} = \frac{b}{2b + y} > 0$$

Note that the change in the equilibrium price depends on the slope of demand and hence on the level of market power. In the case of constant marginal costs, $y = 0$ and the pass-through simplifies to a constant, $\frac{1}{2}$.

The corresponding change in the equilibrium quantity from differentiating equation

(12) is:

$$\frac{\partial q}{\partial x} = -\frac{1}{\sqrt{(2b-y)^2 + 4z(i-x)}} < 0 \quad (15)$$

Following a cost shock, the equilibrium quantity shrinks. Note, this is identical to the total derivative $\frac{dq^*}{di}$ since q is a (direct) function of i, x . With $z = 0, y < 0$

$$\frac{\partial q}{\partial x} = -\frac{1}{2b+y} < 0$$

In the case of constant marginal costs this simplifies to $-\frac{1}{2b}$.

Equations (10), (11), (15) are the components of equation (2) when marginal costs are convex. The following derivation shows that $\frac{dp^*}{dx}$ is equivalent to the first part in equation (2) which is repeated above:

$$\frac{\partial p}{\partial q} \frac{\partial q}{\partial x} = -b * \left(-\frac{1}{\sqrt{(2b-y)^2 + 4z(i-x)}} \right) = \frac{b}{\sqrt{(2b-y)^2 + 4z(i-x)}} = \frac{dp^*}{dx} \text{ q.e.d. } (16)$$

It is easy to see that this also holds true for the cases where marginal costs are linear or constant.

The price change in response to a change in demand is derived by totally differentiating (13) w.r.t. i :

$$\frac{dp^*}{di} = 1 - \frac{b}{\sqrt{(2b-y)^2 + 4z(i-x)}}$$

A demand shock has a direct effect on the price which goes into the same direction of the shock, $\frac{\partial p}{\partial i} = 1$, and an indirect effect, $\frac{\partial p}{\partial q} \frac{\partial q}{\partial i}$, which works in the opposite direction of the direct effect: in the case of a negative demand shock, the direct effect pushes the equilibrium price down. However, the more market power the monopolist has, i.e. the relatively less elastic demand (or the steeper demand), the smaller the price reduction towards the new equilibrium. When $z = 0, y < 0$, this is

$$\frac{dp^*}{di} = 1 - \frac{b}{2b+y}$$

In the case of constant marginal costs this simplifies to $\frac{1}{2}$.

The corresponding change in the equilibrium quantity is:

$$\frac{\partial q}{\partial i} = \frac{dq^*}{di} = \frac{1}{\sqrt{(2b - y)^2 + 4z(i - x)}}$$

When $z = 0, y < 0$, this is

$$\frac{dq^*}{di} = \frac{1}{2b + y}$$

In the case of constant marginal costs this simplifies to $1/2b$.

The following derivation shows that $\frac{dp^*}{di}$ is equivalent to the second part in equation (2) which is repeated above:

$$\left(\frac{\partial p}{\partial i} + \frac{\partial p}{\partial q} \frac{\partial q}{\partial i} \right) di = 1 - b * \frac{1}{\sqrt{(2b + y)^2 + 4z(i - x)}} = \frac{dp^*}{di} \text{ q.e.d.} \quad (17)$$

It is easy to see that this also holds true for the cases where marginal costs are linear or constant.

A.2 Dependence of the pass-through on market power

The following equation derives how the pass-through depends on the slope of demand which measures market power in this framework:

$$\begin{aligned} \frac{d(dp^*/dx)}{db} &= \frac{1}{\sqrt{(2b - y)^2 + 4z(i - x)}} - \frac{b(8b - 4y)}{2[(2b - y)^2 + 4z(i - x)]^{\frac{3}{2}}} \\ &= \frac{y^2 - 2by + 4iz - 4xz}{[(2b + y)^2 + 4z(i - x)]^{\frac{3}{2}}} \end{aligned} \quad (18)$$

The pass-through is smaller for banks with more market power, i.e. $\frac{d(dp/dx)}{db} < 0$ if

$$b > \frac{y}{2} + \frac{2z(i - x)}{y}$$

Intuitively, when demand is “steep enough”, the pass-through can fall in market power. To be precise, as long as demand does not intersect marginal costs in their increasing part of the curve, the pass-through falls in b .

Otherwise, the pass-through is larger the steeper demand, $\frac{d(dp/dx)}{db} > 0$. Note that if marginal costs are linear ($z = 0, y < 0$), the pass-through always increases in b :

$$\frac{d(dp^*/dx)}{db} = \frac{y}{(2b - y)^2} > 0$$

When marginal costs are constant, the pass-through does not depend on the slope of demand. Note that in this model, a monotonic dependence of the Lerner Index on b is always given for the linear version of marginal cost, while it is a possible and plausible case in the quadratic model.

B Appendix: Theoretical background for marginal costs

According to economic theory, banks fulfill an intermediary role, hence a bank’s financial assets, i.e. loans (to customers and banks) as well as securities are considered as its output. As inputs it is assumed that banks use labour, capital and loanable funds.

Following [Clark \(1984\)](#) we assume a (homogenous) Cobb-Douglas production function of the following form:

$$Y_i = AK_j^{\alpha_1}L_j^{\alpha_2}F_j^{\alpha_3}$$

where Y_j is bank j ’s total output, K_j represents capital inputs, L_j labour inputs and F_j loanable funds. While the choice of the functional form may seem arbitrary, [Clark \(1984\)](#) discussed that the assumption of a Cobb-Douglas production function does not appear to be inappropriate.

The cost function of bank j is given by

$$TOC_j = p_j K_j + w_i L_j + r_i F_j$$

where p_j denotes bank j 's price of capital, w_j the price of labour, and r_j the price of loanable funds. Total costs as a function of inputs and outputs can be derived from minimising total costs with respect to the inputs, while having the constraint of the production function:

$$\min TOC_j \text{ subject to } Y_j = AK_j^{\alpha_1} L_j^{\alpha_2} F_j^{\alpha_3}$$

Using the method of Lagrange multipliers, the first order conditions w.r.t. labour, capital and funds, and the Lagrange multiplier λ are:

$$(K_j) : p_j - \lambda A \alpha_1 K_j^{\alpha_1-1} L_j^{\alpha_2} F_j^{\alpha_3} \equiv 0 \quad (19)$$

$$(N_j) : w_j - \lambda A \alpha_2 K_j^{\alpha_1} L_j^{\alpha_2-1} F_j^{\alpha_3} \equiv 0 \quad (20)$$

$$(F_j) : r_j - \lambda A \alpha_3 K_j^{\alpha_1} L_j^{\alpha_2} F_j^{\alpha_3-1} \equiv 0 \quad (21)$$

$$(\lambda) : Y_j - AK_j^{\alpha_1} L_j^{\alpha_2} F_j^{\alpha_3} \equiv 0 \quad (22)$$

From (19) and (20) we obtain

$$K_j = \frac{w_j}{p_j} \frac{\alpha_1}{\alpha_2} L_j$$

and from (20) and (21)

$$F_j = \frac{w_j}{r_j} \frac{\alpha_3}{\alpha_2} L_j.$$

Plugging these expressions into (22) and solving for L_j gives

$$L_j = \left[\frac{Y_j}{A} \left(\frac{p_j}{w_j} \frac{\alpha_2}{\alpha_1} \right)^{\alpha_1} \left(\frac{r_j}{w_j} \frac{\alpha_2}{\alpha_3} \right)^{\alpha_3} \right]^{\frac{1}{\alpha_1 + \alpha_2 + \alpha_3}}$$

The cost function can furthermore be written as

$$TOC_j = p_j \frac{w_j}{p_i} \frac{\alpha_1}{\alpha_2} L + w_j L_j + r_j \frac{w_j}{r_j} \frac{\alpha_3}{\alpha_2} L_j \quad (23)$$

After plugging in the above expression for L_j , total costs can be expressed as a function of output Y_j , and input prices, w_j, r_j, p_j

$$TOC(Y_j, w_j, r_j, p_j) = X A^{-\frac{1}{X}} (\alpha_1^{\frac{\alpha_1}{X}} \alpha_2^{\frac{\alpha_2}{X}} \alpha_3^{\frac{\alpha_3}{X}})^{-1} Y_j^{\frac{1}{X}} p_j^{\frac{\alpha_1}{X}} w_j^{\frac{\alpha_2}{X}} r_j^{\frac{\alpha_3}{X}} \quad (24)$$

where $X = \alpha_1 + \alpha_2 + \alpha_3$. Note, $X A^{-\frac{1}{X}} (\alpha_1^{\frac{\alpha_1}{X}} \alpha_2^{\frac{\alpha_2}{X}} \alpha_3^{\frac{\alpha_3}{X}})^{-1}$ is not bank specific.

Taking logs gives

$$\log(TOC_j) = X A^{-\frac{1}{X}} (\alpha_1^{\frac{\alpha_1}{X}} \alpha_2^{\frac{\alpha_2}{X}} \alpha_3^{\frac{\alpha_3}{X}})^{-1} + \frac{1}{X} \log(Y_j) + \frac{\alpha_1}{X} \log(p_j) + \frac{\alpha_2}{X} \log(w_j) + \frac{\alpha_3}{X} \log(r_j) \quad (25)$$

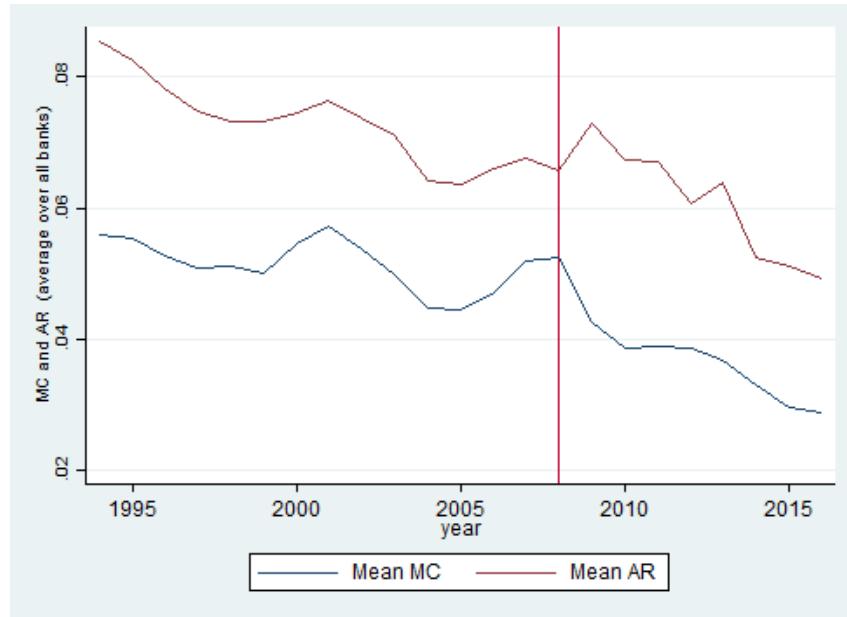
That translog cost function can be estimated from the data and marginal costs derived from it as the first derivative of costs with respect to total output.

Table 8: Summary statistics

variable	N	mean	sd
Total costs, TOC	54228	1.12e+08	9.48e+08
Total revenues, TOR	54228	1.21e+08	9.35e+08
Total output, Y	54228	2.34e+09	1.93e+10
Interbank loans	54228	5.87e+08	6.64e+09
Loans to non-financial customers	54228	1.26e+09	9.50e+09
Securities	54228	4.90e+08	4.27e+09
Cost of fixed labour	52540	62258.81	168385.9
Cost of borrowed funds	54170	.286	57.864
Cost of fixed assets	54228	.243	13.328
Marginal costs, MC	52525	.048	.058
Lerner Index, LI	51565	.301	.092

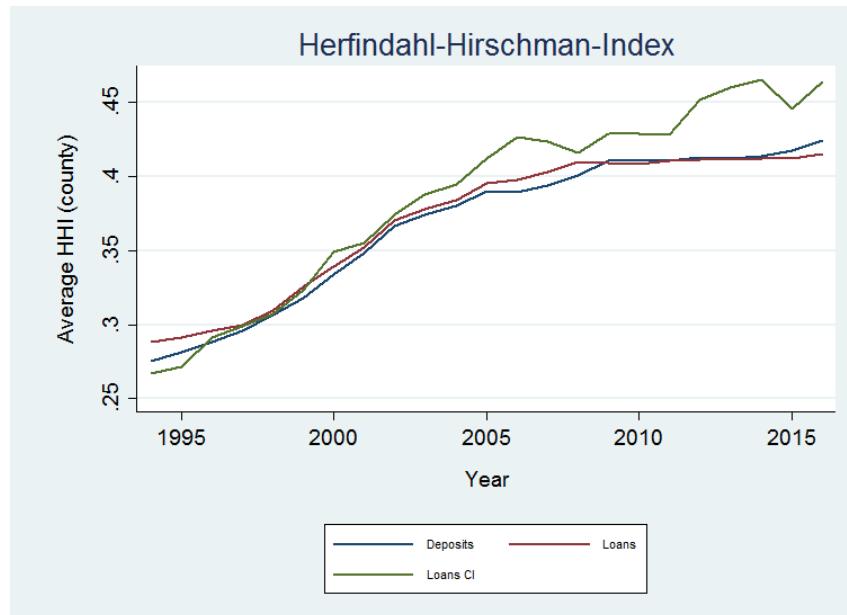
Notes: Summary statistics over the full time period 1994-2016. Source: Bundesbank supervisory data. Own calculations.

Figure F1: Evolution of marginal costs and average revenues over time



Note: Unweighted mean of marginal costs and average revenues of all German banks over time. Vertical red line in (i.e. at the end of) 2008.

Figure F2: Evolution of average concentration over time



Note: The figure shows the unweighted mean of county-level concentration of all German banks over time in the deposit, loan and interbank loan (“Loans CI”) market, respectively. County reforms are taken into account.

C Appendix: Robustness tables

Table C1: Interest rate levels for loans to non-financials, financials and for deposits

	(1) ir _{loans} constant	(2) ir _{bank loans} constant	(3) ir _{deposits} constant	(4) ir _{loans} shock	(5) ir _{bank loans} shock	(6) ir _{deposits} shock
popul. density	-0.343*** (-8.05)	0.041 (1.17)	-0.002 (-0.92)	-0.293*** (-7.63)	0.014 (0.35)	0.071* (1.95)
funding	-0.178 (-0.81)	-0.267** (-2.06)	-0.031 (-1.60)	-0.162 (-0.83)	-0.126 (-0.70)	0.244* (1.94)
excess capital	2.750* (1.92)	-0.057 (-0.24)	-0.089 (-1.37)	3.523*** (2.72)	0.009 (0.02)	-1.632*** (-4.07)
liquidity	0.212 (0.49)	-0.0002*** (-3.05)	-0.000 (-0.38)	0.097 (0.22)	-0.000 (-0.88)	-0.0001* (-1.94)
leverage	-0.025*** (-4.14)	-0.001 (-0.33)	-0.001 (-1.53)	-0.023*** (-3.90)	-0.001 (-0.21)	-0.013*** (-3.35)
Constant	3.739*** (21.71)	0.098 (0.90)	0.054** (2.12)	5.221*** (28.17)	1.857*** (10.58)	0.789*** (6.82)
<i>N</i>	1455	1422	1467	1455	1422	1467
<i>R</i> ²	0.1478	0.0309	0.0282	0.1259	0.0025	0.0621

Notes: Results from estimating specification (I) with municipality-level population density as only competition/concentration measure. The dependent variables interest rates for noted categories and scenarios in percent, winzorised at the upper and lower percentile. Population density is municipality-level population density in 1000's of population per square kilometre. *t* statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the municipality level. Sources: Bundesbank supervisory data & Low-interest-rate survey. Statistisches Bundesamt.

Table C2: Pass-through to rates for interbank loans

	(1)	(2)	PT ir _{bank loans}	(3)	(4)	(5)	(6)
LI	4.171 (0.65)	3.220 (0.51)					
HHI _{bank loans}			0.802 (0.33)	0.384 (0.15)			
population density					-1.098* (-1.87)	-1.137* (-1.79)	
funding		3.917 (0.80)		6.675 (1.49)		7.013 (1.55)	
excess capital		2.455 (0.13)		-0.122 (-0.01)		1.804 (0.11)	
liquidity		0.004* (1.74)		0.004** (1.97)		0.005** (2.26)	
leverage		0.004 (0.02)		-0.049 (-0.29)		-0.033 (-0.18)	
Constant	88.84*** (36.70)	87.09*** (16.34)	89.86*** (66.55)	87.67 (20.15)	91.048*** (145.36)	88.14 (20.45)	
N	1398	1398	1433	1433	1422	1422	
R ²	0.0005	0.0015	0.0001	0.0027	0.0024	0.0054	

Notes: Results from estimating specifications (II) and (III). The dependent variable is the pass-through of the monetary policy shock to interest rates for interbank loans in percent, winzorised at the upper and lower percentile. *t* statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust for column (1) and (3), clustered at the county level for column (2) and (4), and clustered at the municipality level for column (5) and (6). Sources: Bundesbank supervisory data & Low-interest-rate survey. Statistisches Bundesamt.

Table C3: Pass-through for loans to non-financials, and to deposits

	(1) PT ir _{loans}	(2) PT ir _{loans}	(3) PT ir _{deposits}	(4) PT ir _{deposits}
LI	-9.251* (-1.81)		4.703 (0.70)	
HHI _{loans}		-6.479*** (-3.07)		
HHI _{deposits}				-12.85*** (-3.02)
funding	1.638 (0.41)	2.118 (0.47)	14.64** (2.36)	15.39** (2.48)
excess capital	30.16 (1.24)	43.59** (2.39)	-72.18*** (-4.29)	-57.94*** (-3.28)
liquidity	-5.281 (-1.11)	-3.102 (-1.45)	-0.002 (-0.98)	-0.004* (-1.88)
leverage	0.167 (1.34)	0.142 (1.05)	-0.467*** (-3.31)	-0.464*** (-3.09)
Constant	77.84*** (18.95)	76.21*** (17.44)	34.59*** (6.60)	41.03*** (6.27)
N	1427	1466	1438	1478
R ²	0.0100	0.0105	0.0393	0.0509

Notes: Results from estimating specification (II) and (III). The dependent variable is the pass-through of the monetary policy shock to interest rates for noted categories in percent, winzorised at the upper and lower percentile. *t* statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust for columns (1), (3) and (5), and clustered at the county level for columns (2), (4) and (6), respectively. Sources: Bundesbank supervisory data & Low-interest-rate survey.

Table C4: Pass-through to rates for loans to non-financial customers and deposits

	(1)	(2)
	PT ir _{loans}	PT ir _{deposits}
population density	2.399*** (5.47)	3.692* (1.93)
funding	0.962 (0.23)	13.85** (2.35)
excess capital	39.45** (2.06)	-75.85*** (-4.10)
liquidity	-3.941* (-1.84)	-0.00520** (-1.97)
leverage	0.0752 (0.60)	-0.591*** (-3.55)
Constant	73.81*** (18.73)	36.61*** (7.43)
<i>N</i>	1455	1467
<i>R</i> ²	0.0229	0.0636

Notes: Results from estimating (II) with municipality-level population density as only competition/concentration measure. The dependent variable is the pass-through of the monetary policy shock to interest rates for credit to non-financial customers in percent, winzorised at the upper and lower percentile. Population density is municipality-level population density in 1000's of population per square kilometre. *t* statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the municipality level. Sources: Bundesbank supervisory data & Low-interest-rate survey. Statistisches Bundesamt.

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