Mortgage Loan Demand and Banks' Operational Efficiency

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Abstract

Using data for 6,740 U.S. banks from 1996 to 2016, we consider whether mortgage loan demand is a key determinant of banks' cost efficiency and management quality. We estimate mortgage loan demand from loan-level applications at individual banks, and we estimate bank efficiency and management quality score from banks' structural models. In line with theoretical considerations around economies of scale, our results show that loan amount demand improves cost efficiency, but the number of loan applications reduces cost efficiency. In contrast, mortgage loan demand has an economically less significant effect on management quality score. We also find that loan demand is an important factor in shaping banks' loan quality, above and beyond operational efficiency.

Keywords: Banking; Mortgage loan demand; Cost efficiency; Management quality

1. Introduction

Borrower behavior and loan demand are fundamental pillars of the events leading to the subprime crisis. Accordingly, in this study we consider mortgage loan demand an important determinant of bank efficiency and management quality. We examine whether changes in loan amount demand and changes in the number of mortgage loan applications affect banks' ability to process loan applications, provide loans, and operate efficiently. This analysis has important implications for informing banks about their ability to take more risk, as well as informing regulators and policy makers on the system's capacity to deal with higher levels of mortgage loan demand.

Theoretically, changes in loan demand have both positive and negative effects on bank efficiency and management quality. On the positive side, higher loan demand can lead to scale economies via expanding output opportunities. If banks do not operate at full scale and loan demand increases exogenously, banks can process a larger volume of loans and loan applications at similar cost levels. This implies that an exogenous shock, such as the increase in loan demand, increases cost efficiency. Moreover, the opportunity costs for holding liquid assets and capital increase if more profitable opportunities arise, and able bank managers can transform opportunity into efficiency through positive technical changes and better allocation of resources. For this reason, bank management practices might reflect the positive effects of changes in mortgage loan demand.

On the downside, banks working close to economies of scale might be unable to process a higher volume and/or a higher number of loans efficiently when loan demand increases. This leads to two nonexclusive effects. The first is that banks will avoid supplying more loans, thereby falling behind in productivity and efficiency compared to banks that have the capacity to do so without significantly increasing their costs. The second is that banks will supply more credit, but they will do so in a very risky manner, thereby increasing their ultimate costs in the form of non-performing loans in the future. Such excessive risk also manifests itself in managerial inability to handle the related adverse developments. If these effects prevail, increases in mortgage loan demand will negatively affect bank efficiency and/or management quality.

In addition, the relation between mortgage loan demand and bank efficiency/management quality might be nonlinear. A positive loan demand shock will probably allow banks to reap benefits until the costs outweigh the benefits. The structure of the U.S. mortgage loan market, in which many local banks provide mortgage loans, is particularly apt to experience such nonlinear effects because most relatively small banks eventually face capacity problems during sharp increases in mortgage loan demand (the subprime crisis is a perfect example).

We examine these propositions using bank data from the Call Reports and mortgage loans from the Home Mortgage Disclosure Act (HMDA). Our sample covers 6,740 U.S. commercial banks from 1996 to 2016. We estimate bank-year efficiency measures using the stochastic frontier approach (SFA) or the cost-to-assets ratio. Banks' cost efficiency shows how effectively a bank minimizes costs to produce a given output level (e.g., Gaganis and Pasiouras, 2013; Otero et al., 2020). To estimate bank-year management quality, we rely on a cost-share system in which management is a latent input of bank production (Delis and Tsionas, 2018). This measure more tightly relates to management practices vis-à-vis the total level of bank efficiency (Delis et al., 2019). These are the outcome variables of our empirical analysis.

Subsequently, using HMDA data, we estimate loan amount demand by modeling for each year (annual cross-sectional regressions) the log of the loan amount as a function of the log of income, a set of observed applicant characteristics, and bank fixed effects. We estimate these regressions for both accepted and denied loans (to distinguish loan demand from loan supply and associated endogeneity problems), and we include census-tract fixed effects to control for local housing and socioeconomic characteristics. The partial fitted values from these regressions (excluding bank fixed effects), estimate each applicant's mortgage loan amount demanded. We then calculate the average loan amount demanded per bank and year. We also calculate each bank's total mortgage loan applications (both accepted and denied) each year using HMDA data.

Given the estimates of mortgage loan demand, we examine how they affect bank efficiency and management quality score. Our baseline results show that an increase in loan amount demand improves bank cost efficiency, but a rise in the number of loan applications has a negative effect. The economic significance of these results is large: according to our baseline specification, a one-standard-deviation increase in the average loan amount demanded (from \$111,386 to \$173,991) results in a 9.4% increase in the mean cost efficiency. In turn, an equivalent increase in the number of mortgage loan applications (from 37 to 163 applications) reduces cost efficiency by 2.1%. In contrast, loan amount demand and the number of loan applications have economically small effects on management quality score. These results are consistent with economies-of-scale arguments, where the average bank has the capacity to process larger loan amounts but not the capacity to process more loans. Thus, our analysis points to capacity issues in the U.S. banking sector, which banks and regulators need to consider when loan application volumes increase, as this might lead to inefficient credit risk-taking. The results of the management-quality score further corroborate this intuition. These findings are robust to several sensitivity tests, including a Bartik-type instrument for the number of loan applications.

Going one step further, we assess the potentially nonlinear relationship among loan demand, operational efficiency, and credit-risk management. Our findings suggest that loan demand is an important factor that shapes banks' credit-risk management, above and beyond operational efficiency. Specifically, our results show that a one-standard-deviation increase in loan amount demand yields a 3.57% decrease in the mean loan-loss provisions ratio and a 50.95% increase in the mean non-performing loans ratio. The equivalent effects of the number of mortgage loan applications are a 24.47% drop in loan-loss provisions and an 11.46% drop in the non-performing loans ratio.

Our study mainly contributes to three strands of literature. First, we contribute to the literature distinguishing between supply-side and demand-side explanations of banking crises. The majority of studies view banking crises as supply-side phenomena, arguing that due to informational asymmetry problems and the search for yield, banks oversupply credit to risky borrowers and increase credit risk to unsustainable levels.[1] Our results are in line with Rajan (2010), who explains the subprime crisis as partially a demand-side phenomenon: the incentives given to people with middle and lower incomes raised housing and mortgage loan demand, which led banks to lend in order to avoid being left out of the short-term profit surge. Our results further corroborate Mian and Sufi (2009), who note that the increase in credit growth before the Great Recession is closely associated with an increase in subprime lending, part of which occurred without much screening by banks.

The second strand of literature to which our study contributes is the bank efficiency literature. Current research focuses on how various factors, such as competitiveness, governance, diversification, supervision and regulation, and mergers and acquisitions, affect bank efficiency.[2] For example, Lozano-Vivas and Weill (2012) consider the impact of cross-border banks on cost efficiency, profitability, and competition, and Leroy and Lucotte (2016) focus on the interplay of efficiency, competition, and bank risk. Chortareas et al. (2016) study

[1] The highlighted issues include lax monetary conditions and their effect on loan supply (e.g., Jimenez et al., 2014), financial institutions' increased use of subprime lending and housing price speculation (e.g., Albanesi et al., 2017), and generally lax bank supervisors and credit-rating agencies (e.g., Angelides et al., 2011). Demyanyk and Hasan (2010) have also a good discussion of the issues related to mortgage loans during the 2008 crisis.

[2] For comprehensive recent reviews, see Fethi and Pasiouras (2010), Aiello and Bonanno (2018), and De Abreu et al. (2019).

the dynamics between credit market freedom and bank cost efficiency, while Mamatzakis and Bermpei (2015) focus on how corporate governance affects bank performance. In addition, Ayadi et al. (2016) and Bitar et al. (2018) study the importance of regulation and supervision for bank efficiency in the context of the Basel Committee (see also Lozano-Vivas and Pasiouras, 2013; Delis et al., 2011 for the link between regulation and supervision and bank productivity). Recent studies focusing on merger and acquisitions activity and bank efficiency include Halkos and Tzeremes (2013) and Devos et al. (2016).

Finally, our paper contributes to the literature on bank efficiency and risk (for a comprehensive recent review, see Tan, 2016). Kwan and Eisenbeis (1997) and Berger and DeYoung (1997) are among the earliest studies showing that inefficient banks are riskier because of their operational problems. More recent studies focus on credit risk and show that more efficient banks are able to expand their risk-taking opportunities in search of higher yield (e.g., Lozano-Vivas and Pasiouras, 2010; Fiordelisi et al., 2011; Delis et al., 2014; Andreou et al., 2016; Luo et al., 2016). A common characteristic of all these studies identifying the determinants of bank efficiency is that they largely ignore the effect of loan applicant characteristics (the demand side). It is precisely this gap in the literature that we fill in our study.

Our study proceeds as follows. Section 2 discusses the data and empirical methodology. Section 3 discusses the results. Section 4 extends the analysis of the implications for credit-risk management and bank stability. Section 5 concludes.

2. Theoretical considerations and empirical specifications

Our sample covers 1996-2016 using data from two main sources. To estimate bank cost efficiency, we use end-of-year commercial bank-level data from the Federal Financial Institutions Examination Council (FFIEC) 031/041 Call Reports.[3] The FFIEC 031 report

[3] These data are from the Federal Reserve Bank of Chicago up to 2010 and from the Central Data Repository's Public Data Distribution website from 2011 onward.

includes data for commercial banks with domestic and foreign offices, whereas the FFIEC 041 report includes data for commercial banks with domestic offices only.

We next use applicant-level data on mortgage applications from the HMDA files to aggregate loans across bank-year. Every financial institution engaged in home mortgage lending activity must provide application-level data to the FFIEC. These financial institutions include commercial banks (i.e., banks supervised by the Federal Deposit Insurance Corporation, the Office of the Comptroller of the Currency, and the Federal Reserve Board), as well as savings and loan associations, mutual savings banks, and credit unions. Because Call Reports only include data for commercial banks, we restrict our analysis to that type of institution.

2.1. Estimation of banks' cost efficiency

To estimate banks' cost efficiency, we follow the majority of the banking literature and use the stochastic frontier approach (henceforth, SFA) by Battese and Coelli (1995). Studies using this approach, with similar objectives to ours, *inter alia* include Casu and Girardone (2009), Lozano-Vivas and Pasiouras (2010), and Hanousek et al. (2015). The SFA applies to panel data and allows the simultaneous estimation of both cost efficiency and its determinants at the bank-year level. To define bank inputs and outputs, we adopt the intermediation approach based on Berger and Mester (1997; 2003) and many others (e.g., Lozano-Vivas and Pasiouras, 2010; Gaganis and Pasiouras, 2013; Malikov et al., 2016). This approach assumes that banks collect funds (mainly deposits) as inputs and transform them into loans or other assets.

We estimate a specification with three outputs and three input prices. Specifically, the bank outputs are loans secured by real estate (Q_1), all other loans (Q_2), and securities (Q_3), whereas input prices comprise the price of purchased funds (W1), the price of deposits (W2), and the price of labor capital (W3). We also include as fixed netput quantities off-balance-sheet items (Z_1), physical capital (Z_2), and total equity capital (Z_3) to control for differences in risk preferences due to regulation, financial distress, or information asymmetries.[4] We deflate all variables in 2015 prices using the GDP deflator. More information on these variables is in Panel A of Table 1; descriptive statistics are in Panel A of Table 2.

[Insert Tables 1 and 2 around here]

To estimate cost efficiency, we impose linear homogeneity restrictions by normalizing the dependent variable and all input prices by W_3 and all outputs and netputs by Z_3. We also include Fourier trigonometric terms, as in Berger and Mester (1997), to improve the fit of the data, taking into account technological change and other factors that shape bank efficiency.

The multiproduct translog specification gives the following empirical cost-frontier model:

$$\begin{aligned}
\ln\left(\frac{TC}{W_3 Z_3}\right) = {} & b_0 + \sum_{i=1}^{2} b_i \ln\left(\frac{w_i}{w_3}\right) + \frac{1}{2}\sum_{i=1}^{2}\sum_{j=1}^{2} b_{ij} \ln\left(\frac{w_i}{w_3}\right) \ln\left(\frac{w_j}{w_3}\right) + \sum_{k=1}^{3} c_k ln\left(\frac{Q_k}{Z_3}\right) \\
& + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3} c_{km}\, ln\left(\frac{Q_k}{Z_3}\right) ln\left(\frac{Q_l}{Z_3}\right) + \sum_{m=1}^{2} d_m ln\left(\frac{Z_m}{Z_3}\right) + \frac{1}{2}\sum_{n=1}^{2}\sum_{p=1}^{2} d_{np} ln\left(\frac{Z_n}{Z_3}\right) ln\left(\frac{Z_p}{Z_3}\right) \\
& + \sum_{i=1}^{2}\sum_{k=1}^{3} e_{ik} \ln\left(\frac{w_i}{w_3}\right) ln\left(\frac{Q_k}{Z_3}\right) + \sum_{i=1}^{2}\sum_{m=1}^{2} f_{im} ln\left(\frac{w_i}{w_3}\right) ln\left(\frac{Z_m}{Z_3}\right) \\
& + \sum_{k=1}^{3}\sum_{m=1}^{2} g_{km}\, ln\left(\frac{Q_k}{Z_3}\right) ln\left(\frac{Z_m}{Z_3}\right) + \sum_{q=1}^{7}\left[\varphi_q cos(x_q) + \omega_q sin(x_q)\right] \\
& + \sum_{q=1}^{7}\sum_{r=q}^{7}\left[\varphi_{qr} cos(x_q + x_r) + \omega_{qr} sin(x_q + x_r)\right] \\
& + \sum_{q=1}^{7}\left[\varphi_{qqq} cos(x_q + x_q + x_q) + \omega_{qqq} sin(x_q + x_q + x_q)\right] + u_{st} + v_{st} \quad (1)
\end{aligned}$$

TC is the total cost of bank *s* in period *t* (*t=1, 2,..., T*); in other words, it represents total bank expenses calculated as the sum of total interest and noninterest expenses. The x_q terms (q = 1,...,7) are rescaled values of the $ln(w_1/w_3)$, $ln(w_2/w_3)$, $ln(Q_1/Z_3)$, $ln(Q_2/Z_3)$, $ln(Q_3/Z_3)$, $ln(Z_1/Z_3)$, and $ln(Z_2/Z_3)$ terms that take values in the interval [0, 2π]. The terms v_{st} are random errors

[4] Berger and Mester (1997) point out that the normalization by equity capital controls for heteroskedasticity, reduces scale biases in estimation, provides the grounds for economic interpretation, and controls for financial leverage.

assumed to be *iid* $N(0, \sigma_v^2)$, and u_{st} are nonnegative *iid* with truncations at zero on the $N(\mu, \sigma_u^2)$ distribution random variables, reflecting cost inefficiency. We calculate individual bank cost efficiency (*CEF*) scores from the estimated frontiers as $CEFst = exp(-u_{st})$. They take values between 0 and 1, with higher values indicating a more cost-efficient bank.[5]

We also estimate an alternative translog specification with the same three outputs as in (1) and a few differences. First, we use as input prices the price of deposits (W_1') and the price of physical capital, which is the ratio of expenses of premises and fixed assets to premises and fixed assets (including capitalized leases) (W_2'), as well as the price of labor capital (W_3) as before. Second, we use as fixed netput only equity capital. Third, we add a time trend (T = 1 for 1996, …, T = 21 for 2016) and its square to allow for technological change and the changing environment banks face during the sample period (e.g., Lensink et al., 2008).

In further robustness tests, we experiment with a simple accounting measure of cost efficiency (as opposed to the measure from the SFA). Specifically, we use the cost-to-assets ratio (calculated as total cost to total assets) as a measure of bank cost efficiency. This improves the simplicity and transparency of our results vis-à-vis the SFA-based estimates. However, we still prefer the SFA estimates, as they let theory meet empirics and allow for an error term (for additional benefits of frontier-based methods, see Berger and Mester, 1997).

2.2. Estimation of bank management quality

We estimate management quality using the approach in Delis and Tsionas (2018) and Delis et al. (2019), which validation tests show produce management-quality estimates closer to realized

[5] As a robustness check, we also include in equation (1) the nonperforming loans ratio at the state level and its squared term, following Berger and Mester (1997), to account for the (exogenous) credit conditions bank face in states where they conduct their main operations. These cost-efficiency estimates, available on request, lead to similar inferences regarding the relationships among mortgage loan demand, bank cost efficiency, and management-quality score.

managerial practices.[6] We again rely on the cost function and estimate a system of equations, the first of which is equation (1), but we also include management quality as a latent input.

To reflect the way management quality enters our model better, we rewrite the translog as:

$$\log\frac{C}{w_1} = \beta_0 + \beta_1\left(\log w_J^* - \log w_{J-1}\right) + \frac{1}{2}\beta_2\left(\log w_J^* - \log w_{J-1}\right)^2 + \beta_3 \log y \left(\log w_J^* - \log w_{J-1}\right) + \beta_4 \log y + \frac{1}{2}\beta_5 (\log y)^2 + v_{1,it}. \quad (2)$$

The share equation corresponding to management is $S_J^* = \beta_1 + \beta_2\left(\log w_J^* - \log w_{J-1}\right) + \beta_3 \log y$. Thus, we have $C = w_{J-1}x_i + w_J^* x_J^*$ and:

$$S_J^* = \frac{w_J^* x_J^*}{w_{J-1}x_{J-1} + w_J^* x_J^*} + v_{J,it}. \quad (3)$$

In the translog-share system, $w = [w_1, \dots, w_{J-1}, w_J^*]'$ is the vector of input prices of bank i at time t, y is the vector of outputs, and x is the vector of inputs. Also, w_J^* is the unobserved (latent) management price (average managerial compensation across banks).[7] We let $w = [w_1, \dots, w_{J-1}]'$ be the vector of input prices besides management price. We use the same variables as in section 2.1. Moreover, β is the parameter vector to estimate, and $v_{it} = [v_{1,it}, ..., v_{J+1,it}]'$ is the vector of error terms. To impose linear homogeneity with respect to prices, we express all prices relative to the price of labor capital. For the error terms, we assume $v_{it} \sim \mathcal{N}_{J+1}(0, \Sigma), \forall i = 1, \dots, n, t = 1, \dots, T$.

In (3) we observe the dependent variable corresponding to managerial share as $S_J^* =$

[6] Delis and Tsionas (2018) and Delis et al. (2019) are among the few studies examining the validity of the management-quality measures using both a natural experiment and Monte Carlo methods. This is the key issue upon which we use this model. For similar methods, also see Andreou et al. (2016) and Andreou et al. (2017).

[7] Despite the fact that some databases (e.g., BoardEx) report managerial salaries, we are generally unaware (or have very rough estimates) of input prices, especially for unlisted and relatively small banks.

$1 - \sum_{j=1}^{J-1} S_j$; we identify w_J^* through the joint appearance of w_J^* in (2) and (3). The technical problem is that x_2^* implicitly also appears in equation (2) and thus we need additional assumptions and associated equations for the latent variables.

Following Delis et al. (2019) and using the time subscripts *t*, we assume that:

$$\log w_{Jt}^* = \mu_1(1-\rho_1) + \rho_1 \log w_{J,t-1}^* + \overline{x_t'}\boldsymbol{\alpha}_1 + \varepsilon_{t1}, \forall t = 1, \ldots, T, \tag{4}$$

$$\log x_{J,it}^* = \mu_{2i}(1-\rho_2) + \rho_2 \log x_{J,i,t-1}^* + \overline{x_{it}'}\boldsymbol{\alpha}_2 + \varepsilon_{it,1}, \forall i = 1, \ldots, n, t = 1, \ldots, T. \tag{5}$$

The μ and ρ variables are location and persistent parameters, so that when $\rho_1 = 1$, μ_1 disappears and the constant term is zero.[8] In equation (4) we keep, for simplicity, managerial compensation equal across all banks and only allow it to vary with time (which makes the model compatible with the use of panel data). This does not affect our estimates but considerably eases estimation. In contrast, management practices in equation (5) vary by bank and quarter. We also assume that management quality is persistent, and thus we introduce in (5) its latent autoregressive component among the regressors. This is theoretically important because learning-by-doing processes, personnel and director experience, labor immobility, restrictive regulations, and other factors are important sources of persistence in management practices (e.g., Zhang et al., 2015). For similar reasons (e.g., wage stickiness), we also allow managerial compensation to be persistent in equation (5). For the error terms in (4) and (5), we assume $\varepsilon_{t1} \sim \mathcal{N}\left(0, \sigma_{\varepsilon_1}^2\right), \varepsilon_{\iota t,2} \sim \mathcal{N}\left(0, \sigma_{\varepsilon_2}^2\right), \forall i = 1, \ldots, n, t = 1, \ldots, T.$

The next decision is to choose the variables $\overline{x_\iota'}$ and $\overline{x_{\iota t}'}$ to include in equations (4) and (5). To reduce the effect of outliers and ease the interpretation of the coefficient estimates, all variables in these equations are in logs. We include lagged values (annual lags) of input

[8] Specifically, ρ is a usual autoregressive parameter. In the autoregression $x_t = a + bx_{t-1} + e_t$, when $b = 1$, the process $\{x_t\}$ contains a deterministic trend whose coefficient is a. A standard formulation to avoid this instance is to adopt $x_t = \alpha(1-\rho) + \rho x_{t-1} + e_t$, so that when ρ = 1, the intercept drops out; otherwise the steady state is $x^* = \frac{a}{1-\rho}$. For more details, please see the discussion around equation (15) in Schotman and van Dijk (1991).

quantities, current and lagged values of the price of labor (the ratio of total personnel expenses to the total number of full-time-equivalent employees), and a time trend, as well as its square.[9] As the subscripts denote, and symmetrically with the dependent variable, in equation (4) these variables are averages across banks, but in equation (5) these are the usual bank-quarter variables. We use the annual lags of input quantities to reduce concerns on reverse causality (for example, management quality or inefficiency affecting the number of employees and capital, and not vice versa). However, even when using contemporaneous quantities, our management quality estimates are quite similar. We use annual and not quarterly lags, because these managerial choices are relatively sticky.

Banking and management theory justify the use of these variables (e.g., Delis et al., 2014; references therein); thus, we assume that management skill resides in the optimal use of conventional inputs to maximize output. *Optimal* here refers to both absolute and relative input quantities. Also, including the price of labor follows the corporate governance literature identifying compensation as a positive correlate of ability and human capital (e.g., Custódio et al., 2013); it serves as an exogenous variable. Identification through input prices has a long tradition in the production economic literature (e.g., Nevo, 2001). In U.S. banking, where the labor market is fairly competitive, the average price of labor is fairly exogenous.

Our complete model includes equations (2) to (5). Due to the presence of many latent variables in this cost-share system, we use a Bayesian method (structural methods do not converge). For prior selection, we follow Delis et al. (2019). Our prior for the translog parameters and those in associated share equations is the "vague prior," $\beta \sim \mathcal{N}(0, 10^4\mathrm{I})$. We adopt the same prior for $\alpha_1, \alpha_2, a_0, a_1$, and a. For μ_1 and $\mu_{2\iota}$, we assume $\mu_1 \sim \mathcal{N}(0,1)$, $\mu_{2\iota} \sim \mathcal{N}\left(\underline{\mu}, \sigma_{\mu}^2\right), \forall \iota = 1, \dots, n$, where $\underline{\mu} \sim \mathcal{N}(0,1)$. For ρ_1 and ρ_2, we assume a uniform prior

[9] We generally assume that adopting new technology and financial-engineering methods (including risk management) is something that bank managers will do anyway to avoid being behind the competition. Thus, our management quality measure is independent of technological changes.

$\mathcal{U}(-1,1)$. For Σ we assume $\mathrm{p}(\Sigma) \propto |\Sigma|^{-(\mathrm{J}+\mathrm{m}+1)} \exp(-\frac{1}{2}\mathrm{tr}\underline{\mathrm{A}}\Sigma^{-1})$, with $\underline{\mathrm{m}} = 1$ and $\underline{\mathrm{A}} = 10^{-4}\mathrm{I}$. To facilitate SMC/PF, we integrate Σ out of the posterior analytically (Zellner, 1971).[10] All scale parameters $\sigma_{\varepsilon_1}^2$, $\sigma_{\varepsilon_2}^2$, σ_u^2, σ_μ^2, and ω^2 follow proper but vague priors of the form $p(\sigma) \propto \sigma^{-(\underline{n}+1)} \exp\left(-\frac{\underline{q}}{2\sigma^2}\right)$. Also, we set $\underline{n} = 1$, and $\underline{q} = 10^{-4}$. We use 120,000 iterations of the SMC/PF algorithm, discarding the first 20,000 to mitigate possible start-up effects (we generate starting values randomly from the prior). We use 10^6 particles per iteration. We successfully test convergence using Geweke's (1992) diagnostic, and autocorrelation in MCMC never exceeds approximately 0.40 for any parameter.

2.3. Cost efficiency and management-quality scores

Panel A of Table 2 reports statistics for the cost-efficiency scores, the cost-to-assets ratio, and the management-quality score.[11] The average cost efficiency is 0.781 (0.758 with the alterative translog specification) with a standard deviation of 0.104 (0.104 again for the alternative cost-efficiency estimate). Thus, the average bank could reduce its costs by about 22% to match its performance with optimal efficiency.

To get a visual insight on the evolution of the two cost-efficiency scores over the years, Figure 1 plots the cross-sectional average values over the sample period. Cost efficiency peaks in 2007 and deteriorates in the subsequent years, reaching its trough in 2013. In the last part of our sample, 2014-2016, cost efficiency improves sharply. We observe earlier peaks in 2000 and 1997 for cost efficiency and its alternative specification, respectively.

[Insert Figure 1 around here]

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[10] The result is as follows: if the posterior is $p(\beta, \Sigma|D) \propto |\Sigma|^{-\frac{N+1}{2}} exp\left\{-\frac{1}{2} tr\mathrm{A}(\beta)\Sigma^{-1}\right\}$, then $p(\beta|D) = \int p(\beta, \Sigma\,|D) d\Sigma = |A(\beta)|^{-(N+1)/2}$, where β is the parameter vector, D denotes the data, integration is with respect to the different elements of Σ, $N = nT + \underline{m}$, and $A(\beta) = \underline{A} + \sum_{i,t} v_{it}(\beta) v_{it}(\beta)'$, where $v_{it}(\beta)$ denotes residuals from (5).

[11] For expositional brevity, we do not report the parameter estimates of the translog cost functions, as they are too numerous to report and do not provide any substantial insights.

The cost-efficiency scores are lower than the averages reported for U.S. banks in previous studies, which range from 0.84 to 0.88 (Berger and Humphrey, 1997; Berger and Mester, 1997; or Bauer et al., 1998). This is probably attributable to the sample period (1996-2016), which encompasses two financial crises (and subsequent recession periods), namely the dot-com bubble crash (2000-2002) and the 2008 crisis. Figure 1 further supports our finding, showing a drop in the cross-sectional mean cost efficiency of U.S. banks around these two events, especially after the 2008 crisis.

Figure 2 shows the relevant management-quality score estimate. Interestingly, management quality follows a pattern similar to that of cost efficiency, attaining its highest value just before the global financial crisis, sharply dropping to its lowest level in 2013, and gathering pace toward the end of our sample. Also, the pairwise correlation coefficient between management quality and efficiency is as high as 0.45. This finding is consistent with the literature suggesting that management quality is part of firms' overall efficiency (e.g., Andreou et al., 2016; Demerjian et al., 2012). We should also note, however, that management practices do not substantially improve over time. This is an interesting finding and consistent with the premise that banks do not, on average, use prior information and knowledge to improve management practices substantially; they are relatively bad Bayesians (e.g., Hermalin and Weisbach, 2017).

[Insert Figure 2 around here]

Figures 1 and 2 also show that cost efficiency and management scores are cyclical, improving in good economic periods and decreasing in bad economic periods. This dynamic is in line with the findings of Isik and Hassan (2003a), who are the first to note the cyclicality in cost efficiency scores and investigate the relationship between bank efficiency and a financial crisis. Isik and Hassan (2003b) note that changes in management practices is a key component in explaining changes in efficiency and productivity, a result also in line with the dynamics shown in Figures 1 and 2.

2.4. Mortgage loan demand

To measure mortgage loan demand, we use two variables using data from HMDA. The first is the natural logarithm of the bank-year average mortgage loan amount demanded for each bank, denoted as *MLD*. The second is the natural logarithm of the total number of mortgage loan applications (both accepted and denied) per bank and year in the HMDA files, denoted as *NLA*.

An essential issue is that these variables reflect demand-side forces only (i.e., supply-side forces are stripped away). To ensure this is the case for *MLD*, we estimate a loan-demand equation; as for *NLA*, we rely on instrumental variables estimation using a Bartik-style instrument, as we describe later. The general form of loan demand for application *i* for each year in our sample is:[12]

$$l_i^d = (a_{j,}r_i, y_i, \sum_1^k x_{ki}, u_i) \tag{6}$$

where a_j are the *j* parameters to estimate; $\sum_1^k x_{ki}$ is a *k*-dimension vector of the observed applicant's characteristics (i.e., the gender, race, and occupancy status of applicant *i*); and *u* is the stochastic disturbance. The Home Mortgage Disclosure Act (HMDA) provides information on a number of characteristics for each mortgage application including, among others, the requested loan amount, loan status (originated or denied), applicant’s income, applicant’s gender, applicant’s race, state, county, and census-tract codes of the property, as well as the financial institution identity and its supervisory agency. In the estimation of the earlier equation, we use both accepted and denied loans to distinguish loan demand from loan supply. Most

[12] This implies 21 regressions (equal to the number of years). An alternative is to use one regression for the full sample and bank × year fixed effects. However, the number of loan applications requires exceptional computing power. For a similar implementation, see Delis et al. (2019) and Delis and Papadopoulos (2019).

important, we add bank and census-tract fixed effects to strip out the loan supply variation, thus controlling for the bank-year (time-varying supply-side) sources of changes in *MLD* and for determinants of loan demand at the regional level. To homogenize our mortgage loans, we employ only applications for new conventional loans for home purchases. We estimate equation (6) with OLS and get the fitted values without adding the bank fixed effects.[13] Each of these predicted values is the requested mortgage loan amount from each applicant. We then calculate the average value per bank, and in this way we construct *MLD* for each commercial bank over 1996-2016.

Panel B of Table 2 reports the statistics for the mortgage loan demand variables. The mean (log) mortgage loan demand equals 4.713 ($111,386) with a standard deviation of 0.446 ($62,605), and the (log) number of mortgage loan applications ranges from 0.693 (2 applications) to 11.949 (154,662 applications).

Figure 3 shows the cross-sectional mean of *MLD* and *NLA* over our sample period. *MLD* generally follows an upward trend, experiencing two downward spikes: a larger one in 2004 and a smaller one in 2013. The former is possibly attributable to the relatively lower coverage of loan originations in HMDA data for this year (see, e.g., Dell' Ariccia et al., 2012). However, it is highly unlikely these inflection points affect our analysis, as we employ the mortgage loan demand variable at the bank-year level and use a full array of year fixed effects (discussed later). On the other hand, *NLA* peaks just before the financial crisis in 2006 and experiences a sharp drop until 2011. The rapid rise and subsequent fall in *NLA* coincides with the subprime mortgage crisis and shows a classic lending boom-bust scenario in which unsustainable growth leads to the collapse of the market. In the latter years of our sample (2012-2016), the trend is strongly positive.

[13] As a robustness check, we also estimate equation (6) using only bank fixed effects as right-hand-side variables for each year in our sample. These fixed effects are jointly statistically significant in all cases. Subsequently, we use the residuals, averaged across each commercial bank, as our estimates of bank-year loan demand.

[Insert Figure 3 around here]

3. The effect of mortgage loan demand on bank efficiency and management quality

3.1. Modelling the effect of loan demand

To examine whether and how variables related to mortgage loan demand affect bank cost efficiency and management quality, we use an unbalanced bank-year panel sample over 1996-2016 and estimate the following equation:

$$y_{it} = a + \beta_1 MLD_{it} + \beta_2 {MLD_{it}}^2 + \gamma_1 MLA_{it} + \gamma_2 {MLA_{it}}^2 + \sum_j \delta_j x_{jt} + \sum_k \varepsilon_k x'_{kt} + \\ + \delta_i + \varepsilon_t + u_{it} \qquad (7)$$

where the dependent variable is the cost-efficiency score, the cost-to-assets ratio, or management-quality score. Equation (7) is nonlinear with respect to the loan demand-related variables, which are our main explanatory variables; thus, the coefficients of interest are β_1, β_2, γ_1, and γ_2.[14] The variables related to mortgage demand enter contemporaneously in equation (7), as it is natural to assume that demand-driven forces affect cost efficiency and bank management quality in the year this demand materializes. The terms δ_i and ε_t stand for bank and year fixed effects, respectively.

The vector x_j comprises a set of bank characteristics that may affect the dependent variable. This set includes *Equity-to-assets ratio*, which is associated with the level of capitalization, and it takes into account capital risk (see among others, Athanasoglou et al., 2008; Tsionas and Mamatzakis, 2017). *Liquidity ratio* captures liquidity risk (see, e.g., Tsionas and Mamatzakis, 2017), whereas *Nonperforming loans ratio* accounts for bank credit risk (see Fiordelisi et al., 2011; Luo et al., 2016). To proxy for income diversification, we employ *Noninterest income ratio* (Fiordelisi et al., 2011; Laeven and Levine, 2007). *Deposits-to-assets*

[14] We mean-center *MLD* and *NLA* to deal with multicollinearity issues.

ratio and *Loans-to-assets ratio* capture bank penetration in the deposit and loan markets, and the former accounts for bank lending ability. We estimate the standard deviation of *ROA* (*σROA*) with a rolling 12-quarter window and capture volatility in bank profitability (i.e., a measure of bank risk). Finally, we also control for *Size*, which is a significant determinant of both cost efficiency and management quality.

In turn, the vector x'_k comprises state-level variables that capture the market conditions banks face (see, e.g., Tsionas and Mamatzakis, 2017). Specifically, this vector includes the year-on-year *Unemployment rate* and *Growth rate*, along with the (log) of *Personal income*. *Number of bank M&As* for each state-year proxies for the changing competitive forces in the local banking market, whereas the (log) of the mean *House purchase price* accounts for the housing market momentum. Finally, *Interest rate* represents the interest rate environment banks face. More information on the construction of both vectors of variables is in Table 1, Panels D and E; their descriptive statistics are in Panels D and E of Table 2.

We estimate equation (7) with OLS and robust standard errors clustered by bank. We posit that the exogeneity of *MLD*, as we extensively argue in section 2.4, justifies our econometric approach. As for the potentially endogenous nature of *NLA*, in this case the respective OLS coefficient estimates are biased and inconsistent. However, we address this issue below using an IV econometric technique as a robustness check.

3.2. Baseline results

We report our baseline results from equation (7) in Table 3. Our findings suggest that both *MLD* and *MLD squared* load positively and significantly in both cost-efficiency estimates. Similarly, increases in *MLD* negatively affect the cost-to-assets ratio, thus improving cost efficiency. On the other hand, as the number of loan applications increases, cost efficiency decreases significantly. Both *NLA* and *NLA squared* are associated with negative estimates for cost efficiency and positive estimates for the cost-to-assets ratio as expected. With respect to management quality, the impact of mortgage loan demand is marginally positive at the 10% level of significance, but its square, along with *NLA*, is statistically insignificant. In turn, *NLA squared* loads negatively and significantly.

[Insert Table 3 around here]

The overall economic impact of *MLD* on cost efficiency is quite significant. Specifically, a one-standard-deviation increase in *MLD* above its mean (i.e., from $111,386 to $173,991) results in a 9.44% increase in mean cost efficiency from our main translog specification.[15] The impact on the alternative cost-efficiency estimate is somewhat lower (about 5.9%). Turning to the cost-to-assets ratio and applying similar calculations, a one-standard-deviation increase in *MLD* decreases average cost per dollar invested by about 0.93%. Last, management-quality score results rises by 0.26% for a one-standard-deviation increase in *MLD* above its mean. Because the mean management-quality score in our sample equals 1.214, this translates to 0.003 points of improvement in management-quality score, which is economically negligible.

The picture is different for *NLA*. Specifically, a one-standard-deviation increase in the mean number of mortgage loan applications (i.e., from 37 to 163 applications) results in a drop in cost efficiency by a slight 2.14% (a 3.23% decrease for the alternative efficiency estimate) and a 7.96% rise in the cost-to-assets ratio. As for the relevant impact of *NLD* on management-quality score, it amounts to a slight 0.88% drop.

Turning to the effect of bank-level control variables, it appears that the results are in line with expectations. For example, *Liquidity ratio*, *Non-performing loans ratio*, *Noninterest income*, and *sd(ROA)* are negative and significant for both cost efficiency and management quality. On the other hand, *Equity to assets ratio*, *Loan to assets ratio*, *Size*, *ROA*, and *Deposits*

[15] This is calculated as $(2*\beta_2*MLD+\beta_1)$ times the standard deviation of *MLD*, divided by the average cost efficiency: [(2*0.017*4.713+0.005)*0.446] / 0.781 = 9.44%.

to assets ratio are associated with a positive and significant estimate, suggesting that big, profitable banks are more cost and management efficient.

To ensure that omitted local-level variables do not affect our results, we also include in equation (7) state × year fixed effects instead of state-level control variables in vector x'_j. The results, reported in Table A.1 in the appendix, remain intact.

Another potential criticism is that our results capture simultaneity effects, whereby efficient banks attract large loans and fewer applications. To reduce such concerns, we use the loan demand-related variables lagged. The results in appendix Table A.2 provide further support for the causal impact of loan demand on the cost efficiency and management quality of banks.

As a robustness check, we replicate Table 3 using a subsample of banks specializing in mortgages. Specifically, we use thrifts, which are institutions chartered as savings banks or savings and loans associations. We expect that for these banks our results are statistically and economically more significant, as changes in loan demand should heavily affect their efficiency and performance. The results, in appendix Table A.3, verify that *MLD* and *NLA* impact cost efficiency positively and negatively, respectively, whereas their impact on management quality is absent. Moreover, the economic impact of *MLD* on cost efficiency from our main translog specification is larger than the relevant in our baseline results, amounting to a 14.19% increase in bank cost efficiency for a one-standard-deviation increase in *MLD*.[16] In turn, a one-standard-deviation increase in *NLA* decreases cost efficiency by 1.45%.

We also examine the robustness of our results using DEA score as a dependent variable. The results of the loan-demand measures point in the same direction as the baseline results with the SFA cost-efficient estimates, with the exception of the positive sign (instead of negative) for the *NLA squared* variable. This provides, at least partially, further support for our

[16] Calculated as ($2*\beta_2*MLD+\beta_1$) times the standard deviation of *MLD*, divided by the average cost efficiency, aka [(2*0.026*4.921+0.000)*0.433] / 0.781 = 14.19%, using the thrifts' subsample specific descriptive statistics.

conclusions about the role loan demand plays in the operational efficiency of financial institutions.

3.3. Addressing potential endogeneity of the NLA variable and omitted-variables concerns

To address endogeneity concerns for *NLA*, as well as potentially omitted-variables bias issues, we also estimate equation (7) using instrumental variables techniques. For this, we employ as an exogenous instrument for *NLA* a Bartik-like instrument that is arguably exogenous to bank cost efficiency and management quality and thus satisfies the exclusion-restriction criterion.[17]

We define the Bartik-like instrument (see Goldsmith-Pinkham et al., 2018) as:

$$B_{it} = \bar{G}_{1t} Z_{i1}^{0} + \bar{G}_{2t} Z_{i2}^{0} \tag{8}$$

where vector *Z* is the initial period (i.e., in 1995; that is, one year before the start of our sample period) for state-specific shares in HMDA loan applications in two industries denoted as 1 and 2 for state *i*. Vector *G* is the average growth rate in the number of mortgage loan applications for year *t* across states. In our context, *Industry* equals 1 for all financial institutions reporting HMDA data that are supervised by either the OCC, FDIC, FRB, OTS (Office of Thrift Supervision up to 2011, when the OTS ceased to exist), or the National Credit Union Administration (NCUA). *Industry* equals 2 for financial institutions supervised by the Department of Housing and Urban Development (HUD). These ad-hoc definitions represent two differently regulated and supervised shares of the mortgage loan market.[18]

Table 4 reports the related findings. Overall, the first-stage regression results, along with the underidentification and weak identification tests, point to the validity of the employed instrument. Similar to our baseline case, we find that *MLD squared* increases cost efficiency,

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[17] Other studies follow similar approaches with respect to the choice of the instrument (e.g., Acemoglu and Linn, 2004; Beaudry et al., 2018).

[18] The national shares of the number of mortgage loan applications in the HMDA data for industries 1 and 2 in 1995 are about 66% and 34%, respectively.

but *NLA squared* has the opposite effect. As for the management-quality score, the results of the instrumental variables estimation show that the statistical impact of *MLD, MLD squared*, and *NLA* is almost nonexistent, but *NLA squared* exerts a negative effect on management quality.

[Insert Table 4 around here]

3.4. Quantile regressions

To gain more understanding of the distributional nature of the relationship among loan demand, cost efficiency, and management quality, we reestimate our baseline specification via quantile regressions for five quantiles ranging from 0.2 to 0.8. Panels A and B of Table 5 report the related findings. With respect to cost efficiency, we note that both *MLD squared* and *NLA* (along with its squared term) affect cost efficiency for all the banks. Moving from the least efficient banks to the most efficient ones, the effect of *MLD squared* becomes stronger, suggesting that loan demand improves cost efficiency more for the most efficient banks. On the other hand, the negative impact of *NLA squared* is more pronounced for the least efficient banks (below the 50% quantile), but the effect of *NLA* is similar for all banks. Our findings suggest that the most cost-efficient banks have more capacity to process larger loan amounts than the least cost-efficient ones do. In a similar vein, the least cost-efficient banks lack the capacity to process a larger number of loan applications.

Turning to Panel B, we note that the impact of *MLD* decreases as we move from banks with low management-quality scores to banks with high management-quality scores, but it becomes insignificant for quantiles greater than 60% and lower than 40%. In line with our baseline specification, the impact of both *MLD squared* and *NLA* is muted for all quantiles. On the other hand, the negative impact of *NLA squared* is similar to the baseline specification for all quantiles, with the exception of the low management-quality ones where the impact is double. Similarly to our cost-efficiency results, larger numbers of loan applications further deteriorate the poor management quality of banks in the lower end of the management-quality distribution.

[Insert Table 5 around here]

3.5. Different subsample periods

To gauge how the crisis affects the relationships among loan demand, cost efficiency, and management quality, we estimate our baseline specification for three subperiods: the precrisis period of 1996-2006, the crisis period of 2007-2009, and the postcrisis period of 2010-2016. Panels A to C of Table 6 report our findings for the respective periods.

[Insert Table 6 around here]

In general, we observe important differences between the three subperiods, consistent with Hanousek et al. (2015). The results show that the precrisis and the postcrisis periods drive our main findings. This is intuitive because in the crisis period, there is a credit crunch and *MLD* and *NLA* have a very limited effect on the (already struggling) bank efficiency.

Considering cost efficiency, we note that the effect of *MLD* is more pronounced in the postcrisis period, but the impact of *MLD squared* falls to less than half in the postcrisis period compared to the precrisis period. This translates to a larger economic impact of *MLD* on cost efficiency in the precrisis period (7.84%) than in the postcrisis period (4.64%) for a one-standard-deviation increase in *MLD*. On the other hand, the negative effect of *NLA* on cost efficiency is more pronounced in the most recent period (postcrisis). In this case, the coefficient of *NLA squared* is double the precrisis period, along with a significant negative effect of *NLA*. This translates to a 4.23% drop in cost efficiency, relative to a more modest drop of 1.41% in the precrisis period for a one-standard-deviation increase in *NLA*. We note, however, that the negative and significant relationship between *NLA* and cost efficiency uncovered in the postcrisis period is worrisome because it shows that banks did not learn from the precrisis period about the capacity problems they might face in originating a large volume of loans.

Turning to management-quality score, our results suggest that prior to the crisis, only *MLD squared* affects management-quality scores negatively, resulting in a 5.74% drop for a one-standard-deviation increase in *MLD*, whereas *NLA* does not have any impact. On the other hand, for the postcrisis period *MLD* and *NLA squared* contribute significantly to management quality but with opposite signs. Specifically, loan applications (squared) reduce management quality by about 1.83%, but loan demand improves it by about 0.5%.

3.6. Additional sensitivity analysis

Finally, we conduct two sensitivity tests reported in Table 7. First, we consider only large banks (i.e., banks with total assets over $700 million; Panel A) and banks that are not members of a bank holding company (BHC; Panel B). For the cost efficiency of large banks, only the squares of *MLD* and *NLA* are significant with the expected signs. Specifically, mortgage loan demand contributes positively to cost efficiency, but as the number of applications (squared) increases, cost efficiency decreases. The results also suggest that both mortgage loan demand and loan applications do not affect management quality in large banks.

[Insert Table 7 around here]

Turning to non-BHC banks, we note that the negative impact of the number of applications on cost efficiency is stronger for non-BHC banks than for the full set of banks in our baseline specification. Similarly, the positive impact of the amount demanded per application (squared) is also stronger than for the full set of banks. In terms of the management quality of these banks, the effect of mortgage loan demand is insignificant. However, the effect of the number of applications (squared) is more important, judging from the magnitude and significance of the related coefficients.

4. Implications for credit-risk management and the stability of banks

Berger and DeYoung (1997) examine the relationship between loan quality and cost efficiency in commercial banks. The authors test four hypotheses and find support for the "bad luck" hypothesis, in which nonperforming loans are associated with lower cost efficiency due to extra costs of administering these loans. They also find evidence supporting the "bad management" hypothesis, which suggests that low levels of cost efficiency are linked to increases in nonperforming loans because cost-inefficient managers are also poor loan portfolio managers. Consequently, cost efficiency may be an important indicator of future problem loans.

We posit that loan demand also contributes to poor loan quality, signaling credit problems beyond cost efficiency and management quality. To this end, we extend our analysis to explore the potentially nonlinear relationship among mortgage loan demand, operational efficiency, and credit-risk management. Specifically, we estimate the following equation:

$$\begin{gathered} y_{it} = a + \beta_1 MLD_{it} + \beta_2 {MLD_{it}}^2 + \gamma_1 MLA_{it} + \gamma_2 {MLA_{it}}^2 + \\ \beta_1' \, Cost\ Efficiency_{it} + \beta_2' Cost\ Efficiency_{it}^2 + \\ \textstyle\sum_j \delta_j x_{jt} + \sum_k \varepsilon_k x'_{kt} + \delta_i + \varepsilon_t + u_{it} \end{gathered} \tag{9}$$

where the dependent variable is loan-loss provisions, loan-loss reserves, or nonperforming loans. Definitions and descriptive statistics for these variables are in Table 1, Panels C and D and Table 2, Panels C and D, respectively. Table 8 presents the results of this exercise.

[Insert Table 8 around here]

Our findings show that cost efficiency is negatively associated with all the credit risk measures (i.e., loan-loss provisions, loan-loss reserves, or non-performing loans). This suggests that cost-efficient banks are better at managing credit risk, expect fewer future loan problems, and set fewer loan-loss provisions, among other things.

In more detail, as the first column in Table 8 shows, *MLD*, *NLA*, and *NLA squared* load negatively on the loan-loss provisions ratio, indicating that a rise in the volume of loans demanded and/or the number of loan applications is related to a nonlinear reduction in loan-loss provisions. The economic significance of this relationship is quite large: a one-standard-deviation increase in *MLD* corresponds to a 3.57% drop in the loan-loss provision ratio, whereas a relevant increase in *NLA* relates to a 24.47% drop. In turn, cost efficiency loads negatively on loan-loss provisions, yet in a linear manner. A one-standard-deviation increase in cost efficiency relates to an 8.32% increase in loan-loss provisions. These results suggest that banks rely heavily on loan demand to shape their policies against ongoing credit risk.

Turning to the loan-loss reserves ratio, the results in the second column of Table 8 show a negative and linear relationship with both *MLD* and *LNA*, as well as with cost efficiency. A one-standard-deviation increase in one of these variables corresponds to -3.19%, -3.19%, and -2.97% changes in the dependent variable, respectively.

Finally, the third column of Table 8 refers to the relationship between mortgage loan demand and nonperforming loans. Our findings show that the relationship between nonperforming loans and *NLA* is linear, but it is nonlinear among nonperforming loans, *MLD*, and cost efficiency. Overall, the impact of the aforementioned variables is negative with the exception of *MLD* squared. More important, the overall economic impact is negative (with the exception of *MLD*), as a one-standard-deviation increase in *MLD*, *NLA*, and cost efficiency corresponds to a change of 50.95%, -11.46%, and -52.48% in nonperforming loans, respectively.

To gauge how a crisis affects the relationship among credit-risk management, loan demand, and operational efficiency, we estimate our baseline specification for three subperiods: the precrisis period of 1996-2006, the crisis period of 2007-2009, and the postcrisis period of 2010-2016. Table 9 (Panels A to C) reports our findings for the respective periods. The negative impact of loan demand on loan-loss provisions persists and seems more pronounced in the postcrisis period, but in the crisis period this negative effect appears only through loan applications (squared). On the other hand, cost efficiency loads linearly and positively on loan-loss provisions in the precrisis period followed by a negative linear effect in the crisis period, which persists and becomes stronger and nonlinear in the postcrisis period. When considering loan-loss reserves, cost efficiency is important in the precrisis and postcrisis periods in a negative and linear manner only, but no effect is observed in the 2007-2009 period. The negative impact of *MLD* on loan-loss reserves is more pronounced in the precrisis period than in the postcrisis period and appears rather muted during the crisis. However, the opposite holds for *NLA*, where a very strong nonlinear negative effect is apparent in both the crisis and postcrisis periods.

Finally, turning to nonperforming loans, we note that cost efficiency is more important (negative impact) in the postcrisis period but exerts a positive impact in the crisis period. The effect of loan demand is more significant and negative in the precrisis period, turns positive (through the squared term) in the crisis period, and turns insignificant in the most recent period. On the other hand, the negative effect of loan applications becomes more pronounced as we move from the precrisis period to the postcrisis one.

[Insert Table 9 around here]

5. Conclusions

In this paper, we examine whether mortgage loan demand affects banks' cost efficiency and management quality. We estimate bank-year cost efficiency using either the stochastic frontier approach (SFA) or the cost-to-assets ratio. We estimate bank-management quality (again at the bank-year) using a cost-share system, where management is a latent input of bank production.

Our sample includes 6,740 U.S. banks from 1996 to 2016, and we merge information on these banks with estimates of mortgage loan demand from HMDA data.

Our baseline results show that an increase in loan amount demand positively affects bank efficiency, but the number of loan applications has a negative effect. These results are consistent with the arguments on economies of scale, where the average bank has the capacity and liquidity to process larger loans but not more loans. The results of the management-quality specifications further corroborate this intuition. Specifically, the respective effect of loan amount on management quality is an inverted U-shape, showing that bank managers do not have the capacity to process very large loan amounts efficiently beyond a certain threshold.

We also consider alternative specifications of the cost-efficiency and management-quality models; the simple cost-to-assets ratio as an alternative, accounting-based, cost-efficiency measure; and quantile regressions to exploit further the nonlinear effects. The results of these robustness tests support our baseline findings. We also examine how our findings fare in the precrisis, crisis, and postcrisis periods. We find that the precrisis and postcrisis periods drive our main findings. Finally, we examine how our findings fare when separately looking into the precrisis, crisis, and postcrisis periods. We find that the effects of mortgage loan demand in the precrisis period and of loan applications in the postcrisis period are somewhat more potent statistically and economically.

Linking our analysis to credit-risk management and the respective stability of financial institutions, we not only confirm findings in the extant literature regarding how banks' operational efficiency affects credit quality and risk, but also we reveal that loan demand is an additional contributing factor to banks' loan quality. Our premise is that an increase in the number of loan applications (as opposed to an increase in loan volumes demanded) leads to capacity problems in efficiently screening these applications. In turn, a lack of efficient screening and the urge to compete against other banks increases lending, leads banks to oversupply loans to an expanded base of loan applicants, and increases credit risk-taking. These findings are equally important to bank supervisors, who should urge banks to screen loan applications efficiently in periods of high loan demand. In the present era, the current pandemic increased loan demand predominantly via liquidity injections. If this increases the number of loan applications (as opposed to requested loan amount), our results predict that banks might be not ready to meet the demand in an efficient way. We leave such analysis for future endeavors when the data will be available.

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Table 1. List of variables, definitions and sources

Variable	Definition and source
Information for bank variables is from the Federal Financial Institutions Examination Council (FFIEC) 031/041 Call Reports, unless otherwise specified.	
Panel A. Outputs, netputs, and input prices for efficiency estimation	
Outputs	
Real estate loans (Q1)	Loans secured by real estate
All other loans (Q2)	Total loans – Loans secured by real estate
Securities (Q3)	Total held-to-maturity securities + Total available-for-sale securities
Netputs	
Off-balance sheet items (Z1)	Total off-balance sheet items[19]
Physical capital (Z2)	Premises and fixed assets (including capitalized leases)
Total equity capital (Z3)	Total book value of equity
Input prices	
Price of purchased fuds (W1)	(Total interest expenses – interest expenses on deposits) / (Total liabilities – total deposits)
Price of deposits (W2)	Interest expenses on deposits / Total deposits
Labor capital price (W3)	Salaries and employee benefits / Number of full time equivalent employees on payroll at end of current period
Cost	
Total bank expenses	Total interest expenses + Total non-interest expenses
Panel B. Variables reflecting mortgage loan demand	
Mortgage loan demand (MLD)	See the text for the estimation of this variable using HMDA data. It is expressed as the natural logarithm of the average mortgage loan amount demanded at the bank-year level
Number of mortgage loan applications (NLA)	Natural logarithm of number of mortgage applications for each bank-year, calculated from the HMDA data
Panel C. Bank Loan Loss Provisions and Reserves	
Loan loss provisions ratio	Provision for credit losses during the calendar year-to-date / Total loans and leases, gross
Loan loss reserves ratio	Allowance for loan and lease losses / Total loans and leases, gross
Panel D. Bank-level control variables	
Equity to assets ratio	Total book value of equity / Total book value of assets
Liquidity ratio	Cash and balances due from depository institutions / Total book value of assets

[19] Off-balance sheet items comprise i) credit derivatives on which the reporting bank is the guarantor; ii) credit derivatives on which the reporting bank is the beneficiary; iii) total gross notional amount of equity, foreign exchange, interest rate, commodity and other derivative contracts held for trading; iv) total gross notional amount of equity, foreign exchange, interest rate, commodity and other derivative contracts held for purposes other than trading; v) spot foreign exchange contracts; vi) performance standby letters of credit; vii) commercial and similar letters of credit; viii) standby letters of credit and foreign office guarantees; ix) total unused commitments; x) securities lent; xi) all other off-balance sheet assets; xii) all other off-balance sheet liabilities.

Non-performing loans ratio	Total loans and lease finance receivables: Non-accrual / Total loans and leases, gross
Non-interest income ratio	Total non-interest income / (Total interest income + Total non-interest income)
Deposits ratio	Total deposits / Total assets
Loan to assets ratio	Total loans and leases, gross / Total book value of assets
sd(ROA)	Standard deviation of ROA, calculated as income or loss before income taxes and extraordinary items and other adjustments / Total book value of assets, for a rolling 12-quarter window
Size	Natural logarithm of book value of assets
Panel E. State-level control variables	
Unemployment rate	Unemployment rate. Data obtained from the Bureau of Labor Statistics.
Growth rate	y-o-y change of the real GDP in chained USD obtained from Bureau of Economic Analysis
Personal income	Natural logarithm of the real median household income at 2017 CPI adjusted USD obtained from U.S. Census Bureau.
Number of bank M&As	Natural logarithm of the number of commercial bank M&As for each state-year. Data obtained from FFIEC.
House purchase price	Natural logarithm of the mean house purchase price for conventional single-family mortgages, measured in thousands USD. Data obtained from the Federal Housing Finance Agency
Interest rate	The interest rate earned by each bank on held-to-maturity securities and then weighted at the state level using the asset market share of all banks in each state. This variable is used as a proxy for the interest rate environment banks face. Data obtained from the Federal Financial Institutions Examination Council (FFIEC) 031/041 Call Reports.
Panel F. Instrumental variable	
Bartik-style instrument	For details on the construction of this instrument for mortgage loan applications, see the main text.

Table 2. Summary Statistics

The table reports basic summary statistics. The sample period is 1996-2016. All bank variables engaged in cost efficiency estimation are deflated in 2015 prices using the GDP deflator. Outputs, netputs, labor capital price and total bank expenses in Panel A are expressed in thousands USD.

Variable	Obs.	Mean	St. Dev.	Min.	Max.
Panel A. Outputs, Netputs and Input prices, Cost Efficiency and Management Quality Scores					
Outputs					
Real estate loans	61,202	448,422	2,229,112	0	112,000,000
All other loans	61,202	224,200	1,824,725	0	110,000,000
Securities	61,202	197,515	1,117,973	0	74,000,000
Netputs					
Off-balance sheet items	61,202	307,619	4,047,498	0	293,000,000
Premises and fixed assets	61,202	14,809	69,504	5	3,002,058
Equity	61,202	103,417	653,471	951	31,500,000
Input prices					
Price of purchased fuds	61,202	0.028	0.048	0.000	0.979
Price of deposits	61,202	0.018	0.013	0.000	0.209
Labor capital price	61,202	58.916	20.142	0.290	358.541
Cost					
Total bank expenses	61,202	47,749	284,455	53	13,200,000
Cost Efficiency and Management Quality Scores					
Cost efficiency	61,202	0.781	0.104	0.100	0.977
Cost efficiency alternative model	61,202	0.758	0.104	0.062	1.000
Management quality	61,202	1.214	0.171	0.313	1.652
Cost to assets ratio	61,202	0.048	0.017	0.000	0.573
Panel B. Variables reflecting mortgage loan demand					
Mortgage loan demand (MLD)	61,202	4.713	0.446	2.359	7.604
Number of mortgage loan applications (NLA)	61,202	3.605	1.490	0.693	11.949
Panel C. Bank Loan Loss Provisions and Reserves					
Loan loss provisions ratio	61,202	0.005	0.009	-0.113	0.308
Loan loss reserves ratio	61,202	0.014	0.008	0	0.212
Panel D. Bank-level Control Variables					
Equity to assets ratio	61,202	0.102	0.031	0.012	0.725
Liquidity ratio	61,202	0.060	0.057	0.000	0.686
Non-performing loans ratio	61,202	0.013	0.021	0.000	0.400
Non-interest income ratio	61,202	0.130	0.104	-2.373	4.266
Deposits ratio	61,202	0.829	0.074	0.001	0.981
Loan to assets ratio	61,202	0.663	0.140	0.027	0.994
sd(ROA)	61,202	0.005	0.003	0.000	0.047
Size	61,202	12.605	1.192	9.721	19.606
Panel E. State-level Control Variables					
Unemployment rate	61,202	0.058	0.197	0.022	0.139
Growth rate	61,202	0.022	0.025	-0.088	0.224
Personal income	61,202	10.954	0.138	10.437	11.326
Number of bank M&As	61,202	2.461	0.838	0.000	4.317
House purchase price	61,202	5.469	0.343	4.414	6.568
Interest rate	61,202	0.040	0.017	0.006	0.149
Panel F. Instrumental Variable					
Bartik-style instrument	61,202	-0.001	0.014	-0.083	0.064

Table 3. Baseline Results

The table reports coefficient estimates and *t*-statistics (in parentheses) estimated from equation (7). All specifications are estimated with OLS with bank and year fixed effects, with robust standard errors clustered by bank. The dependent variable of each regression is denoted in the first line of the table. Definitions for all variables are provided in Table 1. The sample period is 1996-2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Cost efficiency	Cost efficiency alternative model	Cost to assets ratio	Management quality
Mortgage loan demand (MLD)	0.005**	0.006***	-0.001**	0.007*
	(2.532)	(3.419)	(-1.986)	(1.839)
Mortgage loan demand (MLD) squared	0.017***	0.010***	0.0001	-0.003
	(8.867)	(6.035)	(0.292)	(-0.770)
Number of mortgage loan applications (NLA)	-0.004***	-0.002***	0.0004***	-0.001
	(-5.966)	(-3.038)	(2.751)	(-0.655)
Number of mortgage loan applications (NLA) squared	-0.001***	-0.002***	0.0003***	-0.001***
	(-6.432)	(-8.361)	(4.521)	(-3.611)
Equity to assets ratio	0.183***	0.451***	-0.034***	-0.198***
	(6.426)	(12.760)	(-5.478)	(-4.256)
Liquidity ratio	-0.284***	-0.243***	-0.005***	0.022
	(-20.074)	(-18.033)	(-2.739)	(1.036)
Non-performing loans ratio	-0.270***	-0.358***	0.056***	-0.253***
	(-9.738)	(-12.215)	(13.025)	(-5.408)
Non-interest income ratio	-0.258***	-0.228***	0.050***	-0.251***
	(-9.242)	(-9.488)	(8.006)	(-10.039)
Deposits to assets ratio	0.028**	-0.025**	-0.004*	0.016
	(2.087)	(-1.985)	(-1.852)	(0.817)
Loan to assets ratio	0.031***	0.108***	0.013***	-0.057***
	(4.314)	(14.451)	(12.062)	(-5.027)
sd(ROA)	-1.955***	-1.894***	0.399***	-1.771***
	(-9.242)	(-9.250)	(8.296)	(-5.272)
Size	0.047***	0.051***	-0.005***	0.049***
	(23.200)	(25.223)	(-14.509)	(16.069)
Unemployment rate	0.096*	0.075	0.033***	0.047
	(1.910)	(1.569)	(3.715)	(0.414)
Growth rate	-0.007	0.040***	-0.008***	0.052
	(-0.491)	(3.013)	(-2.777)	(1.287)
Personal income	0.036***	0.029***	-0.002*	0.007
	(4.945)	(3.967)	(-1.949)	(0.441)
Number of bank M&As	0.001*	-0.000	-0.000	-0.002
	(1.839)	(-0.487)	(-0.246)	(-1.012)
House purchase price	0.027***	0.015***	0.0004	0.025***
	(6.833)	(4.170)	(0.843)	(2.963)
Interest rate	0.026	0.027	0.004	0.075
	(0.964)	(1.099)	(0.905)	(1.055)
Constant	-0.355***	-0.327***	0.116***	0.468**
	(-3.980)	(-3.681)	(7.469)	(2.519)
Observations	61,202	61,202	61,202	61,202
Number of banks	6,740	6,740	6,740	6,740
Adj. R-squared	0.741	0.799	0.793	0.195

Table 4. Addressing the potential endogeneity of the number of mortgage loan applications

The table reports coefficient estimates and *t*-statistics (in parentheses), the latter derived from standard errors clustered by bank. The dependent variable is denoted in the first line of the table below. Definitions for all variables are provided in Table 1. Both specifications are estimated with instrumental variable estimation technique and bank and year fixed effects. The sample period is 1996-2016. For ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Cost efficiency	Management quality
Number of mortgage loan applications (NLA)	0.002	-0.016
	(0.216)	(-0.721)
Number of mortgage loan applications (NLA) squared	-0.024**	-0.049*
	(-2.377)	(-1.941)
Mortgage loan demand (MLD)	0.003	-0.005
	(0.615)	(-0.502)
Mortgage loan demand (MLD) squared	0.025***	0.006
	(5.112)	(0.513)
Equity to assets ratio	0.337***	0.116
	(4.318)	(0.641)
Liquidity ratio	-0.293***	-0.008
	(-15.994)	(-0.244)
Non-performing loans ratio	-0.226***	-0.239***
	(-5.120)	(-2.655)
Non-interest income ratio	-0.200***	-0.079
	(-4.580)	(-0.869)
Deposits to assets ratio	0.026	0.013
	(1.317)	(0.358)
Loan to assets ratio	0.022	-0.041
	(1.497)	(-1.298)
sd(ROA)	-1.352***	-0.267
	(-3.430)	(-0.300)
Size	0.065***	0.111***
	(4.775)	(3.369)
Unemployment rate	0.118	-0.010
	(1.541)	(-0.061)
Growth rate	-0.015	0.056
	(-0.726)	(1.073)
Personal income	0.015	-0.030
	(1.112)	(-0.932)
Number of bank M&As	0.002**	0.000
	(2.041)	(0.065)
House purchase price	0.029***	0.023*
	(5.015)	(1.844)
Interest rate	-0.028	-0.031
	(-0.667)	(-0.298)
Kleibergen-Paap rk LM statistic (underidentification test)	13.514	13.514
Kleibergen-Paap rk Wald F statistic (weak identification test)	6.918	6.918
Number of banks	6,740	6,740
Observations	61,202	61,202

First stage regressions

Dependent variable	Number of mortgage loan applications (NLA)	Number of mortgage loan applications (NLA) squared

Bartik-like instrument	-2.964*** (-6.622)	-3.224*** (-2.622)
Bartik-like instrument squared	3.186*** (3.935)	-7.732*** (-3.573)
Mortgage loan demand (MLD)	-0.286*** (-7.937)	-0.163* (-1.748)
Mortgage loan demand (MLD) squared	-0.338*** (-12.395)	0.280*** (4.139)
Equity to assets ratio	-0.483 (-1.443)	6.686*** (6.081)
Liquidity ratio	-0.433*** (-3.028)	-0.479 (-1.215)
Non-performing loans ratio	-2.781*** (-8.507)	1.198 (1.327)
Non-interest income ratio	1.795*** (8.933)	3.033*** (5.777)
Deposits to assets ratio	0.015 (0.084)	-0.064 (-0.106)
Loan to assets ratio	1.233*** (14.788)	-0.052 (-0.217)
sd(ROA)	8.480*** (3.970)	28.668*** (4.391)
Size	0.846*** (33.239)	1.032*** (6.702)
Unemployment rate	-4.509*** (-6.109)	0.013 (0.007)
Growth rate	0.792*** (3.743)	-0.168 (-0.281)
Personal income	0.212** (2.074)	-0.873** (-2.484)
Number of bank M&As	0.010 (1.222)	0.037 (1.317)
House purchase price	-0.254*** (-4.647)	0.063 (0.416)
Interest rate	0.768** (2.033)	-2.587** (-2.463)
Constant	-8.749*** (-7.158)	-2.691 (-0.575)
Adj. R-squared	0.759	0.621

Table 5. Quantile Regressions

The table reports coefficient estimates and *t*-statistics (in parentheses) from quantile regressions where the dependent variable is cost efficiency and management score in Panels A and B, respectively. All specifications are estimated with bank and year fixed effects. Definitions for all variables are provided in Table 1. The sample period is 1996-2016. For brevity, only the coefficients of interest are reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Quantile	**0.2**	**0.4**	**0.5**	**0.6**	**0.8**
Panel A. Dependent variable: Cost efficiency					
Mortgage loan demand (MLD)	0.005	0.005	0.005	0.005	0.004
	(0.761)	(1.099)	(1.249)	(1.241)	(0.934)
Mortgage loan demand (MLD) squared	0.014**	0.016***	0.017***	0.018***	0.019***
	(2.449)	(4.207)	(5.188)	(5.535)	(4.703)
Number of mortgage loan applications (NLA)	-0.004**	-0.004***	-0.004***	-0.004***	-0.004***
	(-2.109)	(-3.299)	(-3.903)	(-4.022)	(-3.232)
Number of mortgage loan applications (NLA) squared	-0.002***	-0.002***	-0.001***	-0.001***	-0.001***
	(-2.610)	(-3.614)	(-4.014)	(-3.900)	(-2.814)
Control variables			Yes		
Observations			61,909		
Number of banks			6,740		
Panel B. Dependent variable: Management quality score					
Mortgage loan demand (MLD)	0.008	0.007*	0.007**	0.007*	0.006
	(1.480)	(1.912)	(1.983)	(1.758)	(1.159)
Mortgage loan demand (MLD) squared	-0.001	-0.002	-0.003	-0.003	-0.004
	(-0.304)	(-0.670)	(-0.878)	(-0.961)	(-0.872)
Number of mortgage loan applications (NLA)	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.606)	(-0.756)	(-0.765)	(-0.660)	(-0.411)
Number of mortgage loan applications (NLA) squared	-0.002***	-0.001***	-0.001***	-0.001***	-0.001**
	(-3.296)	(-4.139)	(-4.211)	(-3.656)	(-2.307)
Control variables			Yes		
Observations			61,909		
Number of banks			6,740		

Table 6. Different Sub-sample periods

The table reports coefficient estimates and *t*-statistics (in parentheses) for the precrisis, crisis and postcrisis periods in Panels A, B and C, respectively estimated from equation (7). The precrisis, crisis and postcrisis periods refer to 1996-2006; 2007-2009 and 2010-2016, respectively. All specifications are estimated with OLS with bank and year fixed effects, with robust standard errors clustered by bank. The dependent variable of each regression is denoted in the first line of the table. Definitions for all variables are provided in Table 1. The sample period is 1996-2016. For brevity, only the coefficients of interest are reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A. Precrisis		**Panel B: Crisis**		**Panel C. Postcrisis**	
Dependent variable:	Cost efficiency	Management quality	Cost efficiency	Management quality	Cost efficiency	Management quality
Mortgage loan demand (MLD)	0.005*	0.009	-0.001	0.016	0.007***	0.015**
	(1.851)	(1.245)	0.158)	(1.245)	(2.623)	(2.237)
Mortgage loan demand (MLD) squared	0.016***	-0.019***	-0.003	-0.008	0.008***	-0.010
	(6.509)	(-3.154)	0.749)	(-0.740)	(2.869)	(-1.609)
Number of mortgage loan applications (NLA)	0.0003	0.002	-0.003**	-0.002	-0.007***	-0.001
	(0.522)	(1.440)	2.129)	(-0.588)	(-6.493)	(-0.486)
Number of mortgage loan applications (NLA) squared	-0.001***	-0.001	-0.0004	0.001	-0.002***	-0.002**
	(-3.032)	(-1.454)	0.673)	(0.545)	(-5.008)	(-2.297)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,744	25,744	10,794	10,794	23,655	23,655
Number of Banks	5,183	5,183	3,811	3,811	4,211	4,211
Adj. R-squared	0.761	0.172	0.816	0.172	0.851	0.275

Table 7. Sensitivity Analysis

The table reports coefficient estimates and t-statistics (in parentheses), the latter derived from standard errors clustered by bank estimated from equation (7). Panel A reports the results of large banks only, i.e., banks with total assets larger than 700mil USD. Panel B reports the results of banks that are not members of a Bank Holding Company. All specifications are estimated with OLS with bank and year fixed effects. The dependent variable of each regression is denoted in the first line of each panel. The sample period is 1996-2016. For brevity, only the coefficients of interest are reported. For ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A. Large banks		**Panel B. Non-BHC member banks**	
Dependent variable:	Cost efficiency	Management quality	Cost efficiency	Management quality
Mortgage loan demand (MLD)	-0.006	0.006	0.0001	-0.011
	(-1.219)	(0.576)	(0.031)	(-1.159)
Mortgage loan demand (MLD) squared	0.021***	-0.005	0.020***	0.004
	(5.671)	(-0.734)	(5.358)	(0.598)
Number of mortgage loan applications (NLA)	-0.001	0.001	-0.010***	-0.005
	(-0.669)	(0.748)	(-4.165)	(-1.444)
Number of mortgage loan applications (NLA) squared	-0.001**	-0.001	-0.003***	-0.004***
	(-2.418)	(-1.617)	(-4.529)	(-3.231)
Control variables	Yes	Yes	Yes	Yes
Observations	12,124	12,124	12,131	12,131
Number of Banks	1,628	1,628	1,890	1,890
Adj. R-squared	0.741	0.190	0.771	0.213

Table 8. Implications for credit risk management and bank stability – Mortgage loan demand, operational efficiency and non-servicing loans

The table reports coefficient estimates and *t*-statistics (in parentheses) estimated from equation (9). All specifications are estimated with OLS with bank and year fixed effects, with robust standard errors clustered by bank. The dependent variable of each regression is denoted in the first line of the table. Definitions for all variables are provided in Table 1. The sample period is 1996-2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Loan loss provisions ratio	Loan loss reserves ratio	Non-performing loans ratio
Mortgage loan demand (MLD)	-0.0004*	-0.001***	-0.004***
	(-1.900)	(-5.066)	(-6.442)
Mortgage loan demand (MLD) squared	-0.000	0.000	0.002***
	(-0.738)	(1.231)	(4.513)
Number of mortgage loan applications (NLA)	-0.0001**	-0.0003***	-0.001***
	(-2.451)	(-6.739)	(-9.536)
Number of mortgage loan applications (NLA) squared	-0.0001***	-0.000	0.000
	(-4.405)	(-0.342)	(0.484)
Cost efficiency	-0.004***	-0.004***	-0.025***
	(-4.098)	(-5.457)	(-11.199)
Cost efficiency squared	0.002	0.001	-0.026**
	(0.296)	(0.210)	(-2.385)
Equity to assets ratio	-0.016***	0.009***	-0.067***
	(-4.765)	(2.832)	(-9.134)
Liquidity ratio	-0.000	0.004***	0.008*
	(-0.168)	(2.841)	(1.768)
Non-performing loans ratio	0.158***	0.135***	
	(27.594)	(22.983)	
Non-interest income ratio	-0.006***	-0.004***	-0.015***
	(-4.977)	(-4.463)	(-5.334)
Deposits to assets ratio	0.001	0.001	0.010***
	(0.982)	(0.788)	(4.289)
Loan to assets ratio	0.004***	-0.008***	-0.010***
	(5.704)	(-12.337)	(-5.701)
sd(ROA)	0.646***	0.437***	1.762***
	(16.631)	(14.163)	(21.423)
Size	0.001***	-0.000***	0.002***
	(9.489)	(-3.278)	(5.144)
Unemployment rate	0.074***	0.013**	0.306***
	(12.337)	(2.341)	(17.750)
Growth rate	-0.007***	-0.002	-0.023***
	(-4.034)	(-1.371)	(-5.682)
Personal income	0.000	-0.002***	-0.010***
	(0.441)	(-2.935)	(-5.248)
Number of bank M&As	0.001***	0.000	0.001***
	(7.847)	(0.580)	(4.858)
House purchase price	-0.000	-0.001***	-0.001
	(-0.296)	(-3.651)	(-1.069)
Interest rate	-0.001	0.003	0.011*
	(-0.203)	(1.270)	(1.749)
Constant	-0.028***	0.050***	0.082***
	(-3.217)	(6.443)	(3.921)
Observations	61,202	61,202	61,202
Number of banks	6,740	6,740	6,740
Adj. R-squared	0.483	0.633	0.494

Table 9. Implications for credit risk management and bank stability – Precrisis, crisis and postcrisis results

The table reports coefficient estimates and *t*-statistics (in parentheses) estimated from equation (9) for the precrisis, crisis and postcrisis periods in Panels A, B and C, respectively. The precrisis, crisis and postcrisis periods refer to 1996-2006, 2007-2009 and 2010-2016, respectively. All specifications are estimated with OLS with bank and year fixed effects, with robust standard errors clustered by bank. The dependent variable of each regression is denoted in the first line of the table. Definitions for all variables are provided in Table 1. The sample period is 1996-2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Precrisis

Dependent variable:	Loan loss provisions ratio	Loan loss reserves ratio	Non-performing loans ratio
Mortgage loan demand (MLD)	-0.001*	-0.001***	-0.001***
	(-1.871)	(-3.337)	(-3.179)
Mortgage loan demand (MLD) squared	-0.000	-0.001***	-0.001***
	(-0.303)	(-3.087)	(-4.477)
Number of mortgage loan applications (NLA)	-0.0001**	-0.0002***	-0.0003***
	(-2.183)	(-3.993)	(-3.556)
Number of mortgage loan applications (NLA) squared	-0.000	0.000	0.0001**
	(-0.705)	(0.752)	(2.028)
Cost efficiency	0.003*	-0.003**	-0.010***
	(1.726)	(-2.239)	(-6.214)
Cost efficiency squared	0.027	0.011	-0.012*
	(1.291)	(0.617)	(-1.931)
Control variables	Yes	Yes	Yes
Observations	25,744	25,744	25,744
Number of banks	5,183	5,183	5,183
Adj. R-squared	0.378	0.646	0.410

Panel B. Crisis

Dependent variable:	Loan loss provisions ratio	Loan loss reserves ratio	Non-performing loans ratio
Mortgage loan demand	-0.001	-0.000	-0.002
	(-1.492)	(-0.750)	(-0.927)
Mortgage loan demand squared	0.000	0.000	0.003*
	(0.335)	(0.107)	(1.881)
Number of mortgage loan applications	-0.000	-0.0004***	-0.001*
	(-1.061)	(-3.017)	(-1.959)
Number of mortgage loan applications squared	-0.0003***	-0.0002**	-0.000
	(-2.931)	(-2.412)	(-0.218)
Cost efficiency	-0.007*	-0.001	0.025**
	(-1.667)	(-0.399)	(2.506)
Cost efficiency squared	-0.042	-0.005	-0.045
	(-1.389)	(-0.363)	(-0.714)
Control variables	Yes	Yes	Yes
Observations	10,794	10,794	10,794
Number of banks	3,811	3,811	3,811
Adj. R-squared	0.687	0.717	0.594

Panel C. Postcrisis

Dependent variable:	Loan loss provisions ratio	Loan loss reserves ratio	Non-performing loans ratio
Mortgage loan demand	0.000	-0.001***	-0.001
	(0.949)	(-2.957)	(-1.580)
Mortgage loan demand squared	-0.001**	-0.000	-0.001
	(-2.259)	(-0.908)	(-1.324)
Number of mortgage loan applications	-0.0001**	-0.0001***	-0.002***
	(-2.575)	(-3.338)	(-5.368)

Number of mortgage loan applications squared	-0.0001***	-0.0001**	-0.0002*
	(-3.688)	(-2.358)	(-1.873)
Cost efficiency	-0.007***	-0.005***	-0.021***
	(-4.461)	(-3.892)	(-5.574)
Cost efficiency squared	-0.016**	0.003	-0.001
	(-2.084)	(0.510)	(-0.045)
Control variables	Yes	Yes	Yes
Observations	23,655	23,655	23,655
Number of banks	4,211	4,211	4,211
Adj. R-squared	0.481	0.792	0.647

Figure 1.

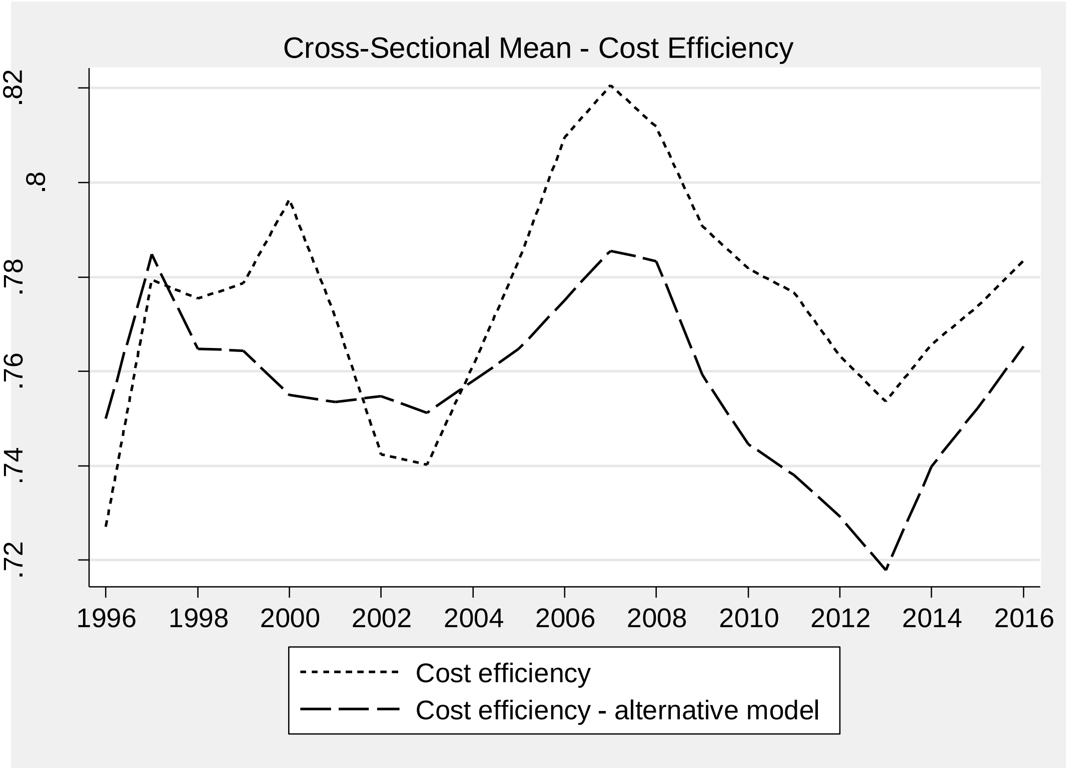


Figure 2.

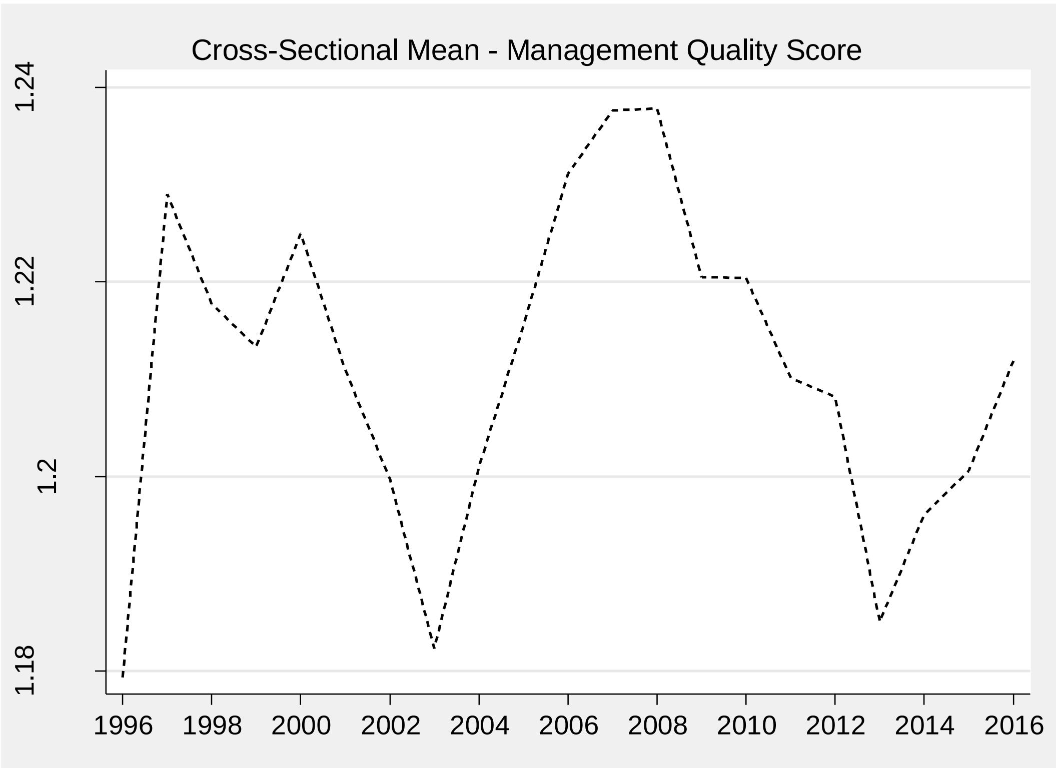
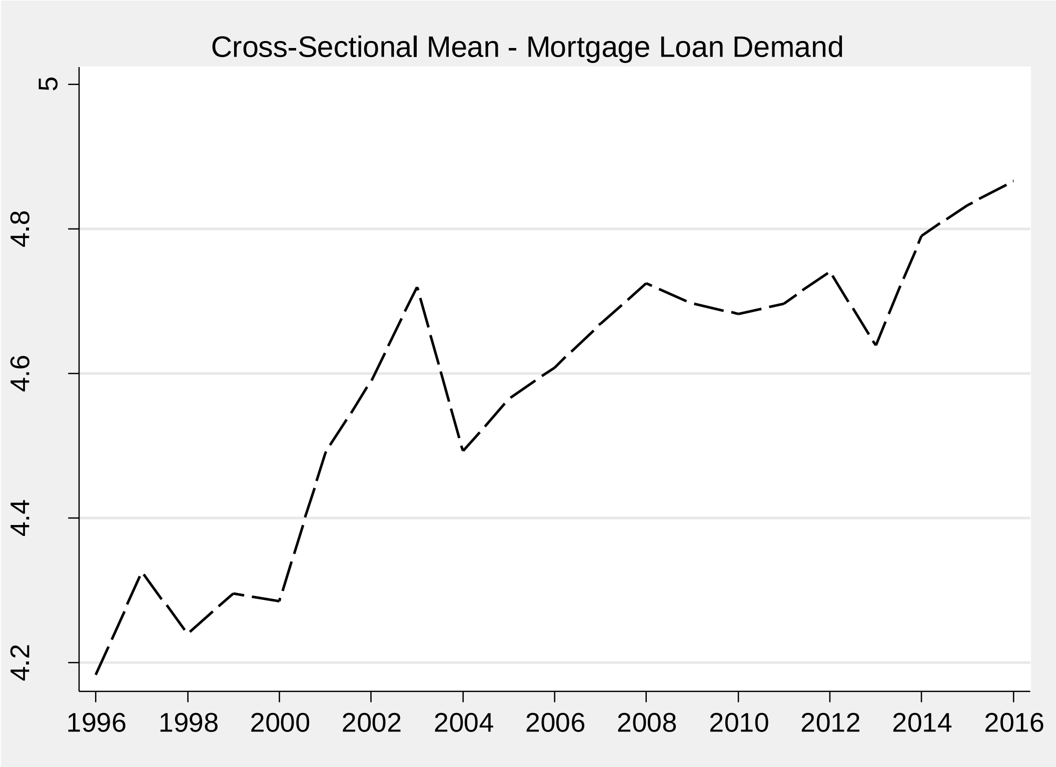
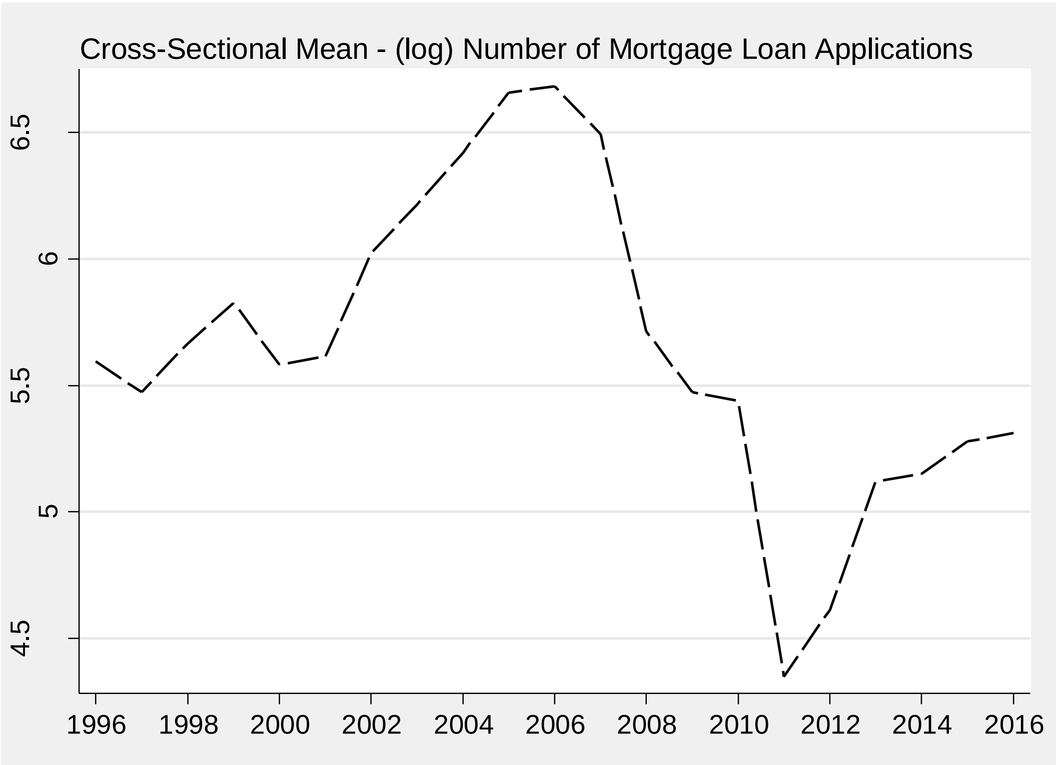


Figure 3.


Cross-Sectional Mean - Mortgage Loan Demand
5
4.8
4.6
4.4
4.2
1996
1998
2000
2002
2004
2006
2008
2010
2012
2014
2016


Cross-Sectional Mean - (log) Number of Mortgage Loan Applications
6.5
6
5.5
5
4.5
1996
1998
2000
2002
2004
2006
2008
2010
2012
2014
2016

Appendix

Table A.1. Including State times Year Fixed Effects

The table replicates the results in Table 3 but also includes state times year fixed effects to control for any omitted local market factors at the state level. Coefficient estimates and t-statistics (in parentheses) are reported, estimated from equation (7). All specifications are estimated with OLS with bank and year fixed effects, with robust standard errors clustered by bank. The dependent variable of each regression is denoted in the first line of the table. Definitions for all variables are provided in Table 1. The sample period is 1996-2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Cost efficiency	Cost efficiency alternative model	Cost to assets ratio	Management quality
Mortgage loan demand (MLD)	0.004**	0.006***	-0.001*	0.008**
	(2.296)	(3.683)	(-1.929)	(1.965)
Mortgage loan demand (MLD) squared	0.011***	0.006***	0.000	-0.006*
	(5.718)	(3.423)	(0.140)	(-1.683)
Number of mortgage loan applications (NLA)	-0.005***	-0.003***	0.001***	-0.001
	(-6.737)	(-4.004)	(4.088)	(-0.968)
Number of mortgage loan applications (NLA) squared	-0.001***	-0.002***	0.0003***	-0.001***
	(-5.727)	(-7.955)	(4.555)	(-3.487)
Equity to assets ratio	0.185***	0.454***	-0.034***	-0.196***
	(6.527)	(12.983)	(-5.668)	(-4.129)
Liquidity ratio	-0.284***	-0.234***	-0.006***	0.025
	(-20.015)	(-17.539)	(-3.194)	(1.184)
Non-performing loans ratio	-0.254***	-0.345***	0.058***	-0.235***
	(-9.165)	(-11.781)	(13.159)	(-4.891)
Non-interest income ratio	-0.251***	-0.225***	0.049***	-0.251***
	(-8.937)	(-9.280)	(8.000)	(-9.767)
Deposits to assets ratio	0.030**	-0.027**	-0.003	0.007
	(2.262)	(-2.280)	(-1.396)	(0.342)
Loan to assets ratio	0.023***	0.096***	0.013***	-0.070***
	(3.206)	(12.758)	(10.819)	(-6.077)
sd(ROA)	-1.920***	-1.893***	0.405***	-1.680***
	(-9.051)	(-9.408)	(8.427)	(-4.955)
Size	0.047***	0.052***	-0.005***	0.048***
	(22.956)	(25.056)	(-14.711)	(15.084)
Constant	0.190***	0.075**	0.098***	0.713***
	(6.076)	(2.428)	(18.771)	(14.959)
Observations	61,164	61,164	61,164	61,164
Number of banks	6,739	6,739	6,739	6,739
Adj. R-squared	0.750	0.809	0.804	0.197

Table A.2. Loan demand-related variables lagged

The table reports coefficient estimates and *t*-statistics (in parentheses) estimated from equation (7). All specifications are estimated with OLS with bank and year fixed effects, with robust standard errors clustered by bank. The dependent variable of each regression is denoted in the first line of the table. Definitions for all variables are provided in Table 1. The sample period is 1996-2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Cost efficiency	Cost efficiency alternative model	Cost to assets ratio	Management quality
Mortgage loan demand $_{t-1}$	0.005**	0.006***	-0.000	-0.001
	(2.335)	(3.376)	(-0.320)	(-0.126)
Mortgage loan demand squared $_{t-1}$	0.020***	0.013***	-0.000	0.008**
	(9.180)	(6.663)	(-0.280)	(2.000)
Number of mortgage loan applications $_{t-1}$	-0.003***	-0.001**	0.001***	-0.001
	(-4.291)	(-2.281)	(3.892)	(-1.298)
Number of mortgage loan applications squared $_{t-1}$	-0.001***	-0.002***	0.000***	-0.000
	(-5.256)	(-7.023)	(3.863)	(-1.036)
Equity to assets ratio	0.158***	0.456***	-0.031***	-0.270***
	(4.345)	(11.393)	(-3.828)	(-4.947)
Liquidity ratio	-0.282***	-0.236***	-0.005***	0.020
	(-18.574)	(-16.580)	(-2.603)	(0.853)
Non-performing loans ratio	-0.215***	-0.309***	0.049***	-0.212***
	(-7.479)	(-10.289)	(10.789)	(-4.115)
Non-interest income ratio	-0.255***	-0.228***	0.049***	-0.246***
	(-7.367)	(-7.668)	(6.463)	(-8.302)
Deposits to assets ratio	0.036**	-0.021	-0.005*	0.012
	(2.368)	(-1.451)	(-1.694)	(0.527)
Loan to assets ratio	0.028***	0.109***	0.014***	-0.065***
	(3.449)	(12.886)	(10.894)	(-4.918)
sd(ROA)	-2.353***	-2.266***	0.444***	-2.318***
	(-10.031)	(-10.329)	(8.393)	(-6.179)
Size	0.048***	0.053***	-0.005***	0.052***
	(20.397)	(22.101)	(-13.968)	(14.068)
Unemployment rate	0.074	0.037	0.034***	0.046
	(1.404)	(0.739)	(3.865)	(0.371)
Growth rate	-0.008	0.035***	-0.007***	0.032
	(-0.543)	(2.618)	(-2.629)	(0.714)
Personal income	0.040***	0.029***	-0.003***	0.014
	(5.341)	(3.889)	(-2.784)	(0.769)
Number of bank M&As	0.001	0.000	-0.000	-0.002
	(1.170)	(0.409)	(-0.308)	(-0.982)
House purchase price	0.021***	0.010***	0.000	0.021**
	(5.142)	(2.681)	(0.718)	(2.253)
Interest rate	0.050*	0.038	0.007	0.109
	(1.788)	(1.527)	(1.395)	(1.404)
Constant	-0.381***	-0.331***	0.130***	0.389*
	(-4.087)	(-3.551)	(8.581)	(1.925)
Observations	48,905	48,905	48,905	48,905
Number of banks	5,897	5,897	5,897	5,897
Adj. R-squared	0.767	0.822	0.802	0.201

Table A.3. Only banks chartered as savings banks or savings and loans associations (thrifts)

The table reports coefficient estimates and *t*-statistics (in parentheses) estimated from equation (7). All specifications are estimated with OLS with bank and year fixed effects, with robust standard errors clustered by bank. The dependent variable of each regression is denoted in the first line of the table. Definitions for all variables are provided in Table 1. The sample period is 1996-2016. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Cost efficiency	Cost efficiency alternative model	Cost to assets ratio	Management quality
Mortgage loan demand	0.001	-0.005	-0.003**	-0.018
	(0.188)	(-0.708)	(-2.293)	(-1.033)
Mortgage loan demand squared	0.026***	0.019***	0.000	0.002
	(3.323)	(2.756)	(0.216)	(0.130)
Number of mortgage loan applications	-0.008**	-0.005	0.001	-0.002
	(-2.389)	(-1.467)	(1.415)	(-0.389)
Number of mortgage loan applications squared	-0.002	-0.003***	0.000	-0.002
	(-1.639)	(-3.034)	(1.119)	(-1.450)
Equity to assets ratio	0.157	0.449**	-0.012	-0.271*
	(1.486)	(2.523)	(-0.338)	(-1.694)
Liquidity ratio	-0.121***	-0.121***	0.001	0.266***
	(-3.404)	(-2.808)	(0.161)	(3.963)
Non-performing loans ratio	-0.412***	-0.341**	0.044**	-0.066
	(-3.048)	(-2.493)	(2.041)	(-0.282)
Non-interest income ratio	-0.276***	-0.233***	0.084***	-0.270***
	(-4.424)	(-4.112)	(4.265)	(-4.405)
Deposits to assets ratio	0.063*	-0.008	-0.003	0.024
	(1.726)	(-0.193)	(-0.232)	(0.421)
Loan to assets ratio	0.101***	0.191***	0.006	0.076**
	(4.010)	(6.993)	(1.115)	(2.197)
sd(ROA)	-2.151**	-2.010*	0.431**	-3.756***
	(-2.556)	(-1.916)	(2.381)	(-3.187)
Size	0.068***	0.069***	-0.009**	0.062***
	(6.526)	(6.767)	(-2.502)	(4.345)
Unemployment rate	0.239	0.391*	0.182**	0.282
	(1.190)	(1.830)	(2.178)	(0.616)
Growth rate	0.077	0.146***	-0.019	0.075
	(1.603)	(2.937)	(-1.508)	(0.475)
Personal income	-0.020	-0.049**	0.000	-0.038
	(-0.822)	(-1.985)	(0.079)	(-0.677)
Number of bank M&As	0.002	-0.001	0.000	0.004
	(1.138)	(-0.675)	(0.377)	(0.797)
House purchase price	0.041**	-0.011	-0.000	0.004
	(2.399)	(-0.757)	(-0.063)	(0.134)
Interest rate	0.129	-0.007	0.009	0.043
	(1.424)	(-0.072)	(0.510)	(0.165)
Constant	-0.206	0.333	0.129	0.785
	(-0.634)	(0.958)	(1.414)	(1.207)
Observations	6,069	6,069	6,069	6,069
Number of banks	805	805	805	805
Adj. R-squared	0.769	0.806	0.716	0.233