How Monetary Policy Shaped the Housing Boom

Itamar Drechsler, Alexi Savov, and Philipp Schnabl*

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Abstract

Between 2003 and 2006, the Federal Reserve raised rates by 4.25%. Yet it was precisely during this period that the housing boom accelerated, fueled by rapid growth in mortgage lending. There is deep disagreement about how, or even if, monetary policy impacted the boom. Using differences in exposure to the deposits channel of monetary policy, we show that Fed tightening induced a large reduction in banks' deposit funding, which led banks to contract portfolio mortgage lending by 32%. However, this contraction was largely offset by substitution to privately-securitized (PLS) mortgages, led by nonbank originators. Fed tightening thus induced a shift in mortgage lending away from stable, insured deposit funding toward run-prone and fragile capital markets funding with little impact on overall lending. We find similar results during the most recent tightening cycle over 2014–2017 when PLS lending reemerged.

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*Drechsler is at The Wharton School of the University of Pennsylvania and NBER, idrechsl@wharton.upenn.edu; Savov is at New York University Stern School of Business and NBER, asavov@stern.nyu.edu; Schnabl is at New York University Stern School of Business, NBER, and CEPR, pschnabl@stern.nyu.edu. We thank Andreas Fuster, Arpit Gupta, Anil Kashyap, Amir Sufi, Joseph Vavra, James Vickery, Toni Whited, an anonymous referee, and seminar participants at the NBER Summer Institute Macro, Money, and Financial Frictions group, Chicago Booth, Harvard Business School, UCLA, Northwestern University, the Philadelphia Federal Reserve Bank, and Cornell University for helpful comments. We thank Pauline Liang and Andrew Teodorescu for excellent research assistance.

1 Introduction

More than a decade after the 2008 financial crisis, an unresolved question remains: what role, if any, did monetary policy play in the housing boom that precipitated the crisis? This question has been the subject of an intense debate. On one side, Taylor (2007, 2010) argues that the Fed kept rates "too low for too long" during the housing boom, and that this led to excessive investment in housing. On the other side, Bernanke (2010a,b) argues that monetary policy was not too loose, and that the real culprit was a decline in mortgage lending standards that accompanied the shift from traditional bank lending to securitized lending. He emphasizes the role of private-label securitization (PLS), which did not conform to the stricter lending standards of the government-sponsored enterprises (GSEs).

Underlying this debate is an empirical ambiguity: even if rates were too low in the early years of the housing boom, the peak phase of the boom coincided with a period of Fed tightening. Between 2003 and 2006 the Fed raised rates by 4.25%, a substantial hike on par with prior cycles. Yet, surprisingly, PLS lending accelerated just as the Fed shifted to a tightening stance in mid 2003. Justiniano, Primiceri, and Tambalotti (2017) label this turning point "the mortgage rate conundrum."

Figure 1 illustrates the conundrum by plotting the PLS share of mortgage loans against the one-year Treasury forward rate, a measure of the stance of monetary policy. The PLS share is computed as PLS loans divided by PLS loans plus portfolio loans. Portfolio loans are loans held on bank balance sheets. We leave out GSE loans to emphasize that they are not driving the shift. The PLS share is fairly low and stable in the late 1990s and early 2000s. It then accelerates around 2003 just as the Fed shifts to a tightening stance. After that, the PLS share keeps climbing as the Fed tightens until both series peak around 2006. Interestingly, the PLS share and Fed tightening have continued to co-move closely in the years after the crisis. In particular, PLS reemerged just as the Fed embarked on its most recent tightening cycle.

These observations raise the possibility that Fed tightening between 2003 and 2006 contributed to the shift to PLS lending. In fact, this is a prediction of the "deposits channel of monetary policy" of Drechsler, Savov, and Schnabl (2017). Under the deposits channel, Fed tightening allows banks to use their market power over deposits to increase profits by charging higher deposit spreads (i.e., by keeping deposit rates low). This induces some depositors to withdraw their funds, and since deposits are far and away the largest source of bank funding—one that banks value for its unique safety and stability—the contraction in deposits leads banks to shrink their loan portfolios. Long-term loans such as mortgages are especially affected because they rely more heavily on deposit funding (Drechsler, Savov, and Schnabl, 2021). As portfolio mortgages shrink, PLS provides an alternative source of financing for the mortgage market, particularly since it is funded in part by recycled deposits (Mian and Sufi, 2018; Xiao, 2020). The deposits channel thus potentially explains why Fed tightening was associated with a shift away from bank portfolio mortgage lending toward PLS lending. This shift in turn can explain why Fed tightening did not significantly curb overall mortgage lending during the housing boom.

In this paper, we examine how Fed tightening impacted mortgage lending during the housing boom through the deposits channel. We highlight four main findings. First, banks responded to Fed tightening by sharply increasing deposit spreads, which led to a 12% reduction in the stock of deposits. Second, banks absorbed this reduction by cutting the flow of new portfolio mortgage lending by 32%. Third, substitution to PLS lending led by nonbank originators (nonbanks) largely offset this contraction. We estimate that absent Fed tightening the PLS share of non-GSE mortgage originations would have remained stable between 2003 and 2006. And fourth, with PLS offsetting the contraction in bank portfolio lending, Fed tightening had only a modest impact on total mortgage lending. Overall, the shift from stable deposit funding to fragile capital markets funding exposed the housing market to a credit freeze like the one that arrived with the 2008 financial crisis.

Given the presence of confounding factors in the aggregate time series and the endogeneity of monetary policy, an important advantage of the deposits channel is that it can be tested in the cross section. The reason is that exposure to the deposits channel varies with bank market power. Following Drechsler, Savov, and Schnabl (2017), we measure this exposure with the "deposit spread beta": the sensitivity of a bank's deposit spread to the Fed funds rate. The deposit spread beta captures a bank's market power over its deposit franchise. A high beta indicates that the bank is able to charge higher deposit spreads when the

Fed raises interest rates, increasing its profits. The higher spreads induce greater deposit outflows, which makes the bank's lending more exposed to the deposits channel. We estimate deposit spread betas at the branch, bank, and county levels. In each case we use data only up to 2002 so that our betas predate the housing boom period.

We begin by analyzing the impact of Fed tightening on deposit supply during the boom period from 2003 to 2006. We first confirm that bank branches with higher pre-2002 deposit spread betas increased deposit spreads by more during this period. We then test if they also had lower deposit growth. We run this test both across all branches and by comparing different branches of the same bank (within-bank estimation). This approach controls for unobserved variation in local loan demand because banks are free to raise deposits at one branch and lend them at another.

We find that branches with higher deposit spread betas had significantly lower deposit growth during the housing boom. The estimated coefficient using within-bank estimation is -21% and highly significant. In the cross section, a branch at the 95^{th} percentile of beta had 6% lower deposit growth than a branch at the 5^{th} percentile. A simple way to quantify the aggregate impact of the deposits channel is to multiply the cross-sectional coefficient by the average beta. The idea is to use a zero-beta branch as a counterfactual for the average branch because it is not exposed to the deposits channel by construction. Since no branch in our data has a beta equal to zero, this calculation involves extrapolation, giving us a rough estimate. This estimate suggests that Fed tightening contracted bank deposits by 12.4%. This is a large contraction because banks rely on deposits for the vast majority of their funding and because absorbing such a contraction in the *stock* of deposits requires a much larger contraction in the *flow* of new lending.

We then show that the impact of Fed tightening on deposit supply aggregates up to the bank level. We find that high-beta banks raised their deposit spreads more and had lower deposit growth than low-beta banks. Turning to the asset side, high-beta banks grew their real estate loans much less than low-beta banks. The passthrough from deposits to real estate loans is roughly dollar-for-dollar, while the passthrough to other types of asset is much smaller and there is little substitution to wholesale (non-deposit) funding. The disproportionate impact of the deposit contraction on real estate loans reflects the suitability of deposits for real estate lending and the high demand for real estate loans during the housing boom.

To see how Fed tightening impacted the broader mortgage market including PLS lending, we turn the analysis to the county level. We use administrative data from the Home Loan Mortgage Disclosure Act (HMDA) dataset, which provides information on bank portfolio loans and securitized loans originated by both banks and nonbanks. We focus on bank portfolio loans and privately sold (PLS) loans and remove GSE loans. We do so because GSE loans are effectively a separate segment of the market due to the stricter criteria needed to qualify for the subsidized GSE guarantee. We calculate a county-level deposit spread beta by weighting the betas of the banks that lend in a county by their shares of local mortgage lending as of 2002.

Consistent with the predictions of the deposits channel, high-beta counties saw much lower growth in bank portfolio lending over 2003–2006 than low-beta counties. Our estimates are largely unchanged when we control for county characteristics. The controls are needed to absorb potential differences in loan demand across counties with different betas. Among the controls we use is a deposit-weighted county beta, which is similar to our main county beta but uses banks' shares of local *deposits* as weights. Conditional on this beta, our lending-weighted county beta picks up variation in local exposure to the deposits channel driven by deposit market power in *other* counties where local lenders raise deposits. Another control we use is the county-level growth in GSE lending, which also picks up differences in local loan demand. Our most stringent specification implies that bank portfolio lending was 59% lower in a maximally exposed county with a beta of one compared to a hypothetical unexposed county with a beta of zero (11% lower in a county at the 95^{th} versus 5^{th} percentile). And since the average county beta is 0.55, this estimate implies that Fed tightening reduced bank portfolio lending by 32% from 2003 to 2006.

Next, we examine the shift to PLS. Under the deposits channel, Fed tightening shrinks bank portfolio lending, which should induce a shift toward securitized lending, and in particular PLS. Thus, counties with a higher exposure to the deposits channel should experience a larger increase in the PLS share of mortgage originations. This is indeed what we see: regressing the change in the PLS share of mortgage originations on our county betas, we find a large positive and significant coefficient that is robust to our array of controls. The coefficient implies that a county with a beta of one experienced a 20.4 percentage point greater increase in the PLS share than a county with a beta of zero (3.7 percentage point greater at the 95$^{\text{th}}$ versus 5$^{\text{th}}$ percentile). Multiplying this coefficient by the average county beta, we find that Fed tightening induced an 11.2 percentage point increase in the PLS share, nearly equal to the observed 11.4 percentage point increase in the average county in the HMDA dataset. Our estimates thus suggest that without Fed tightening PLS would have grown in line with the overall mortgage market so that its share of originations would have remained stable.

While both banks and nonbanks originated PLS mortgages, the expansion of PLS allowed nonbanks, which specialized in PLS, to gain market share. Regressing the change in the nonbank share of total lending on county beta gives a positive and significant coefficient that is robust to all of our controls. We estimate that the nonbank share grew by 16.9 percentage points more in a maximally exposed county than an unexposed county (3 percentage points more at the 95$^{\text{th}}$ versus 5$^{\text{th}}$ percentile). This estimate is large compared to the 27% average market share of nonbanks in 2002.

We then look at total mortgage originations, which nets out the impact of the contraction in bank portfolio lending with the shift to PLS. The coefficient on county beta is just −11% and is statistically insignificant (−2% at the 95$^{\text{th}}$ versus 5$^{\text{th}}$ percentile). Thus, total lending growth did not differ significantly between exposed and unexposed counties, despite their large differences in bank portfolio lending growth. This is explained by the shift to PLS, which filled the gap created by the contraction in bank portfolio lending. We thus find that Fed tightening had only a modest impact, if any, on total mortgage lending. Instead, it accelerated the shift to PLS, which increased the fragility of the mortgage market.

As a final exercise, we replicate our analysis of the housing boom period during the most recent Fed tightening cycle from 2014 to 2017. We find a similar pattern: bank portfolio lending declines and the PLS share of mortgage originations increases in high-beta counties compared to low-beta counties. However, the shift to PLS is smaller than during the housing boom, consistent with tighter regulation decreasing the availability of PLS funding after the 2008 crisis.

Taken together, our results show that tighter monetary policy shifts the composition of mortgage financing away from bank portfolio lending toward PLS. The strength of this shift depends on the elasticity of supply of PLS. This elasticity is jointly determined by investors' willingness to fund PLS and by financial regulation, which imposes limits on their ability to do so. When investors are willing to fund PLS, and when financial regulation is loose, PLS supply is elastic and the shift to PLS is strong. In such an environment, tighter monetary policy mostly affects the composition of mortgage lending rather than the overall amount. This both lessens its impact on economic activity and adversely affects financial stability by increasing exposure to credit freezes. Tighter regulation can improve the effectiveness of monetary policy and strengthen financial stability by making PLS supply less elastic. Importantly, to do so it must extend to the entire financial sector and not just traditional banks. A main takeaway from our paper therefore is that the effectiveness of monetary policy depends on the strength and scope of financial regulation.

The rest of this paper is organized as follows. Section 2 discusses the literature. Section 3 describes the data and empirical approach. Section 3 contains our empirical approach and cross-sectional results. Section 5 examines the aggregate implications of our main results. Finally, Section 6 concludes.

2 Related Literature

Our paper is related to the large literature on the housing boom of the mid 2000s. The literature has highlighted the role of the expanded availability of mortgage credit in fueling the boom (Mian and Sufi, 2009). Within this literature, the role of monetary policy has received relatively little attention despite its potential significance. Moreover, consensus has proven elusive (Taylor, 2007; Mishkin, 2007; Bernanke, 2010b; Bean et al., 2010; Svensson, 2011). One reason for this is that the literature has relied on aggregate time series data, which are confounded by many factors (e.g., the business cycle). Our contribution is to analyze this question through a framework that emphasizes the role of the financial sector in the transmission of monetary policy (Drechsler, Savov, and Schnabl, 2018a, 2020). A key advantage of this approach is that unlike other frameworks (e.g., New Keynesian models), the deposits channel has a heterogeneous impact across banks and the geographic areas they serve. This allows us to control for aggregate factors using cross sectional data.

Our results offer an explanation for the finding in Justiniano, Primiceri, and Tambalotti (2017) that PLS lending accelerated right as the Fed shifted to a tightening stance. As Keys et al. (2010) show, PLS loans came with looser lending standards. This explains the finding in Mian and Sufi (2018) that areas with more PLS lending had a bigger housing boom and subsequent bust. Our results show that exposure to the deposits channel predicts these cross-sectional differences in the growth of PLS.

The literature has proposed several explanations for the growth in PLS lending. These explanations center on the broader phenomena of a "global savings glut" (Bernanke, 2005), weak regulation (Gorton and Metrick, 2010; Pozsar et al., 2010), low volatility (Minsky, 1992), and risk neglect (Gennaioli, Shleifer, and Vishny, 2012). These theories explain why PLS was available as a substitute for bank portfolio lending when the Fed tightened. Our results imply that if PLS had not been available, as was the case in prior cycles, monetary policy would have been more effective in curbing mortgage lending.

Our results also show how monetary policy affects the funding structure of the mortgage market. We find that Fed tightening induced a shift from stable deposit funding to run-prone capital markets funding. The shift was led by nonbank mortgage originators outside the scope of traditional banking regulation (Buchak et al., 2018a,b; Fuster et al., 2019). Lacking a large balance sheet, nonbanks securitize mortgage loans in the PLS market, selling them off to asset-backed commercial paper conduits, collateralized debt obligations, and structured investment vehicles. These institutions ended up holding significant amounts of PLS mortgages and were funded in part by the recycled deposits of banks (Acharya, Schnabl, and Suarez, 2013; Xiao, 2020). Importantly, even if the same deposit dollars ended up funding mortgages, they were transformed in the process from stable core deposits to run-prone wholesale funding (Hanson et al., 2015; Moreira and Savov, 2017). This increased fragility contributed to the severity of the 2008 financial crisis (Brunnermeier, 2009).

3 Data and Estimation

1. Mortgage lending data. We use administrative data on residential mortgage lending in the U.S. provided under the Home Mortgage Disclosure Act (HMDA). The HMDA dataset contains loan-level information on residential mortgages in the U.S. at an annual frequency. We focus on purchase loans made between 2002 and 2006. We do not include refinance loans because they usually do not require additional deposit funding (we show later that our results are robust to including refinance loans). We use the number of loans rather than dollar amounts in order to avoid the influence of home prices. We classify lenders as banks and nonbanks using a file provided by the Federal Reserve Bank of New York. The file also contains an identifier that allows us to match banks to the U.S. Call Reports.

We distinguish between portfolio loans, PLS loans, and agency (GSE) loans. We classify loans following the same procedure as in Mian and Sufi (2018). The only difference is that we classify loans held by nonbanks and not sold by the end of the year as PLS loans. The reason is that nonbanks securitize almost all loans and do not hold loans long-term. This affects only a small number of loans and our main result are similar if we code these loans as portfolio loans instead.

We restrict our main sample to non-GSE (i.e., portfolio and PLS) loans. The reason is that during this period the GSEs offered an underpriced credit guarantee (Crippen, 2001; Acharya et al., 2011), which gave lenders a strong incentive to securitize all GSE-eligible loans through the GSEs. Consistent with such an incentive, Agarwal, Chang, and Yavas (2012) find that banks retained only 7% of "prime-like" loans, a proxy for GSE-eligible loans that likely overstates their prevalence due to data limitations. Given this fact, a contraction in deposits is not predicted to affect GSE securitization. By contrast, since banks retained substantial amounts of GSE-ineligible loans, a contraction in deposits is predicted to increase PLS. Therefore, by restricting the sample to non-GSE loans we focus on the relevant universe that is exposed to the deposits channel. To validate this approach and verify that it does not drive our results, we analyze GSE loans directly and find they did not substitute for portfolio loans in our sample.

2. Bank Data. Our bank-level data are from the U.S. Call Reports provided by the

Federal Reserve Bank of Chicago. We use data from January 1986 to December 2006. The data contain quarterly observations of the income statements and balance sheets of all U.S. commercial and savings banks.

3. Deposit Quantities. Data on deposit quantities are from the Federal Deposit Insurance Corporation (FDIC). The data cover the universe of U.S. bank branches and are released annually in June. We use the data from June 2003 to June 2007. The data contain branch characteristics, including the parent bank, address, and geographic coordinates for a total of 58,546 branches. We link the data to the U.S. Call Reports using the FDIC bank identifier.

4. Deposit Rates. Data on deposit rates are from Ratewatch. Ratewatch collects weekly branch-level data on deposit rates for new accounts at the product level. We use the data from January 1997 to December 2006. We focus on branches that actively set their own deposit rates ("rate-setters"). There are 5,501 such branches. We link the data to the U.S. Call Reports using the FDIC bank identifier.

We analyze the rates on three main types of retail deposits (savings, interest checking, and small time deposits) by focusing on the most widely offered product within each type: (i) money market deposit accounts with an account size of $25,000 (savings deposits), (ii) interest checking accounts with no minimum account size (interest checking deposits), and (iii) 12-month certificates of deposit with an account size of $10,000 (small time deposits). We convert the rates on each of these products into deposit spreads by subtracting them from the Fed funds rate.

5. County Data. We collect data on county population, employment, and median household income from the U.S. Bureau of Labor Statistics and the Census Bureau. We match the data to the HMDA data using the county identifier.

6. Fed Funds Rate Data. We obtain the monthly Fed funds target rate and the effective Fed funds rate from Federal Reserve Economic Data (FRED). We convert the data to an annual frequency by taking the December observation of each year.

3.1 Deposit spread betas

Our empirical analysis uses cross-sectional variation in exposure to monetary policy via the deposits channel. We measure exposure with the "deposit spread beta" introduced by

Drechsler, Savov, and Schnabl (2017). The deposit spread beta measures the sensitivity of a bank's deposit spread, the difference between the Fed funds rate and the bank's deposit rate, to the Fed funds rate. For instance, a bank with a beta of 0.6 raises its deposit spread by 60 basis points for every 100 bps increase in the Fed funds rate (i.e., it raises its deposit rate by 40 bps). Drechsler, Savov, and Schnabl (2017) show empirically and theoretically that a bank's spread beta captures its market power in retail deposit markets. As the Fed tightens, banks with a lot of market power keep their deposit rates low, raising the spreads they charge their depositors. This leads some depositors to withdraw, inducing outflows.

We estimate deposit spread betas at the branch, bank, and county levels. In each case, we use data only up to 2002, which is before the housing boom period from 2003 to 2006 when all of our outcome variables are measured. This ensures that our betas are predetermined with respect to the housing boom and hence not affected by it. We then use these betas to predict the behavior of deposits and lending during the housing boom.

The branch betas use quarterly observations of deposit spreads between 1997 and 2002 from the Ratewatch dataset. We estimate branch betas by assuming all branches in a given county share the same beta. This allows us to assign betas to branches that appear in the FDIC dataset but not Ratewatch. The interpretation is that deposit market power varies at the county level as a function of local characteristics. Drechsler, Savov, and Schnabl (2017) show that these characteristics include local market concentration, household income, education, and demographic variables.

We estimate branch betas by running the following panel regression separately for each of the three representative deposit products (checking, savings, and small time deposits):

$$\Delta Spread_{b,c,t} = \alpha_c + \sum_{\tau=0}^{3} \beta_{c,\tau} \Delta FedFunds_{t-\tau} + \varepsilon_{b,c,t}, \quad (1)$$

where $\Delta Spread_{b,c,t}$ is the change in the deposit spread of branch b in county c from $t-1$ to t, α_c is a county fixed effect, and $\Delta FedFunds_{t-\tau}$ is the change in the Fed funds rate from $t-\tau-1$ to $t-\tau$. Including three lags of the Fed funds rate change allows deposit spreads to adjust over a full year. We then sum the coefficients $\beta_{c,\tau}$ to obtain a single beta for each product and winsorize at the 5% level to remove outliers due to estimation error. Finally, we average across the three products to get a single beta for each branch, $BranchBeta_b$.

We estimate bank-level betas by following a similar procedure using the Call Reports from January 1986 to December 2002. The outcome variable is a bank's interest expense spread, the difference between the Fed funds rate and the ratio of its annualized interest expense to its average quarterly assets. The interest expense spread includes the cost of non-deposit funding, which gives us a comprehensive measure of banks' total cost of funding. Nevertheless, since deposits account for the vast majority of banks' funding, and since non-deposit funding earns similar rates across banks, our results are robust to estimating banks' spread betas using only their deposit interest expense.

We estimate bank betas by running the following panel regression:

$$\Delta Spread_{j,t} = \alpha_j + \sum_{\tau=0}^{3} \beta_{j,\tau} \Delta FedFunds_{t-\tau} + \varepsilon_{j,t}, \quad (2)$$

where $\Delta Spread_{j,t}$ is the change in the interest expense spread of bank j from $t-1$ to t and α_j is a bank fixed effect. We construct a single beta for each bank by summing the coefficients on the current and lagged changes in the Fed funds rate. We winsorize the bank betas at the 1%-level and refer to them as $BankBeta_j$.

We construct a beta for each county as the weighted average of the bank betas of all banks that make mortgage loans in that county. Since we are interested in the impact of the deposits channel, the weight each bank receives is given by its share of total portfolio mortgage lending in the county as of 2002, $s_{j,c}$:

$$CountyBeta_c = \sum_j s_{j,c} \times BankBeta_j. \quad (3)$$

Thus, a high-beta county is one whose mortgage market is served by banks with a high ex-ante exposure to the deposits channel.

Figure 2 shows a map of the estimated county betas. We find significant variation in county betas across the United States. There is some clustering of counties with high betas in the Northeast but there remains significant variation both across and within states. Some of the variation is due to restrictive deposit regulation dating back to the 1970s (Drechsler, Savov, and Schnabl, 2020).

3.2 Summary statistics

Table 1 presents summary statistics at the branch level (Panels A and B), bank level (Panel C), and county level (Panel D). The first two columns of each panel report the mean and standard deviation of each variable. The next two columns report means for high- versus low-beta subsamples based on the median beta in each sample. The last column reports the significance level of a t-test for the difference between the high- and low-beta subsamples.

From Panel A, the average branch beta is 0.581 with a standard deviation of 0.077. It is 0.523 in the low-beta half of the sample versus 0.640 in the high-beta half. The panel also shows that deposit spreads rose substantially during the housing boom period from 2003 to 2006: the spread on savings deposits rose by 3.374 percentage points, the spread on small time deposits by 1.709 percentage points, and the spread on interest checking accounts by 4.044 percentage points. The Fed funds rate rose by 4.250 percentage points over this period, hence these are large increases. Their relative magnitudes line up with the relative liquidity of the deposit products (checking deposits are the most liquid, followed by savings deposits, and small time deposits). This is consistent with the literature on the liquidity premium, which argues that deposits are valued for their liquidity and that the price of this liquidity rises with the nominal interest rate (Drechsler, Savov, and Schnabl, 2018b).

Panel A shows that high-beta branches increased spreads by more than did low-beta branches: 3.522 versus 3.226 percentage points for savings deposits, 1.806 versus 1.613 percentage points for small time deposits, and 4.100 versus 3.988 percentage points for interest checking. This shows that the pre-period branch betas are persistent and predict deposit spreads well out of sample.

Panel B reports branch-level summary statistics on deposit amounts. The average bank branch has $76.3 million in deposits, and experiences deposit growth of 23.4% during the housing boom period. As predicted by the deposits channel, deposit growth is lower at high-beta branches than low-beta branches (20.5% versus 26.2%). Thus, the pre-housing-boom branch betas also predict deposit growth during the housing boom.

Panel C reports bank-level summary statistics. The average bank beta is 0.626 with a standard deviation of 0.094. These estimates are quite close to those for the branch betas, even though they are based on different datasets. Below the bank beta is the change in the bank deposit spread, which is the difference between the Fed funds rate and the bank's deposit expense rate (interest expense on core deposits divided by quarterly average core deposits). Banks on average raised their deposit spread by 3.236 percentage points during the housing boom, again similar to the branch-level data. The increase is 3.457 percentage points for high-beta banks versus 3.015 percentage points for low-beta banks.

Below the deposit spread, core deposits grew by 24.6% overall, reflecting the strong economic growth during the boom. Consistent with the deposits channel, high-beta banks had much lower deposit growth than low-beta banks (19.5% versus 29.8%). Also consistent, high-beta banks had lower growth in real estate loans.

Taken together, Panels A, B, and C show that a higher pre-boom deposit spread beta predicts a larger increase in deposit spreads (prices) and lower deposit growth (quantities) during the housing boom. The combination of higher prices and lower quantities implies an inward shift in the supply curve for deposits. This shift is predicted by the deposits channel under which Fed tightening induces banks to contract deposit supply.

Panel D of Table 1 presents summary statistics at the county level. Low- and high-beta counties are roughly similar in terms of market size, employment, and income prior to the housing boom in 2002. They are also similar in terms of mortgage market concentration. Following (Scharfstein and Sunderam, 2016), we measure market concentration as the combined share of mortgage lending by the county's top four mortgage lenders. We find that low-beta counties are slightly larger and have somewhat higher 2002 PLS and nonbank shares than high-beta counties.

The panel shows significant cross-county differences in lending growth during the housing boom from 2003 to 2006. Consistent with the deposits channel, high-beta counties see lower growth in bank portfolio lending than low-beta counties (9.8% versus 15.5%). They also see lower growth in total bank lending (36.4% versus 44.4%), which is the sum of bank portfolio lending and bank-originated PLS lending. There is evidence of substitution to PLS lending, led by nonbanks, as high-beta counties have a greater increase in their PLS and nonbank shares of lending. Substitution to PLS narrows the gap in total lending growth between high- and low-beta counties to 41.1% versus 44.4%.

Panel D also shows summary statistics for a variable called the county deposit-weighted beta, which we use as a control. Similar to the county beta in equation (3), the county deposit-weighted beta is a weighted average of the bank betas. However, it uses banks' deposit market shares rather than their lending shares as weights. This allows us to control for any variation in county beta that is due to deposit market power in the county where the lending takes place. Unsurprisingly, the deposit-weighted county beta is also higher in high-beta counties than low-beta counties, but its correlation with county beta is only 0.45. This shows that our county beta contains substantial independent variation coming from other counties where local mortgage lenders raise deposits.

4 Results

The deposits channel predicts that Fed tightening during the housing boom induced an inward shift in deposit supply (higher deposit spreads and lower deposit growth). The deposits channel further predicts that the contraction in deposits induced a contraction in bank portfolio lending, which can in turn explain why the mortgage market shifted toward PLS. In this section we test these predictions.

The main empirical challenge is the potential for omitted factors that could have impacted deposit supply and lending during the housing boom. The most important such factor is loan demand. High loan demand played an important role in the housing boom (Adelino, Schoar, and Severino, 2016; Gao, Sockin, and Xiong, 2020; DeFusco, Nathanson, and Zwick, 2017). As a result, it likely contributed to the Fed's decision to raise rates. At the same time, high loan demand is predicted to induce an outward shift in deposit supply as banks seek to expand lending. This could potentially mask the impact of the deposits channel. We address this issue by analyzing the cross section. In particular, we difference out aggregate loan demand by comparing areas with different deposit spread betas—that is, different levels of exposure to the deposits channel.

Turning to the cross section does not fully solve the empirical challenge because loan demand could vary in a way that is correlated with our deposit spread betas. For example, if banks with higher betas saw lower loan demand during the housing boom, then their deposit and lending growth would be lower even absent any influence from the deposits channel. In order to address this challenge, we conduct our cross sectional analysis at different levels of aggregation: the branch, bank, and county levels. The granularity of the branch-level analysis allows us to fully control for the influence of loan demand on deposit supply. The bank- and county-level analyses, which are necessarily coarser, allow us to examine bank lending and the shift to PLS while controlling for loan demand using observables.

4.1 Branch-level results

We use the branch-level data to obtain variation in exposure to the deposits channel that is independent of loan demand. This variation comes from comparing different branches of *the same bank* located in counties with different deposit spread betas. Since a bank can raise a deposit dollar at one branch and lend it at another, the decision of how many deposits to raise at a given branch is independent from the decision of how many loans to make at that same branch. This means that we can control for loan demand by examining within-bank differences in deposit supply.

We proceed in two steps. First, we show that our branch betas, which are estimated from data before the housing boom, predict deposit spreads during the housing boom. This step is a necessary first stage showing that our betas are able to generate variation in deposit spreads that is independent of shocks that occurred during the housing boom. Second, we show that our branch betas predict deposit growth, both across and within banks. This shows the impact of the deposits channel on deposit supply during the housing boom.

We start with deposit spreads, focusing on the three main deposit products (savings, small time, and interest checking). For each product, we estimate the following cross-sectional regression:

$$\Delta DepositSpread_b = \alpha + \gamma BranchBeta_b + \varepsilon_b, \tag{4}$$

where $\Delta DepositSpread_b$ is the change in the deposit spread of branch b from January

2003 to December 2006, $BranchBeta_b$ is the branch beta (estimated from pre-2003 data), and α is a constant. We cluster standard errors at the county level to account for the overlap in branch betas across branches located in the same county.

Figure 3 shows binned scatter plots of the change in deposit spreads from 2003 to 2006 against branch beta for savings deposits (Panel A), small time deposits (Panel B), and interest checking (Panel C). The plots show that high-beta branches increased their spreads by more than low-beta branches. Savings deposit spreads increased by 3.6 percentage points at branches with a spread beta of 0.7 versus 3.0 percentage points at branches with a spread beta of 0.4. Small time deposit spreads increased by 1.8 percentage points versus 1.5 percentage points over the same range of spread betas, and checking deposit spreads increased by 4.1 versus 3.9 percentage points. The relationships are tight and linear. This shows that the pre-2003 deposit spread betas do a good job of predicting deposits spreads out of sample during the housing boom period.

Table 2 presents the corresponding regressions. Panel A shows a coefficient of 1.801 for savings deposits (column (1)), 1.056 for small time deposits (column (2)), and 0.819 for interest checking (column (3)). All of the coefficients are significant at the 1% level. The implied aggregate increases in deposits spreads are economically large although smaller than the realized aggregate spread increases over this period. One reason for this is attenuation of our pre-period betas. Another is that we are using a single beta obtained by averaging across deposit products to predict the spreads on individual products. This impacts checking accounts the most because they tend to have much less variation in betas (most banks barely raise their rates on checking accounts when the Fed tightens).

Turning to deposit growth, we estimate the following cross-sectional regression:

$$DepositGrowth_b = \alpha + \gamma BranchBeta_b + \varepsilon_b \tag{5}$$

where $DepositGrowth_b$ is the log deposit growth of branch b from June 2003 to June 2007, $BranchBeta_b$ is the branch beta, and α is a constant. We again cluster standard errors at the county level.

Figure 4 shows binned scatter plots of deposit growth against the branch betas. Panel A shows the raw relationship and Panel B controls for bank fixed effects, which implements our within-bank estimation. In both cases, there is a strong negative relationship: high-beta branches experience lower deposit growth than low-beta branches. From Panel A, branches with a beta of 0.7 have deposit growth of about 20% versus 29% for branches with a beta of 0.4. The difference narrows a bit in Panel B to 21% versus 27%, likely because branches belonging to the same bank are not fully independent in setting rates.

Panel B of Table 2 presents the corresponding regressions. Column (1) shows the simple univariate regression while column (2) adds in the bank fixed effects. The coefficients are −0.321 and −0.210, respectively. Both are statistically significant at the 1% level. Cross-sectionally, they imply that a branch at the 95$^{\text{th}}$ percentile of beta (0.723) had 9% less deposit growth than a branch at the 5$^{\text{th}}$ percentile (0.441) based on column (1) and 6% based on column (2). Taking the coefficients and multiplying by the average beta of 0.590, the predicted aggregate decline in deposit growth is 18.9% based on column 1 and 12.4% based on column (2). This decline is relative to a counterfactual in which the Fed did not raise rates during the housing boom (abstracting from other channels). Our estimates suggest that in such a counterfactual deposit growth would have been significantly higher.

Our estimates imply that bank profits from deposits increased as banks raised deposit spreads. The growth in profits is given by the percentage change in deposit spreads plus the growth in deposits. Scaling the coefficients in Panel A of Table 2 by the average spread for each product in 2003, the percentage increases in deposit spreads are 54%, 107%, and 18% for savings, small time, and interest checking, respectively. These increases more than offset the deposit outflows in Panel B, implying an increase in profits. This finding shows that by reducing the supply of deposits banks increased their profits on deposits, as predicted by the deposits channel (Drechsler, Savov, and Schnabl, 2017).

Overall, the branch-level analysis shows that as the Fed tightened between 2003 and 2006, banks raised deposit spreads by more and saw lower deposit growth at high-beta branches versus low-beta branches. These results are not due to differences in loan demand as they hold within banks. Rather, they show that Fed tightening induced a large contraction in deposit supply during the housing boom.

4.2 Bank-level results

In this section we examine the effects of the deposits channel at the bank level. This allows us to verify that our branch-level results aggregate up using a separate dataset (the Call Reports). It also allows us to analyze the asset side of bank balance sheets.

Figure 5 shows binned scatter plots of the change in deposit spreads and deposit growth at the bank level. Panel A shows that high-beta banks increased deposit spreads by more than low-beta banks. Deposit spreads increase by 2.6 percentage points at banks with a beta of 0.4 versus 3.7 percentage points for banks with a beta of 0.8. Panel B looks at core deposit growth. There is a strong negative relationship: banks with a beta of 0.4 have deposit growth of 40% versus 13% for banks with a beta of 0.8. Taken together, Panels A and B confirm our branch-level results at the bank level by showing that high-beta banks contracted deposit supply relative to low-beta banks as predicted by the deposits channel.

Our next task is to examine whether the contraction in deposits affected lending. The implications of the deposits channel for lending arise due to the uniqueness of deposits as a source of funding. This uniqueness is due to their stability (Hanson et al., 2015) and low interest-rate sensitivity (Drechsler, Savov, and Schnabl, 2021). It explains why banks use deposits for the vast majority of their funding. At the same time, exercising market power over deposits requires banks to restrict deposit supply. Deposit market power thus induces a tradeoff between increasing deposit profits and providing loans. The key mechanism of the deposits channel is that monetary policy tips the balance of this tradeoff. As the Fed raises the nominal interest rate, banks are able to increase deposit profits by charging higher spreads. This, however, induces outflows and leaves less deposit funding for lending.

We test this prediction by regressing the change in different components of banks' balance sheets on our bank-level measure of exposure to the deposits channel, bank beta. We scale the change in each component by core deposits at the start of the period in 2003. The common scaling allows us to compare coefficients across components and interpret them as dollar amounts per dollar of 2003 deposits. We run the following OLS regression:

$$\frac{\Delta Y_j}{\text{Core dep.}_j} = \alpha + \gamma BankBeta_j + \delta X_j + \varepsilon_j, \tag{6}$$

where ΔY_j is the change in bank j's balance sheet component (e.g, deposits, assets) from January 2003 to December 2006, Core dep.$_j$ is bank j's core deposits in January 2003, $BankBeta_j$ is the bank's deposit spread beta estimated using pre-2002 data, X_j are control variables, and α is a constant. The controls we use are bank size (log assets), capitalization (the ratio of equity to assets), and the ratio of loans to assets. They help to pick up differences in banks' business models that may affect loan demand in a way that is correlated with bank betas.

Panel A of Table 3 presents the results. Column (1) looks at core deposits. In this case the left-hand variable is simply core deposit growth. The estimated coefficient is -0.385 and highly significant. This number is similar to our branch-level estimate without bank fixed effects and somewhat larger than the one with bank fixed effects. It implies that core deposits grew by 38.5% less at a bank with a beta of one compared to a bank with a beta of zero. To get a sense of the cross-sectional variation, deposits grew by 13.8% less at a bank at the 95$^{\text{th}}$ percentile of bank beta (0.784) compared to a bank at the 5$^{\text{th}}$ percentile (0.425). And since the average bank beta is 0.616, the implied aggregate contraction in deposits due to Fed tightening and the deposits channel is 23.7%.

Columns (2)–(6) look at the asset side of banks' balance sheets. From column (2), high-beta banks saw a much lower increase in real estate loans than low-beta banks. The estimated coefficient is -0.364 and highly significant. Hence, a bank with a beta of one grew its real estate book by \$0.364 less per dollar of 2003 deposits than a bank with a beta of zero. Recall that that same bank grew its deposits by \$0.385 less. Thus, high-beta banks reduced deposits and real estate loans roughly one for one. This supports the view that deposits are especially well-suited to real estate lending.

Columns (3)–(6) show a much smaller impact of bank beta on other types of assets. Consumer and industrial (C&I) loans decline by just \$0.084 per dollar of 2003 deposits, personal loans (e.g., credit cards) are unaffected, cash declines by \$0.078, and securities by \$0.114. In addition to the suitability of deposits to real estate lending, the disproportionate impact on real estate likely also reflects the historically high demand for real estate loans during the housing boom. Given this high demand, it makes sense for banks to channel the marginal dollar of deposits primarily into real estate lending.

Columns (7) and (8) look at the liabilities side. From column (7), there is a significant effect of −\$0.270 on large time deposits and, from column (8), an insignificant effect of −\$0.019 on wholesale funding. This shows that large time deposits are closer to core deposits than wholesale funding in the cross section. This is not surprising because large time deposits are defined as accounts with balances of \$100,000 or more during this period. The relatively low cutoff means that at a typical bank many of these accounts are retail accounts and as such are exposed to the deposits channel. Note that while this observation holds in the cross section, in the aggregate large time deposits are dominated by the few largest banks, which issue much larger institutional (non-retail) CDs, making them closer to wholesale funding.

Panel B of Table 3 runs two-state least squares regressions on core deposit growth instrumented by bank beta. From column (1), \$0.944 of every dollar of deposit growth due to a lower beta is channeled into real estate (this number can also be obtained by taking the ratio of the coefficients in columns (2) and (1) in Panel A). From columns (2)–(5), another \$0.218 is channeled to C&I loans, \$0.202 to cash, and \$0.295 to securities. Column (6) shows that the additional funding for this comes from large time deposits, which grow by \$0.700 for every dollar of deposit growth. By contrast, wholesale funding in column (8) does not increase significantly.

We note that the effect on large time deposits could be contributing to the large effect on real estate loans. As an extreme, if banks allocate large time deposits in exactly the same way as core deposits, then the passthrough of (total) deposits to real estate loans is 0.555 $(= 0.944/(1+0.7))$. While this is possible, the evidence of Drechsler, Savov, and Schnabl (2021) is that core deposits (especially savings accounts) are particularly well suited to real estate lending due to their low interest rate sensitivity. Under this view, banks allocate core deposits to long-duration real estate loans and large time deposits to short-term or floating-rate assets such as C&I loans. In this case, the pass-through of core deposits to real estate loans is 0.944 as estimated in column (1). The two estimates give us a plausible range for the passthrough of deposits to real estate loans. Both show it was high.

Figure 6 uses binned scatter plots to depict the relationships in Table 3. The effects are linear across the distribution of bank beta and not driven by outliers. Moreover, since the plots are univariate, the figure shows that the results are not sensitive to the control variables. Overall, the results in Table 3 and Figure 6 support the prediction of the deposits channel that Fed tightening during the housing boom induced a contraction in bank deposits and loans, with a disproportionate impact on real estate loans.

4.3 County-level analysis

In this section, we examine the impact of the contraction in deposits on mortgage lending at the county level, and in particular on the shift to PLS lending. We run regressions of the form:

$$\Delta Y_c = \alpha + \gamma CountyBeta_c + \delta X_c + \varepsilon_c, \tag{7}$$

where ΔY_c is the change in a county-level outcome variable (e.g. the logarithm of bank portfolio mortgage lending) from 2003 to 2006, $CountyBeta_c$ is the county beta estimated using data up to 2002, X_b are control variables, and α is a constant.

4.3.1 Bank portfolio lending

Figure 7 presents a binned scatter plot of the growth in bank portfolio mortgage lending from 2003 to 2006 against the county betas. There is a strong negative relationship: high-beta counties had much lower growth in bank portfolio lending than low-beta counties. Bank portfolio lending grew by a cumulative 23% from 2003 to 2006 in counties with a beta of 0.4, versus 0% for counties with a beta of 0.7. This is consistent with the prediction of the deposits channel that Fed tightening and the ensuing contraction in deposits led banks to contract portfolio real estate lending.

Table 4 estimates this relationship in a regression. From column (1), the univariate coefficient is -0.748 and highly significant. Note that this coefficient captures the impact of the deposits channel on the flow of new lending, not the stock of loans on the balance sheet. This explains why the magnitude is larger than the estimated contraction in the stock of deposits. In terms of cross-sectional variation, portfolio mortgage lending grew by 13.7% less in a county at the 95$^{\text{th}}$ percentile of county beta (0.642) compared to one at the 5$^{\text{th}}$ percentile (0.459). Note that county betas are less disperse than bank betas because they are averages of bank betas. Nevertheless, the variation in county betas and the associated predicted variation in bank portfolio mortgage lending are substantial.

Column (2) adds in characteristics that control for the size of the mortgage market, employment, and income, which could be correlated with loan demand. The coefficient on county beta grows slightly to -0.827. The coefficients on the controls show that bank portfolio lending grew more in counties with less lending in 2002, but also in counties with higher income and employment. Overall, column (2) shows that the effect of county beta is not driven by the size of the mortgage market or economic conditions as of 2002.

Column (3) adds in controls for the structure of the mortgage market, which could be correlated with loan demand or supply independent of the deposits channel. The coefficient on county beta declines somewhat to -0.522 and remains highly significant. One reason for the decline is the impact of the first additional control, the amount of bank portfolio lending in 2002. This control has a negative coefficient, indicating that bank portfolio lending grew more in places where it was relatively low in 2002. This shows that there was some mean reversion among counties. We note that mean reversion in bank portfolio lending could itself result from the deposits channel due to the cycles in the Fed funds rate.

The next two controls in column (3) are the PLS and nonbank lending shares. Following Mian and Sufi (2018), these measures capture the initial level of penetration of the mortgage market by PLS and nonbank lenders, which could be correlated with their subsequent growth and hence also with the growth of bank portfolio lending. Both shares come in with a positive coefficient but are insignificant.

Column (3) further controls for local market power on the lending side using the market share of the top four lenders from Scharfstein and Sunderam (2016). The coefficient on the top-four lenders share is negative and significant, indicating that bank portfolio lending decreased more in counties whose lending markets were more concentrated. This result is somewhat surprising since loan market power is expected to dampen the impact of Fed tightening on lending by partly absorbing it through tighter loan spreads (Scharfstein and Sunderam, 2016; Wang et al., 2020). A possible explanation is that mortgages are more homogeneous and less informationally-intensive than other types of loans, which leaves less scope for monopoly rents in mortgage lending.

The next control in column (3) is the deposit-weighted county beta, which controls for local deposit market power. Its coefficient is insignificant. Thus, local deposit shares do not explain lending. Instead, it is lending shares that matter, consistent with the view that banks can raise deposits in one county and lend them in another. Moreover, conditional on the deposit-weighted beta, the lending-weighted beta exploits variation in deposit market power from *other* counties where local lenders raise deposits. This helps to rule out omitted factors such as local loan demand that might be correlated with deposit market power.

Column (4) adds direct controls for loan demand to see if they have any impact on our results. The controls are the growth in GSE lending (by both banks and nonbanks), employment, and income. GSE lending provides a proxy for local mortgage demand because it is not exposed to the deposits channel. As discussed in Section 3, during this period GSE-eligible loans were almost always sold to the GSEs in order to receive their underpriced guarantee. As a result, a contraction in bank portfolio lending is unlikely to induce an increase to GSE lending. This leaves local loan demand as the primary driver of GSE lending.

Consistent with the idea that GSE lending picks up loan demand, we find that higher GSE lending growth predicts higher bank portfolio lending growth. Similarly, higher employment and income growth also predict higher portfolio lending since they reflect a stronger local economy. Nevertheless, these controls have almost no effect on the impact of county beta, which if anything becomes more negative (-0.596) and remains highly significant. The stability of this coefficient suggests that county beta is robust to controlling for local loan demand. The results in Table 4 are thus consistent with the prediction that Fed tightening induced a contraction in bank portfolio mortgage lending via the deposits channel.

A simple way to quantify the implied aggregate impact of Fed tightening on bank portfolio lending is to multiply the coefficient in Table 4 column (4) by the average county beta from Table 1. The idea is that a county with a beta of zero is by construction not exposed to the deposits channel, hence it provides us with a counterfactual. An implicit assumption behind this calculation is that we can extrapolate our estimates to a zero-beta county even though no such county exists in our sample. If the relationship between county beta and bank portfolio lending growth is nonlinear, this could bias the calculation. Yet Figure 7 and all earlier figures show no sign of nonlinear effects within the range of the data we see. This suggests that linear extrapolation is reasonable. Using it, we find that the deposits channel induced a 32.5% contraction in bank portfolio lending ($= -0.596 \times 0.545$). In other words, bank portfolio lending would have been about a third higher if the Fed had not tightened. We discuss this type of aggregation further in Section 5.

4.3.2 PLS lending

Next, we analyze whether PLS lending offset the contraction in bank portfolio lending. Figure 8 shows a binned scatter plot of the change in the PLS lending share between 2003 and 2006 against county beta. Focusing on the PLS share implicitly controls for overall loan demand by scaling by total (non-GSE) lending. Figure 8 shows a strong positive relationship: counties with high betas see a much larger shift toward PLS. The PLS lending share rises by 14 percentage points in counties with a beta of 0.7 versus only 9 percentage points in counties with a beta of 0.4. Thus, counties with high exposure to the deposits channel saw a large shift toward PLS lending.

Column (1) of Table 5 provides a formal estimate of this relationship. Regressing the change in the PLS lending share on county beta gives a highly significant coefficient of 0.190. In the cross section, the PLS share grew by 3.5 percentage points more in a county at the 95$^{\text{th}}$ percentile of county beta (0.642) than one at the 5$^{\text{th}}$ percentile (0.459). Note that for the PLS share to rise by 3.5 percentage points from its initial mean of 49.7% (Table 1), the growth rate of PLS lending has to exceed that of bank portfolio lending by 13.9%, which is substantial. Also note that the estimated intercept is zero, hence a hypothetical unexposed county (beta of zero) is predicted to have *no* growth in the PLS share. This points to a very large effect of exposure to the deposits channel on the PLS share of lending.

Column (2) adds in the controls for county characteristics. The coefficient on county beta rises slightly to 0.205. The coefficients on the controls are small and insignificant. Column (3) adds in the additional market structure controls. The coefficient on county beta declines to 0.141, mainly because PLS lending grew more in areas that had a lot of bank portfolio lending as of 2002. This is the same reversion to the mean seen in Table 4. The coefficients on county deposit-weighted beta and the top-four lenders share are negative, which again shows that what matters for our results is deposit market power, not lending market power, and specifically the deposit market power of banks that lend in the county, not banks that raise deposits in the county. This helps to rule out omitted factors that might be correlated with local deposit market power.

Column (4) controls for loan demand using the growth of GSE lending, employment, and income as proxies. The coefficient on county beta rises to 0.204, which is very close to the univariate estimate in column (1). Hence, the effect of county beta on the change in PLS share is unlikely to be explained by cross-county differences in loan demand. Indeed, since the coefficient on county beta rises slightly from column (3) to column (4), loan demand, if anything, masks part of the substitution to PLS lending induced by exposure to the deposits channel.

As with bank portfolio lending, we can relate the cross-sectional estimate in Table 5 column (4) to the aggregate growth in PLS by multiplying the coefficient by the average county beta. This gives a predicted aggregate increase in the PLS share of 11.1 percentage points ($= 0.204 \times 0.545$). This number is close to the actual observed increase in HMDA as reported in Table 1. Thus, the deposits channel can explain close to the full increase in the PLS share in our sample. Note that this does not mean that it can explain the full increase in PLS lending. Since total mortgage lending grew rapidly during this period, PLS lending would have grown significantly even if its share had remained constant.

4.3.3 Bank versus nonbank lending

Figure 9 and Table 6 look at total bank lending, which includes both bank portfolio lending and bank PLS lending (but does not include nonbank lending). Here the controls have a more pronounced effect, as the coefficient on county beta declines in magnitude from -0.863 in the univariate specification in column (1) to -0.372 with the full set of controls in column (4). Among the controls, the nonbank share in column (3) stands out with a large positive coefficient, again consistent with mean reversion in market structure. And in column (4) employment growth has a large positive coefficient, suggesting that loan demand plays a significant role.

Total bank lending thus declines by much less than bank portfolio lending as county beta rises. This suggests that as banks contracted their portfolio lending, they made up for it in part by expanding into PLS lending. This is consistent with the deposits channel because, unlike portfolio lending, PLS lending does not require balance sheet funding.

Figure 10 and Table 7 present evidence that nonbanks contributed heavily to the shift toward PLS. Figure 10 shows that there is a strong negative relationship between the nonbank lending share and county beta. Counties with a beta of 0.4 see a one percentage point *reduction* in the nonbank share, versus a five percentage point *increase* for counties with a beta of 0.7. Column (1) of Table 7 shows that the corresponding univariate coefficient on county beta is 0.219. The nonbank share thus grew by 3.1 percentage points more in a county at the 95^{th} percentile of county beta than one at the 5^{th} percentile. The difference in growth rates between banks and nonbanks required for this shift starting at the initial mean of 26.6% (Table 1) is 15.8%. This again indicates a large shift.

The coefficient on county beta remains unchanged in column (2), in which we add controls for market size and economic conditions as of 2002. In column (3) it drops to 0.112, driven mainly by the impact of the initial nonbank share. As in the previous tables, this indicates mean reversion in market structure. Finally, column (4) adds the loan demand controls and the coefficient on county beta grows to 0.169. The implied aggregate impact is thus a 9.2 percentage point increase in the nonbank share. This requires a 47% differential growth rate between banks and nonbanks. Overall, Figure 10 and Table 7 show that the growth in PLS lending was largely driven by nonbanks.

4.3.4 Total lending

As a final outcome variable, Figure 11 and Table 8 look at total (non-GSE) lending. The univariate coefficient on county beta is a large and significant −0.477. However, it drops to −0.117 and becomes insignificant once we add in all the controls in column (4). This suggests that loan demand has a significant impact on total lending, as expected. Moreover, the controls we use are able to capture this impact. Among the controls, the nonbank share, the top-four lenders share, and employment growth have the strongest impact. Once these controls are added, high-beta counties see only a small and insignificant decline in total mortgage lending relative to low-beta counties.

The combination of a large contraction in bank portfolio lending (Table 4) and a small contraction in total lending implies a high degree of substitutability between bank portfolio lending and PLS lending. As a result of this substitutability, as the Fed raised rates between 2003 and 2006 and bank portfolio lending contracted, mortgage lending migrated to the PLS market with no significant impact on overall lending. The shift to PLS thus substantially mitigated the contractionary effect of Fed tightening on mortgage lending through the deposits channel. This had an important negative impact on the stability of the mortgage market, as stable and run-free government-insured deposit funding was replaced with run-prone capital markets funding.

4.4 Robustness

This section discusses the several robustness tests for our main results.

4.4.1 GSE lending

In our main analysis we restrict the sample to non-GSE loans. As mentioned above, the reason is that lenders overwhelmingly securitize GSE-eligible loans with the GSEs because of the underpriced subsidy. This means that GSE loans are not affected by the deposits channel, hence our focus on non-GSE loans. It is nevertheless useful to check whether this restriction has any impact on our results. For instance, it could be that GSE lending expanded in high-beta counties and this is why we see a contraction in bank portfolio lending. We note this is unlikely given the evidence in Table 4 that controlling for GSE-lending growth has no impact on our results.

We address this issue directly by analyzing substitution to GSE lending. Specifically, we re-estimate our country-level regressions (7) using GSE lending growth as the outcome variable. If GSE lending provides a substitute for bank portfolio lending, then county beta (our measure of exposure to the deposit channel) would predict GSE lending positively.

Table 9 presents the results. Column (1) finds an insignificant and economically small effect of county beta on GSE securitization growth. The point estimate is negative, which is the wrong sign if GSE lending provided a substitute for bank portfolio lending. Columns (2) to (4) add the same control variables as in Table 4 (except of course GSE lending growth).

The coefficient on county beta remains small and statistically insignificant. Table 9 thus shows that our main results are not affected by focusing on non-GSE loans.

4.4.2 Mortgage refinancing

Our main analysis focuses on purchase loans, which does not include refinancings. As discussed above, we focus on purchase loans because they require incremental deposit funding and are therefore subject to the deposits channel. To ensure robustness, we replicate our results including refinancings. Panel A of Table 10 replicates the regressions in Table 4 using the growth in the sum of purchase loans and refinancings as the outcome variable. We find that the coefficients are almost identical to the ones in the original Table 4. Panel B of Table 10 replicates Table 5 using as outcome variable the change in the PLS market share including refinancings. Again, we find that the coefficients are almost identical to the ones in the original table.

4.4.3 Risky loans

The housing boom period saw an increase in risky loans such as subprime and Alt-A loans. A potential concern is that our results may be affected by increased demand for risky loans during the boom. Specifically, if risky loan demand increased more in high-beta counties, and if banks were less willing to make such loans, then this could explain why we see an increase in the PLS lending share in high-beta counties. Note that some of our controls such as employment and income are likely to pick up these effects.

We address the issue of risky loan demand by controlling for county-level variation in the risky loan share. We measure it in two ways. The first is the HMDA application denial rate, which Mian and Sufi (2009) use as a proxy for risky loan demand. The second is the fraction of subprime borrowers proposed by Gerardi, Shapiro, and Willen (2008). It is constructed as the fraction of loans originated by subprime lenders, as classified by the U.S. Department of Housing and Urban Development (HUD). For both proxies, we control for their level in 2002 to capture initial conditions and their change from 2003 to 2006 to capture the increase in the demand for risky loans during the boom.

Panel A of Table 11 presents the results. Column (1) presents the benchmark specification with controls from column (4) in Table 4. Columns (2) and (3) add the controls for the HMDA denial rate and the subprime lending share, respectively. We find that the coefficient is largely unchanged. Column (4) controls for both the HMDA denial rate and the subprime lending share in a single specification. The coefficient is similar. Panel B estimates the corresponding regressions from Table 5. The results are again similar to the original tables. In sum, we find that our results are robust to controlling for risky loan demand.

4.4.4 Pre-trends

A potential concern with our analysis is that we are picking up trends that started before 2003. To address this issue, we examine pre-trends in loan growth, PLS market share, household income growth, and house price growth. We compute loan growth and PLS market share from HMDA data. We compute household income growth based on the Census Bureau's Small Area Income and Poverty Estimates (SAIPE) program data. We compute house price growth from house price indices created by Zillow, which covers large counties (1,582 counties). We start the pre-trend analysis in 1996 because this is the first year for which we have data on all four variables.

We add the four pre-trend variables as controls to our main specifications in Tables 4 and 5. Panel A of Table 12 presents the results with bank portfolio lending growth as the outcome variable. Column 1 is our benchmark specification corresponding to column 4 in Table 4. Column 2 adds the controls for loan growth, the change in the PLS lending share, and income growth over the years 1996 to 2002. We find that the coefficient on county-beta is almost unchanged from that in column 1. Column 3 reports the same regression as in column 1 but restricts the sample to counties with data on house price growth. Column 4 adds house price growth from 1996 to 2002 as a control variable in addition to the control variables in column 2. We find that the coefficient on county beta is almost unchanged relative to column 3. Panel B of 12 estimates the corresponding coefficients for the regressions in Table 5 and also finds that the results are robust.

4.4.5 Weighted least squares

We analyze whether our results are robust to putting more weight on large counties. Panel A of Table 13 re-estimates our preferred specification from column 4 in Table 4 using weighted least squares with various sets of weights. We use weighting by population (column 1), bank portfolio lending (column 2), total lending (column 3), and deposits (column 4). We measure the weighting variables as of 2002. The results are similar to the ones in Table 4 and robust to the alternative weighting schemes. Panel B of Table 13 re-estimates our preferred specification from Table 5 and finds robust results. This shows that our results are not driven by small counties and thus persist in the aggregate.

4.5 Recent tightening cycle

Figure 1 shows that the most recent Fed tightening cycle is associated with an uptick in the PLS securitization share similar to that in the housing boom period. This provides an opportunity for an out-of-sample test of the hypothesis that Fed tightening induces a shift to PLS through the deposits channel.

One challenge in analyzing the most recent tightening cycle is that it was preceded by a prolonged period of zero nominal interest rates. This limits the amount of variation available to estimate bank betas, making them unreliable. We address this challenge by using ex-post realized betas, which we calculate by simply dividing the change in a bank's interest expense spread by the change in the Fed funds rate. We calculate these changes between 2014 and 2017, a comparable three-year period to our main analysis. As Figure 1 shows, during this period the stance of monetary policy shifted toward tightening and the PLS share began to rise.

Table 14 reproduces the analysis in Tables 4–8 for the 2014–2017 period. Each column represents a different outcome variable: bank portfolio lending (column 1), the PLS lending share (column 2), total bank lending (column 3), the nonbank lending share (column 4), and total non-GSE lending (column 5). The controls are the same as in the strictest specification in column 4 of the original tables. The only difference is that they are computed as of 2013 for the lagged control variables and between 2014 and 2017 for the contemporaneous ones.

Column 1 of Table 14 shows that high-beta counties had significantly lower bank portfolio lending growth over 2014–2017. The coefficient is -0.675, similar to our main result in Table 4. This confirms that the deposits channel continues to influence bank portfolio lending during tightening cycles.

Column 2 shows that high-beta counties saw a significantly higher increase in the PLS share of lending. The coefficient is 0.117, which is about half the value in Table 5. The smaller magnitude is consistent with the fact that PLS lending did not grow as rapidly during this period as it did during the housing boom period. This could be because of stricter regulation of shadow banks and the financial sector, or because of reduced appetite for PLS among investors. Nevertheless, the effect is substantial, suggesting that the same mechanism that prevailed during the housing boom period was still at play during the recent tightening cycle.

Column 3 shows that total bank lending contracted less than bank portfolio lending, again implying that banks shifted toward PLS. Column 4 finds a positive but insignificant coefficient on the nonbank lending share. This is explained by the fact that nonbanks primarily originated GSE loans during this period. Finally, column (5) reports a negative but insignificant coefficient on total (non-GSE) mortgage lending, matching our result for the housing boom period in Table 8.

The analysis of the most recent tightening cycle thus confirms and extends our main results. In addition to providing external validity, this analysis also implies that the financial stability implications of monetary tightening for mortgage lending remain relevant and are not confined to the housing boom period.

5 Aggregate impact and discussion

In this section we discuss the aggregate implications of our main cross-sectional results. These results compare mortgage lending in one county to another as a function of exposure to the deposits channel. For instance, from Table 5 column (4), the PLS share of lending increased by 11.2 percentage points more in a county with an average beta (0.545) than a county with a zero beta. This number is close to the average increase in the PLS share in our sample (see column (1) in Panel D of Table 1). Since the zero-beta county is not exposed to the deposits channel, it gives us a counterfactual for how the PLS share would have evolved if the Fed had not tightened. Recall that there is no zero-beta county in our sample, hence this calculation is based on extrapolation. This could introduce bias if the underlying relationship is nonlinear. From Figure 8, there is no sign of nonlinearity within the observed range of county beta, which suggests that extrapolation is reasonable. Based on this approach, Fed tightening explains most of the observed increase in the PLS share during the housing boom.

There are two important general equilibrium assumptions behind this interpretation. The first is that it ignores other channels of monetary policy. The standard channel is the New Keynesian channel, which works through the influence of monetary policy on real interest rates due to nominal price rigidities. However, this channel is unlikely to explain our results because it affects all forms of lending equally. This is why it is often said that, as Stein (2013) puts it, monetary policy "gets in all of the cracks." One of the insights of the paper is that this is not true of the deposits channel, which mainly affects banks. As a result, monetary policy influences not only the amount of lending but also its composition. Our finding is that during the housing boom the compositional effect was large. This is important because it affects the stability of credit markets. In particular, the shift from deposit-based portfolio lending to wholesale-funded PLS lending increased the vulnerability of the mortgage market to credit freezes and runs, which precipitated the 2008 financial crisis (Hanson et al., 2015; Moreira and Savov, 2017).

The second equilibrium assumption is that there are no spillovers across counties. For instance, it is possible that some of the PLS lending that went to high-beta counties would have gone to low-beta counties instead if the Fed had not tightened. Under this view, the aggregate supply of PLS lending is fixed exogenously and Fed tightening only affects its distribution across counties. This view is difficult to rule out, but it is also difficult to square with three pieces of available evidence.

First, when bank deposits flow out due to the deposits channel, they flow into money-market funds and other "shadow banking" instruments that pay competitive rates (Xiao, 2020). For instance, shadow banking instruments such as asset-backed and financial commercial paper grew by $661 billion between 2003 and 2006. The institutions that issued these instruments (investment banks, asset-backed commercial paper conduits) invested heavily in PLS mortgages (Acharya and Schnabl, 2010; Acharya, Schnabl, and Suarez, 2013). In this way money market funds ended up financing PLS mortgages (Kacperczyk and Schnabl, 2010, 2013). Recycled deposits were thus an important funding source for PLS lending. Rather than being fixed exogenously, the PLS supply was endogenously elastic in part due to the recycling of deposits triggered by the deposits channel.

Second, the part of PLS funding that was not from recycled deposits could in principle have been used to fund other investments. As Mian and Sufi (2018) point out, PLS was one outlet for savings imbalances generated by a global savings glut (Bernanke, 2005) or extrapolative beliefs (Gennaioli and Shleifer, 2018). Under either of these theories, the supply of PLS was not fixed. Instead, it drew funding from a much larger pool of savings searching for high-return opportunities. Our findings suggest that Fed tightening and the deposits channel created such an opportunity—a "crack" to fill.

Finally, the idea that aggregate PLS lending was fixed goes against the time series evidence. As Justiniano, Primiceri, and Tambalotti (2017) and Mian and Sufi (2018) document, and as Figure 1 shows, there was an inflection point in PLS lending just as the Fed shifted to a tightening stance in mid 2003. Moreover, Figure 1 also shows that the PLS lending share has been moving closely with the stance of monetary policy in the years after the 2008 crisis. In particular, the reemergence of PLS lending between 2014 and 2017 tracks the Fed's most recent tightening cycle. The aggregate time series thus suggests that PLS lending is sensitive to Fed tightening. This is consistent with our cross-sectional results and the aggregate estimates they imply.

With this discussion in mind, we illustrate these aggregate estimates in Figure 12. The figure shows the actual (solid lines) and counterfactual (dashed lines) amounts of PLS and bank portfolio lending, as well as their sum, total (non-GSE) lending. The underlying data is the same as in Figure 1. We focus on the years 2000 to 2009, which are centered around the housing boom period from 2003 to 2006.

The figure shows that total non-GSE lending grew from $1,420 billion in 2003 to $1,839 billion in 2006 (black line with square markers). Our counterfactual estimate, which is based on column (4) in Table 8, is that this number is 6.4% smaller than it would have been if the Fed had not tightened (again, ignoring other channels). Hence, the counterfactual amount of total lending for 2006 is $1,964 billion (we use the same calculation for 2004 and 2005 for illustrative purposes). This result shows that while Fed tightening may not have been very effective in curbing total mortgage lending, it changed the composition of mortgage financing. However, it does not follow from our results that the Fed should not have tightened. Rather, as Bernanke (2010b) suggests, the implication is that other tools like tighter lending standards were needed. This is especially true given the compositional effect we highlight.

Figure 12 illustrates this compositional effect by contrasting the actual and counterfactual amounts of PLS and bank portfolio lending. The actual amount of PLS rose from $665 billion in 2003 to $1,278 billion in 2006 (red line with triangle markers), whereas the actual amount of bank portfolio lending dropped from $755 billion to $561 billion (blue line with diamond markers). To construct their counterfactual amounts, we follow the implication of column (4) in Table 5 that the PLS share would have remained constant if the Fed had not tightened. Under this counterfactual, PLS lending would have been only $919 billion in 2006. Thus, it would have still grown by as much as 38% from 2003, but this growth would have been in line with the overall mortgage market and not disproportionate. Making up the difference, the counterfactual amount of bank portfolio lending in 2006 is $1,045 billion, also up 38% from 2003. Thus, while total lending is only slightly higher in the counterfactual scenario, its composition is very different.

We note that there are other ways to map our cross-sectional results to an aggregate counterfactual. For instance, while the 11.2 percentage point increase in the PLS share implied by column (4) in Table 5 is close to the full increase in the HMDA dataset, it is smaller than the increase in Figure 1, which is based on SIFMA data. The reason is that HMDA has a somewhat broader definition of PLS. To address this issue we can also calculate a counterfactual amount of PLS based on the assumption that the PLS market share increase observed in SIFMA would have been 11.2 percentage points lower. This calculation gives us a more conservative estimate. Under this estimate, PLS would have been $1,037 billion in 2006, higher than the counterfactual amount in Figure 12 but still much lower than the actual amount. Thus, the counterfactual results are similar.

Overall, the aggregate implications of our cross-sectional results, while subject to important assumptions, suggest that Fed tightening during the housing boom played an important role in reshaping the mortgage lending market.

6 Conclusion

Between 2003 and 2006, the Fed raised rates by 4.25%. This tightening induced a large contraction in deposits, leading banks to substantially reduce their portfolio mortgage lending. Yet, the contraction did not translate into a significant reduction in total mortgage lending. Rather, an unprecedented expansion in private-label securitization (PLS), led by nonbank mortgage originators, substituted for most of the reduction in bank portfolio lending and thus largely undid the impact of Fed tightening on the mortgage lending boom.

In addition to its impact on total lending, the shift to PLS had the important effect of making the mortgage market more fragile and run-prone. Unlike GSE mortgages, which receive an effective government guarantee, or bank portfolio mortgages, which are funded with government-insured deposits, PLS mortgages do not benefit from government support. They are therefore much more exposed to the kind of wholesale funding run and market freeze that began in 2007 and was only ended by government intervention in 2008.

These findings shed light on the debate between Taylor (2007) and Bernanke (2010b). Taylor (2007) argues that more aggressive tightening would have prevented the boom. Since our point estimates are that tightening did induce a modest contraction in total mortgage lending, it is possible that much more aggressive tightening would have contracted lending enough to arrest the boom. However, this may not be an effective or even realistic course as drastically higher interest rates are likely to damage other sectors in the economy.

In this sense, our results are closer to Bernanke's (2010b) view that tighter supervision of mortgage lending standards would have been more effective. It is difficult to predict, however, whether this would have fully insulated the mortgage market from instability once government-insured deposits were replaced with capital markets funding. Ultimately, it was the willingness of investors to supply this funding that enabled the boom and limited the effectiveness of monetary policy.

Since the financial crisis, regulators have favored stable funding sources such as insured deposits. Our findings suggest that this helps to make monetary policy more effective in influencing mortgage lending. Nevertheless, as the Fed once again tightened after 2014, a similar dynamic to the housing boom period played out on a smaller scale. As deposit growth slowed, banks pulled back on portfolio lending and PLS reemerged to fill the gap. This makes the lessons of the housing boom a useful guide for future policy.

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Table 1
Summary statistics.

This table provides summary statistics at the branch, bank, and county levels. All panels provide breakdowns by high and low beta partitioned by the median beta for the respective sample. Panel A presents branch-level summary statistics on branch beta and the change in deposit spread by product (in percentage points) from January 2003 to December 2006. The data are from Ratewatch. Panel B presents branch-level summary statistics on branch size (in millions of dollars) and deposit growth (in percent) from June 2003 to June 2007. The data are from the FDIC. Panel C presents bank-level summary statistics on bank beta and the change in deposit spread (in percentage points), the natural logarithm-transformed growth rate of core deposits, the (dollar-difference) percentage growth in core deposits, real estate loans, commercial and industrial (C&I) loans, personal loans, cash, securities, large time deposits, and wholesale funding from January 2003 to December 2006. The data are from the U.S. Call Reports. Panel D presents county-level summary statistics on county beta and the growth in bank portfolio lending, total bank lending, total lending (in percent) and the change in the private-label market share and the bank market share (in percentage points) from 2003 to 2006. All lending measures exclude GSE lending except for "Δ Log Bank GSE lending" and "Δ Log Nonbank GSE lending." The data are based on mortgage originations reported under HMDA. The table also reports county characteristics measured in 2002. The data are from the Bureau of Labor Statistics and the Census Bureau.

Panel A: Branch-level characteristics (rates)

	All branches		Low beta	High beta	T-test
	Mean	St.Dev.	Mean	Mean	Sig. Level
	(1)	(2)	(3)	(4)	(5)
Branch beta	0.581	(0.077)	0.523	0.640	***
Δ Savings deposit spread	3.374	(0.992)	3.226	3.522	***
Δ Small time deposit spread	1.709	(0.664)	1.613	1.806	***
Δ Interest checking deposit spread	4.044	(0.386)	3.988	4.100	***
Observations	5,501		2,750	2,751	5,501

Panel B: Branch-level characteristics (amounts)

	All branches		Low beta	High beta	T-test
	Mean	St.Dev.	Mean	Mean	Sig. Level
	(1)	(2)	(3)	(4)	(5)
Branch beta	0.590	(0.088)	0.525	0.656	***
Deposit growth	0.234	(0.468)	0.262	0.205	***
Deposits (mill. $; 2007)	76.325	(600.329)	66.673	85.938	***
Observations	58,546		29,215	29,331	58,546

Table 1—continued.

Panel C: Bank characteristics

	All banks		Low beta	High beta	T-test
	Mean	St.Dev.	Mean	Mean	Sig. Level
	(1)	(2)	(3)	(4)	(5)
Bank beta	0.626	(0.094)	0.556	0.695	***
Δ Core deposit spread	3.236	(0.690)	3.015	3.457	***
Δ Core deposits/Core deposits	0.246	(0.314)	0.298	0.195	***
Δ Real estate loans/Core deposits	0.306	(0.333)	0.360	0.253	***
Δ C&I loans/Core deposits	0.049	(0.084)	0.058	0.040	***
Δ Personal loans/Core deposits	−0.001	(0.035)	−0.001	−0.001	
Δ Cash/Core deposits	0.009	(0.086)	0.016	0.001	***
Δ Securities/Core deposits	0.050	(0.145)	0.066	0.034	***
Δ Large time/Core deposits	0.125	(0.151)	0.150	0.099	***
Δ Wholesale funding/Core deposits	0.040	(0.086)	0.045	0.034	***
Observations	6,463		3,231	3,232	6,463

Panel D: County characteristics

	All counties				
	Mean	St.Dev.	Mean	Mean	Sig. Level
	(1)	(2)	(3)	(4)	(5)
County beta	0.545	(0.056)	0.501	0.588	***
Δ Bank portfolio lending	0.126	(0.505)	0.155	0.098	***
Δ Bank lending	0.404	(0.426)	0.444	0.364	***
Δ Total lending	0.428	(0.365)	0.444	0.411	**
Δ PLS lending share	0.114	(0.144)	0.105	0.123	***
Δ Nonbank lending share	0.019	(0.129)	0.005	0.032	***
Log total lending (2002)	5.109	(1.871)	5.282	4.937	***
Log employment (2002)	9.209	(1.523)	9.349	9.069	***
Log median income (2002)	10.464	(0.241)	10.461	10.466	
Log bank portfolio lending (2002)	4.356	(1.817)	4.473	4.239	***
PLS lending share (2002)	0.497	(0.173)	0.525	0.468	***
Nonbank lending share (2002)	0.266	(0.150)	0.295	0.236	***
County deposit-weighted beta	0.578	(0.069)	0.550	0.606	***
Top 4 lenders share	0.505	(0.172)	0.479	0.531	***
Δ Bank GSE lending	−0.086	(0.515)	−0.095	−0.077	
Δ Nonbank GSE lending	−0.146	(0.709)	−0.138	−0.153	
Δ Employment	0.039	(0.082)	0.042	0.035	**
Δ Income	0.096	(0.045)	0.095	0.097	
Observations	3,033		1,516	1,517	3,033

Table 2
Deposits channel at the branch-level.

This table examines the deposits channel at the branch level. Panel A presents regressions of the branch-level change in the deposit spread from January 2003 to December 2006 on the branch beta. The branch beta is the equal-weighted average of branch-product betas estimated for the three main deposit products (savings, small time, and interest checking) for all branches in a county using data before 2002. The outcome variables are the change in the deposit spread for savings deposits (column (1)), small time deposits (column (2)), and interest checking deposits (column (3)). Panel B presents regressions of the branch-level growth in deposits from June 2003 to June 2007 on the branch beta. Bank FE denotes whether the regression includes controls for bank fixed effects. The standard errors are clustered at the county level.

Panel A: Deposit spreads			
	Savings (1)	Time (2)	Checking (3)
Branch beta	1.801***	1.056***	0.819***
	(0.211)	(0.151)	(0.080)
Observations	5,194	5,462	5,376
R^2	0.019	0.015	0.027

Panel B: Deposit growth		
	(1)	(2)
Branch beta	−0.321***	−0.210***
	(0.052)	(0.060)
Bank FE	No	Yes
Observations	58,546	56,347
R^2	0.004	0.186

Table 3

Deposits channel at the bank level.

This table presents regressions of the growth in assets (loans, securities, and cash) and liabilities (deposits and equity) on bank beta and core deposits growth. Bank beta is the average spread beta estimated over the years 1986 to 2002. The two panels correspond to two different estimation techniques: reduced form estimation and two-stage least squares (2SLS). Panel A includes the reduced form estimates of regressions of growth variables for core deposits (column (1)), real estate (RE) loans (column (2)), commercial and industrial (C&I) loans (column (3)), personal loans (column (4)), cash and Fed funds repos (column (5)), securities (column (6)), large time deposits (i.e., time deposits greater than $100,000; column (7)), and wholesale deposits (column (8)) on bank beta. Panel B presents the second stage estimates from 2SLS regressions (corresponding to the first-stage regressions on bank beta in Panel A) for these all of these variables (except core deposits growth) on core deposits growth. The growth variables are calculated as dollar-difference changes from 2003 to 2006 divided by 2003 core deposits. Bank betas are winsorized at the 1% level while the growth variables are each winsorized at the 5% level. All regressions include controls for the natural logarithm of total bank assets, the equity ratio, and the loan-to-assets ratio as of December 2002. Standard errors are robust.

Panel A: Reduced form estimation

		Assets					Liabilities	
	$\frac{\Delta\text{Core dep.}}{\text{Core dep.}}$	$\frac{\Delta\text{RE loans}}{\text{Core dep.}}$	$\frac{\Delta\text{C\&I loans}}{\text{Core dep.}}$	$\frac{\Delta\text{Personal loans}}{\text{Core dep.}}$	$\frac{\Delta\text{Cash}}{\text{Core dep.}}$	$\frac{\Delta\text{Securities}}{\text{Core dep.}}$	$\frac{\Delta\text{Large time}}{\text{Core dep.}}$	$\frac{\Delta\text{Wholesale}}{\text{Core dep.}}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Bank beta	−0.385***	−0.364***	−0.084***	−0.007	−0.078***	−0.114***	−0.270***	−0.019
	(0.052)	(0.054)	(0.014)	(0.005)	(0.014)	(0.023)	(0.025)	(0.014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,441	6,431	6,441	6,431	6,441	6,441	6,431	6,441
R^2	0.104	0.164	0.037	0.004	0.026	0.023	0.109	0.049

Panel B: 2SLS estimation

	Assets					Liabilities	
	$\frac{\Delta\text{RE loans}}{\text{Core dep.}}$	$\frac{\Delta\text{C\&I loans}}{\text{Core dep.}}$	$\frac{\Delta\text{Personal loans}}{\text{Core dep.}}$	$\frac{\Delta\text{Cash}}{\text{Core dep.}}$	$\frac{\Delta\text{Securities}}{\text{Core dep.}}$	$\frac{\Delta\text{Large time}}{\text{Core dep.}}$	$\frac{\Delta\text{Wholesale}}{\text{Core dep.}}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\frac{\Delta\widehat{\text{Core dep.}}}{\text{Core dep.}}$	0.944***	0.218***	0.019	0.202***	0.295***	0.700***	0.050
	(0.099)	(0.032)	(0.013)	(0.037)	(0.057)	(0.086)	(0.036)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,431	6,441	6,431	6,441	6,441	6,431	6,441

Table 4
Bank portfolio lending.

This table presents regressions of the growth in bank portfolio lending from 2003 to 2006 on county beta. County beta is the average beta of all banks lending in the county, weighted by 2002 lending shares. Column (2) adds controls for the size of the mortgage market (total lending, employment, and median income). Column (3) adds controls for the structure of the mortgage market (bank portfolio lending, PLS lending share, nonbank lending share, county-weighted deposit beta, and top four lenders share). The county deposit-weighted beta is the average beta of all banks that raise deposits in a county, weighted by 2002 deposit shares. The top four lenders share is the combined share of the top four lenders in 2002. Column (4) adds controls for loan demand (Bank GSE lending growth, nonbank GSE lending growth, employment growth and income growth). Standard errors are robust.

	Δ Bank portfolio lending			
	(1)	(2)	(3)	(4)
County beta	−0.748***	−0.827***	−0.522***	−0.596***
	(0.164)	(0.159)	(0.177)	(0.177)
Log total lending (2002)		−0.134***	0.094	0.101
		(0.014)	(0.094)	(0.092)
Log employment (2002)		0.073***	0.088***	0.102***
		(0.016)	(0.016)	(0.016)
Log median income (2002)		0.165***	0.065	0.008
		(0.046)	(0.046)	(0.045)
Log bank portfolio lending (2002)			−0.263***	−0.269***
			(0.095)	(0.093)
PLS lending share (2002)			0.134	0.084
			(0.215)	(0.215)
Nonbank lending share (2002)			0.036	−0.019
			(0.083)	(0.082)
County deposit-weighted beta			0.177	0.352**
			(0.149)	(0.146)
Top 4 lenders share			−0.285***	−0.416***
			(0.077)	(0.076)
Δ Bank GSE lending				0.120***
				(0.017)
Δ Nonbank GSE lending				0.038***
				(0.012)
Δ Employment				0.427***
				(0.111)
Δ Income				0.149
				(0.186)
Constant	0.533***	−1.137**	−0.438	0.038
	(0.090)	(0.475)	(0.481)	(0.472)
Observations	3,000	2,999	2,999	2,751
R^2	0.007	0.073	0.139	0.177

Table 5
PLS lending share.

This table presents regressions of the change in the PLS lending share from 2003 to 2006 on the county beta. PLS lending share is the change in market share of PLS from 2003 to 2006. The county beta is the average beta of all banks lending in the county, weighted by their 2002 lending shares. The control variables in columns (2) to (4) are the same as those in Table 4. Standard errors are robust.

	Δ PLS lending share			
	(1)	(2)	(3)	(4)
County beta	0.190***	0.205***	0.141***	0.204***
	(0.047)	(0.047)	(0.051)	(0.047)
Log total lending (2002)		0.003	−0.042	−0.035
		(0.004)	(0.027)	(0.024)
Log employment (2002)		0.006	0.009*	0.013***
		(0.005)	(0.005)	(0.004)
Log median income (2002)		−0.026*	0.015	0.025**
		(0.013)	(0.013)	(0.012)
Log bank portfolio lending (2002)			0.042	0.027
			(0.027)	(0.025)
PLS lending share (2002)			−0.206***	−0.280***
			(0.061)	(0.056)
Nonbank lending share (2002)			0.009	0.049**
			(0.024)	(0.022)
County deposit-weighted beta			−0.094**	−0.167***
			(0.043)	(0.038)
Top 4 lenders share			−0.067***	−0.002
			(0.022)	(0.020)
Δ Bank GSE lending				−0.025***
				(0.005)
Δ Nonbank GSE lending				−0.002
				(0.003)
Δ Employment				0.117***
				(0.029)
Δ Income				−0.074
				(0.049)
Constant	0.011	0.206	0.028	−0.093
	(0.025)	(0.139)	(0.138)	(0.124)
Observations	3,028	3,027	3,027	2,755
R^2	0.005	0.012	0.120	0.188

Table 6
Total bank lending.

This table presents regressions of the total bank lending growth from 2003 to 2006 on the county beta. Total bank lending is the sum of bank portfolio lending and bank PLS lending. The county beta is the average beta of all banks lending in the county, weighted by their 2002 lending shares. The control variables in columns (2) to (4) are the same as those in Table 4. Standard errors are robust.

	Δ Bank lending			
	(1)	(2)	(3)	(4)
County beta	−0.863***	−0.925***	−0.412***	−0.372***
	(0.137)	(0.133)	(0.145)	(0.144)
Log total lending (2002)		−0.139***	−0.146*	−0.139*
		(0.012)	(0.077)	(0.075)
Log employment (2002)		0.102***	0.123***	0.147***
		(0.013)	(0.013)	(0.013)
Log median income (2002)		0.156***	0.160***	0.093**
		(0.038)	(0.038)	(0.036)
Log bank portfolio lending (2002)			−0.044	−0.066
			(0.077)	(0.075)
PLS lending share (2002)			0.108	0.005
			(0.175)	(0.174)
Nonbank lending share (2002)			0.665***	0.689***
			(0.068)	(0.066)
County deposit-weighted beta			−0.053	−0.024
			(0.122)	(0.118)
Top 4 lenders share			−0.276***	−0.308***
			(0.063)	(0.062)
Δ Bank GSE lending				0.073***
				(0.014)
Δ Nonbank GSE lending				0.016*
				(0.010)
Δ Employment				0.695***
				(0.090)
Δ Income				0.164
				(0.151)
Constant	0.874***	−0.953**	−1.300***	−0.769**
	(0.075)	(0.398)	(0.395)	(0.382)
Observations	3,020	3,019	3,019	2,754
R^2	0.013	0.081	0.177	0.238

Table 7
Nonbank lending share.

This table presents regressions of the change in the nonbank lending share from 2003 to 2006 on the county beta. Nonbank lending share is the change in market share of nonbanks from 2003 to 2006. The county beta is the average beta of all banks lending in the county, weighted by their 2002 lending shares. The control variables in columns (2) to (4) are the same as those in Table 4. Standard errors are robust.

	Δ Nonbank lending share			
	(1)	(2)	(3)	(4)
County beta	0.219***	0.219***	0.112**	0.169***
	(0.041)	(0.041)	(0.045)	(0.043)
Log total lending (2002)		0.014***	0.020	0.015
		(0.004)	(0.024)	(0.022)
Log employment (2002)		−0.009**	−0.010**	−0.006
		(0.004)	(0.004)	(0.004)
Log median income (2002)		0.019	−0.003	0.000
		(0.012)	(0.012)	(0.011)
Log bank portfolio lending (2002)			−0.002	−0.002
			(0.024)	(0.023)
PLS lending share (2002)			0.046	0.008
			(0.054)	(0.052)
Nonbank lending share (2002)			−0.323***	−0.300***
			(0.021)	(0.020)
County deposit-weighted beta			−0.014	−0.044
			(0.038)	(0.036)
Top 4 lenders share			−0.054***	−0.042**
			(0.019)	(0.019)
Δ Bank GSE lending				−0.021***
				(0.004)
Δ Nonbank GSE lending				0.004
				(0.003)
Δ Employment				0.070***
				(0.027)
Δ Income				−0.015
				(0.045)
Constant	−0.101***	−0.289**	0.091	0.035
	(0.023)	(0.123)	(0.123)	(0.115)
Observations	3,028	3,027	3,027	2,755
R^2	0.009	0.027	0.124	0.161

Table 8
Total lending.

This table presents regressions of the total non-GSE lending growth from 2003 to 2006 on the county beta. Total non-GSE lending is the sum of bank portfolio lending, bank and nonbank PLS lending, and bank lending. The county beta is the average beta of all banks lending in the county, weighted by their 2002 lending shares. The control variables in columns (2) to (4) are the same as those in Table 4. Standard errors are robust.

	Δ Total lending			
	(1)	(2)	(3)	(4)
County beta	−0.477***	−0.547***	−0.208	−0.117
	(0.118)	(0.114)	(0.128)	(0.124)
Log total lending (2002)		−0.127***	−0.166**	−0.170***
		(0.010)	(0.068)	(0.064)
Log employment (2002)		0.095***	0.115***	0.137***
		(0.012)	(0.012)	(0.011)
Log median income (2002)		0.210***	0.186***	0.095***
		(0.033)	(0.033)	(0.031)
Log bank portfolio lending (2002)			−0.006	−0.017
			(0.068)	(0.065)
PLS lending share (2002)			0.223	0.140
			(0.154)	(0.149)
Nonbank lending share (2002)			0.182***	0.209***
			(0.059)	(0.057)
County deposit-weighted beta			−0.075	−0.080
			(0.107)	(0.101)
Top 4 lenders share			−0.373***	−0.392***
			(0.055)	(0.053)
Δ Bank GSE lending				0.036***
				(0.012)
Δ Nonbank GSE lending				0.022***
				(0.008)
Δ Employment				0.813***
				(0.077)
Δ Income				0.196
				(0.130)
Constant	0.687***	−1.709***	−1.519***	−0.751**
	(0.065)	(0.341)	(0.347)	(0.329)
Observations	3,028	3,027	3,027	2,755
R^2	0.005	0.075	0.126	0.186

Table 9
GSE lending.

This table presents regressions of the total GSE lending growth from 2003 to 2006 on the county beta. The county beta is the average beta of all banks lending in the county, weighted by their 2002 lending shares. The control variables in Columns (2) to (4) are the same as those in Table 4 (except for Bank GSE and Nonbank GSE lending growth in column (4)). Standard errors are robust.

	Δ Total GSE lending			
	(1)	(2)	(3)	(4)
County beta	−0.199	−0.213	0.091	0.126
	(0.150)	(0.142)	(0.163)	(0.162)
Log total lending (2002)		−0.068***	0.047	0.048
		(0.012)	(0.086)	(0.085)
Log employment (2002)		−0.001	−0.005	0.016
		(0.014)	(0.015)	(0.015)
Log median income (2002)		−0.194***	−0.211***	−0.260***
		(0.040)	(0.042)	(0.042)
Log bank portfolio lending (2002)			−0.115	−0.134
			(0.086)	(0.086)
PLS lending share (2002)			−0.024	−0.073
			(0.196)	(0.195)
Nonbank lending share (2002)			−0.059	−0.088
			(0.075)	(0.075)
County deposit-weighted beta			−0.469***	−0.406***
			(0.136)	(0.135)
Top 4 lenders share			0.075	0.028
			(0.070)	(0.070)
Δ Employment				0.676***
				(0.105)
Δ Income				−0.556***
				(0.178)
Constant	0.009	2.400***	2.634***	3.062***
	(0.082)	(0.420)	(0.438)	(0.439)
Observations	2,992	2,991	2,991	2,991
R^2	0.001	0.118	0.128	0.142

Table 10
Home purchases and refinancing.

This table presents regressions that include refinancings when computing lending growth. Panel A presents the same specifications as in Table 4 using the growth in the sum of bank portfolio lending and refinancings as the outcome variable. Panel B presents the same specifications as in Table 5 using the change in the PLS market share as the outcome variable. The PLS share is computed from the sum of purchase loans and refinancings. The coefficients on the control variables are not shown.

Panel A: Bank portfolio lending

	Δ Bank portfolio lending			
	(1)	(2)	(3)	(4)
County beta	−0.732***	−0.725***	−0.620***	−0.703***
	(0.133)	(0.126)	(0.140)	(0.138)
Characteristics controls		Yes	Yes	Yes
Market structure controls			Yes	Yes
Δ Demand controls				Yes
Observations	3,031	3,030	3,030	2,922
R^2	0.010	0.117	0.166	0.205

Panel B: PLS lending share

	Δ PLS lending share			
	(1)	(2)	(3)	(4)
County beta	0.139***	0.161***	0.150***	0.165***
	(0.037)	(0.037)	(0.040)	(0.039)
Characteristics controls		Yes	Yes	Yes
Market structure controls			Yes	Yes
Δ Demand controls				Yes
Observations	3,033	3,032	3,032	2,923
R^2	0.005	0.043	0.148	0.166

Table 11
Risky loan analysis.

This table presents regressions that control for the risky loan share. Column (1) of Panel A presents the benchmark specification from column (4) in Table 4. Columns (2) adds controls for the HMDA denial rate. The HMDA denial rate is computed as the number of denials divided by the sum of: denials, originations, and "approved not accepted." Column (3) adds controls for the subprime lending share. Subprime lender share is computed as the number of non-GSE loans originated by subprime lenders divided by the total number of non-GSE originations. The list of subprime lenders is from the United States Department of Housing and Urban Development (HUD). Column (4) adds controls for both the HMDA denial rate and the subprime lending share. Panel B presents the same specifications using PLS market share as the outcome variable. The coefficients on the other control variables are not shown.

Panel A: Bank portfolio lending

	Δ Bank portfolio lending			
	(1)	(2)	(3)	(4)
County beta	−0.596***	−0.613***	−0.493***	−0.450***
	(0.177)	(0.174)	(0.176)	(0.174)
Δ HMDA denial rate		−1.834***		−1.693***
		(0.148)		(0.146)
HMDA denial rate (2002)		−0.628***		−0.387***
		(0.119)		(0.121)
Δ Subprime lender share			−1.390***	−1.254***
			(0.123)	(0.122)
Subprime lender share (2002)			−0.685***	−0.526***
			(0.138)	(0.138)
Controls	Yes	Yes	Yes	Yes
Observations	2,751	2,727	2,751	2,727
R^2	0.177	0.224	0.215	0.253

Panel B: PLS lending share

	Δ PLS lending share			
	(1)	(2)	(3)	(4)
County beta	0.204***	0.199***	0.176***	0.160***
	(0.047)	(0.046)	(0.046)	(0.045)
Δ HMDA denial rate		0.197***		0.141***
		(0.039)		(0.038)
HMDA denial rate (2002)		−0.063**		−0.158***
		(0.032)		(0.031)
Δ Subprime lender share			0.409***	0.429***
			(0.032)	(0.031)
Subprime lender share (2002)			0.197***	0.249***
			(0.036)	(0.036)
Controls	Yes	Yes	Yes	Yes
Observations	2,755	2,730	2,755	2,730
R^2	0.188	0.210	0.236	0.264

Table 12
Pre-trend analysis.

This table presents regressions that control for pre-trends in lending growth, housing prices, and median household income. Column (1) of Panel A presents the benchmark specification from column (4) in Table 4. Column (2) adds controls for the growth in total lending from 1996 to 2002, the change in the PLS lending share from 1996 to 2002, and the growth in median household income from 1996 to 2002. Column (3) restricts the sample to counties with Zillow housing price data (1,582 counties). Column (4) adds the controls from column (2) as well as controls for the growth in the Zillow house price from 1996 to 2002. Panel B presents the same specifications as in Table 5 using PLS market share as the outcome variable. The coefficients on the other control variables are not shown.

Panel A: Bank portfolio lending

	Δ Bank portfolio lending			
	(1)	(2)	(3)	(4)
County beta	−0.596***	−0.662***	−0.739***	−0.758***
	(0.177)	(0.180)	(0.214)	(0.218)
Δ Total lending (96–02)		−0.002		−0.013
		(0.016)		(0.020)
Δ PLS lending share (96–02)		0.125***		0.047
		(0.046)		(0.055)
Δ Income (96–02)		0.012		0.086
		(0.147)		(0.159)
Δ Home value (96–02)				−0.024
				(0.046)
Controls	Yes	Yes	Yes	Yes
Observations	2,751	2,750	1,582	1,582
R^2	0.177	0.179	0.268	0.269

Panel B: PLS lending share

	Δ PLS lending share			
	(1)	(2)	(3)	(4)
County beta	0.204***	0.225***	0.153***	0.169***
	(0.047)	(0.047)	(0.055)	(0.056)
Δ Total lending (96–02)		0.012***		0.005
		(0.004)		(0.005)
Δ PLS lending share (96–02)		−0.019		−0.022
		(0.012)		(0.014)
Δ Income (96–02)		0.025		0.005
		(0.039)		(0.041)
Δ Home value (96–02)				0.010
				(0.012)
Controls	Yes	Yes	Yes	Yes
Observations	2,755	2,754	1,582	1,582
R^2	0.188	0.192	0.297	0.299

Table 13
Weighted least squares.

This table presents regressions weighted by population, loan market size, and deposits. Panel A presents the benchmark specification from column (4) in Table 4 using each of the following variables as weights: population (column (1)), bank portfolio lending (column (2)), total lending (column (3)), and deposits (column (4)) as of 2002. Panel B presents the same specifications using PLS market share as the outcome variable. The coefficients on the other control variables are not shown.

Panel A: Bank portfolio lending

	Δ Bank portfolio lending			
	Population weights (1)	Bank portfolio lending weights (2)	Total lending weights (3)	Deposits weights (4)
County beta	−0.588***	−0.398***	−0.530***	−0.780***
	(0.133)	(0.131)	(0.127)	(0.123)
Controls	Yes	Yes	Yes	Yes
Observations	2,750	2,751	2,751	2,751
R^2	0.424	0.459	0.544	0.443

Panel B: PLS lending share

	Δ PLS lending share			
	Population weights (1)	Bank portfolio lending weights (2)	Total lending weights (3)	Deposits weights (4)
County beta	0.206***	0.207***	0.222***	0.178***
	(0.032)	(0.032)	(0.030)	(0.030)
Controls	Yes	Yes	Yes	Yes
Observations	2,754	2,755	2,755	2,755
R^2	0.368	0.434	0.456	0.395

Table 14
2014–2017 analysis.

This table presents regressions of the growth in bank portfolio lending, PLS lending share, bank lending, nonbank lending share, and total lending from 2014 to 2017 on the county beta. The county beta is the average realized beta of all banks lending in the county, weighted by their 2013 lending shares. Realized betas are calculated as the difference between year-end 2017 and 2014 interest expense rates divided by the difference in year-end 2017 and 2014 Fed funds rate. Realized betas are winsorized at the 1% level. All models include as controls the 2013 levels of log total lending, log employment, log median income, log bank portfolio lending, PLS lending share, nonbank lending share, top four lenders share, and realized county deposit-weighted beta. Further controls include the 2014–2017 county-level growth in bank GSE lending, nonbank GSE lending, employment, and income. The coefficients on the control variables are omitted for compactness.

	Δ Bank portfolio lending	Δ PLS lending share	Δ Total bank lending	Δ Nonbank lending share	Δ Total lending
	(1)	(2)	(3)	(4)	(5)
County beta	−0.675***	0.117***	−0.323***	0.062	−0.176*
	(0.136)	(0.038)	(0.115)	(0.039)	(0.096)
Controls	Yes	Yes	Yes	Yes	Yes
Observations	2,727	2,746	2,742	2,746	2,746
R^2	0.095	0.045	0.074	0.048	0.116

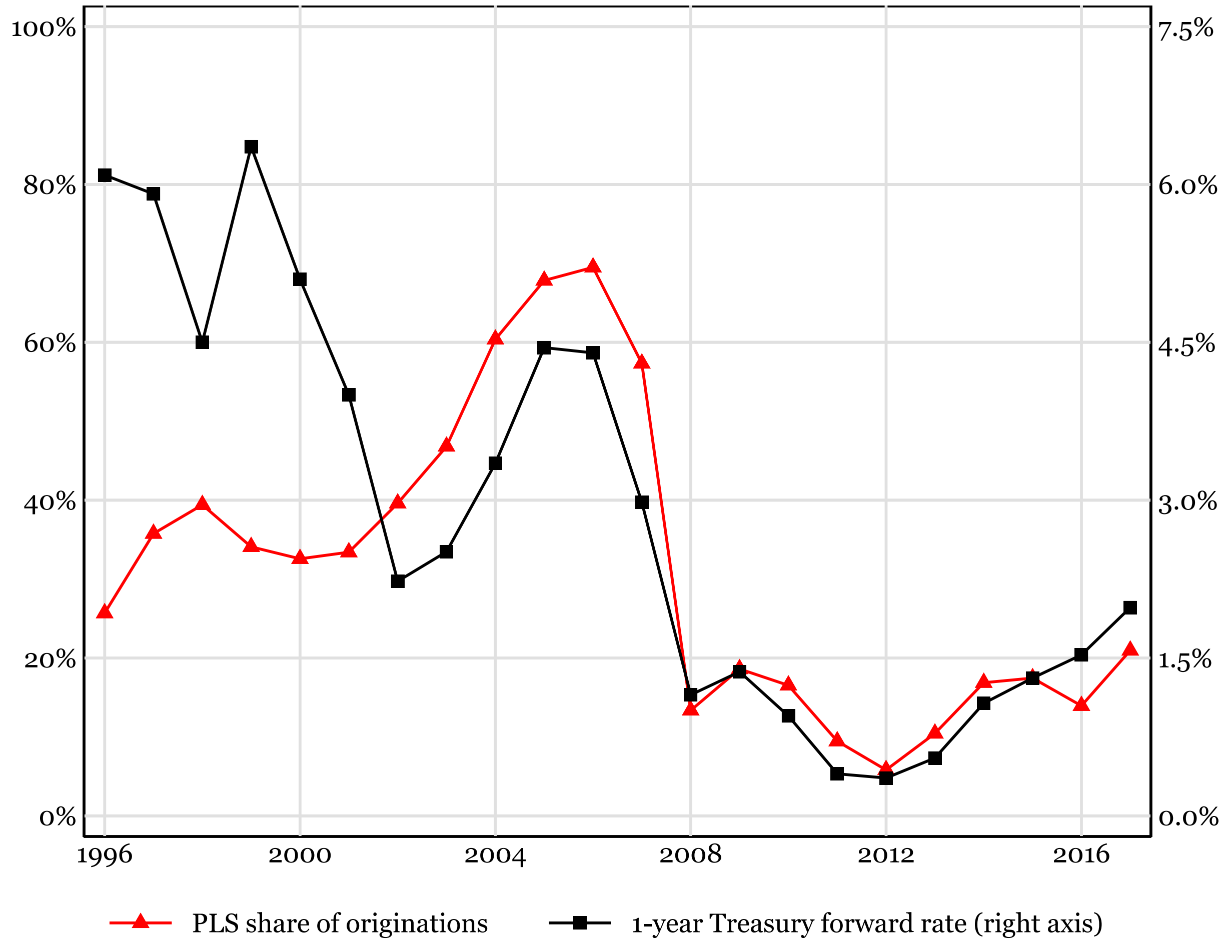

Fig. 1. Private-label securitization and monetary policy. The figure plots the private-label securitization (PLS) share of originations against the one-year Treasury forward rate, a measure of the stance of monetary policy. The PLS share is computed as the ratio of PLS originations divided by the sum of PLS originations and bank portfolio loans. GSE originations are excluded to focus on the shift from portfolio loans to PLS. PLS originations are from the Securities Industry and Financial Markets Association (SIFMA). Portfolio loans are from the Home Mortgage Disclosure Act (HMDA) dataset. The one-year forward rate is from the Federal Reserve. The sample is from 1996 to 2017.

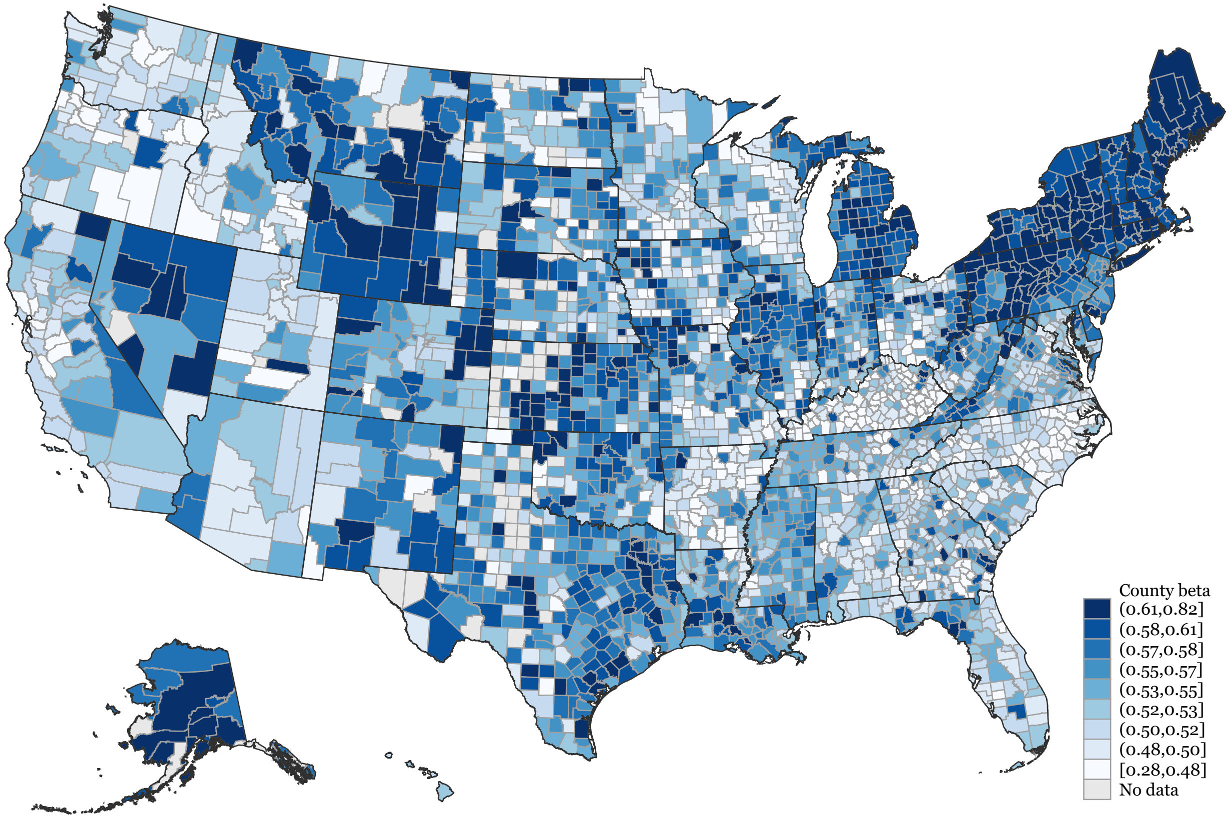

Fig. 2. County betas. This figure shows the map of county betas. The county beta is the average bank beta of all banks lending in the county, weighted by 2002 lending shares. The bank beta is estimated separately for each bank and captures the sensitivity of the deposit spread to changes in the nominal interest rate using quarterly Call Reports data from 1986 to 2002.

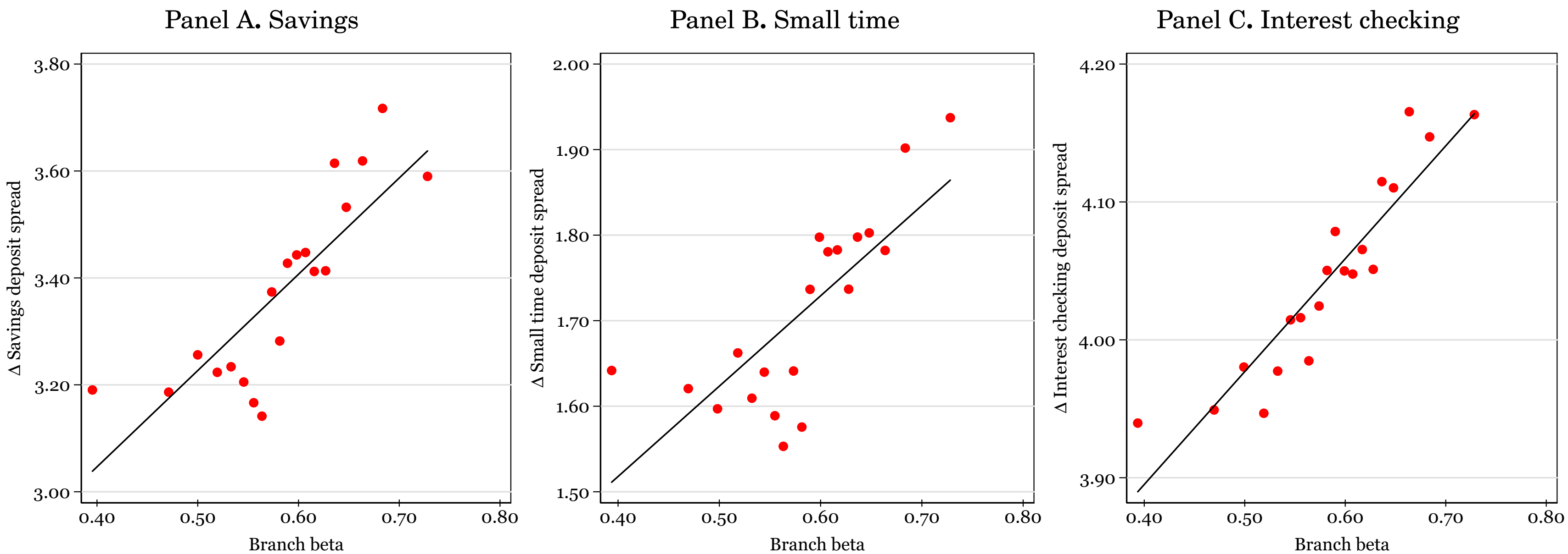

Fig. 3. Branch-level deposit spreads. This figure shows binned scatter plots of the change in deposit spreads from January 2003 to December 2006 against the branch beta. The branch beta is the equal-weighted average of branch-product betas estimated for the three main deposit products (i.e., savings, small time, and interest checking) for all branches in a county over the years 1997 to 2002. Branches are sorted into 20 bins based on their branch beta. The figure plots the average change in the deposits spread of savings deposits (Panel A), small time deposits (Panel B), and interest checking deposits (Panel C) against the average branch beta in each bin.

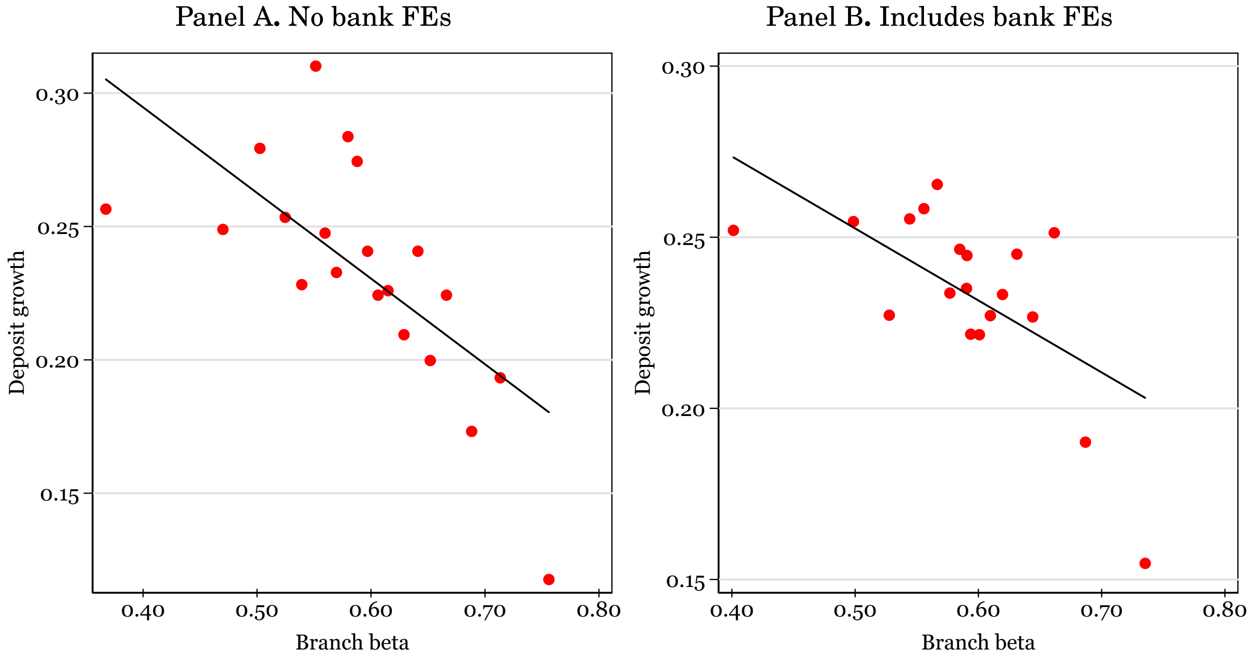

Fig. 4. Branch-level deposit growth. This figure shows binned scatter plots of deposit growth against the branch beta. The branch beta is the same as in Figure 3. Branches are sorted into 20 bins based on their branch beta. Panel A plots the average deposit growth against the average branch beta in each bin. Panel B plots the same relationship plotted in Panel A after controlling for bank fixed effects.

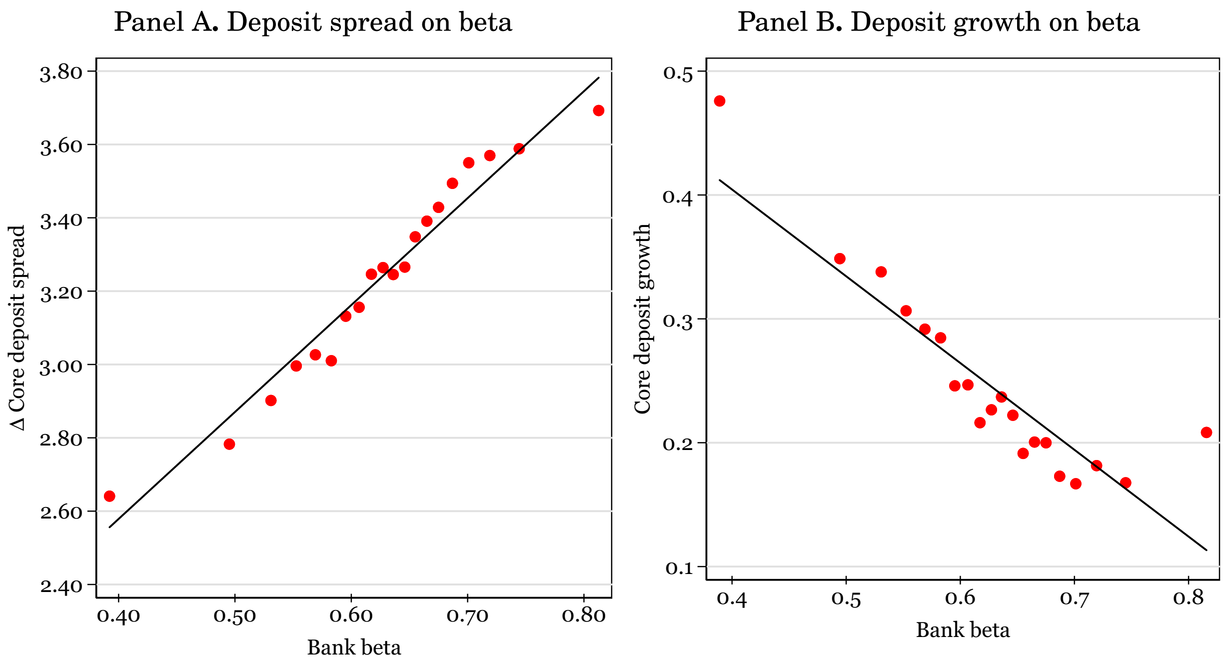

Fig. 5. Bank-level deposit spreads and deposit growth. This figure shows binned scatter plots of deposit spreads and deposit growth against bank beta. The bank beta is estimated separately for each bank and captures the sensitivity of the deposit spread to changes in the nominal interest rate using quarterly call report data from 1986 to 2002. Banks are sorted into 20 bins based on their bank beta. The figure plots averages by bin. Panel A shows the change in the core deposit spread from January 2003 to December 2006 against the bank beta. Panel B shows core deposit growth from January 2003 to December 2006 against the bank beta. Core deposit growth is measured in dollar differences from 2003 to 2006 and scaled by 2003 core deposits. Bank betas are winsorized at the 1% level; core deposit spread and core deposit growth are both winsorized at the 5% level.

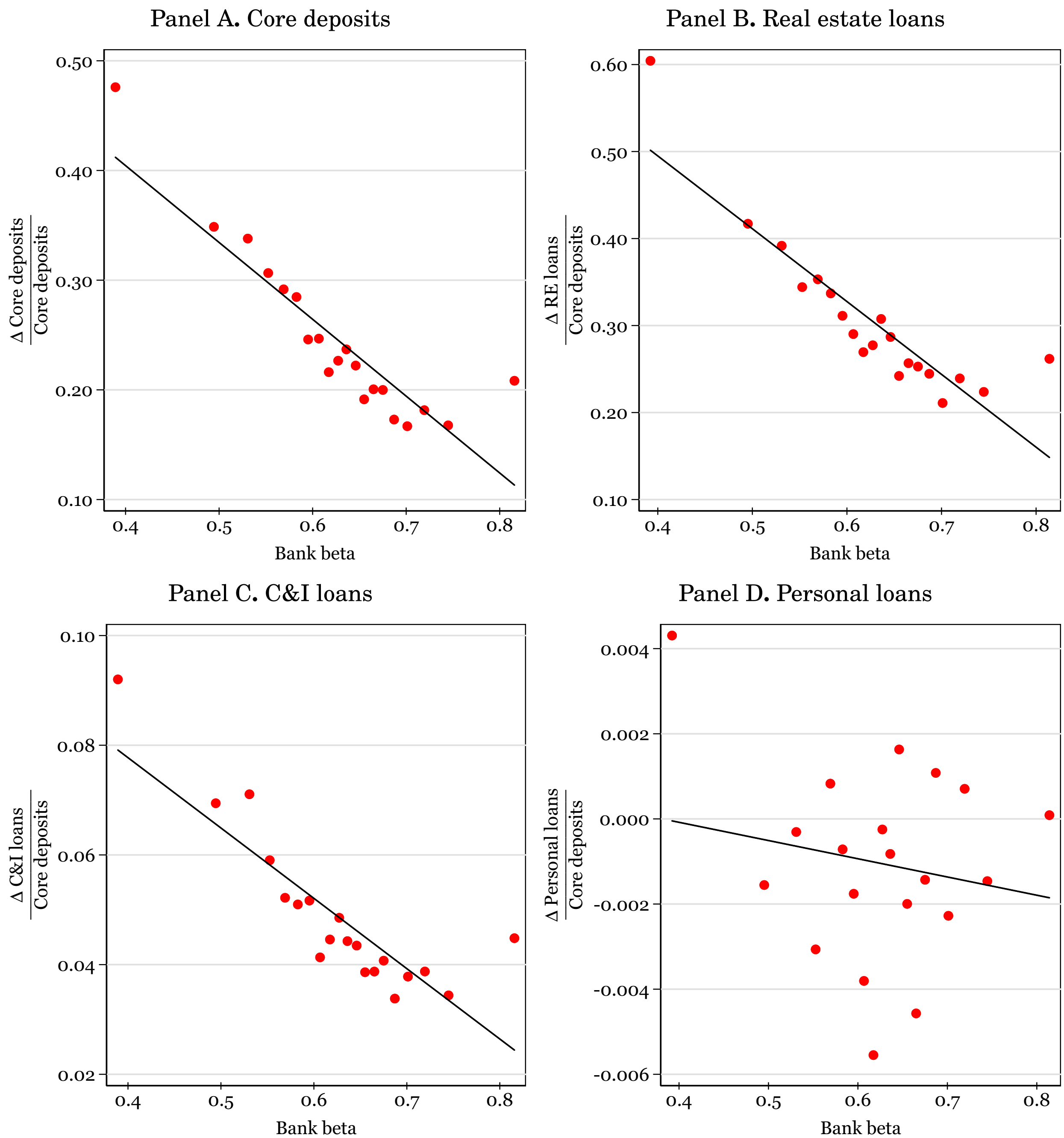

Fig. 6. Bank-level assets and liabilities growth. This figure shows binned scatter plots of bank core deposits (Panel A), real estate (RE) loans (Panel B), commercial and industrial (C&I) loans (Panel C), personal loans (Panel D), cash and Fed funds repos (Panel E), securities (Panel F), large time deposits (i.e., time deposits greater than \$100,000; Panel G), and wholesale deposits (Panel H) against bank beta. Bank beta is the average spread beta estimated over the years 1986 to 2002. Banks are sorted into 20 bins based on their bank beta. The figure plots the average growth by bin. The growth variables are calculated as dollar-difference changes from 2003 to 2006 divided by 2003 core deposits. Bank betas are winsorized at the 1% level while the growth variables are each winsorized at the 5% level.

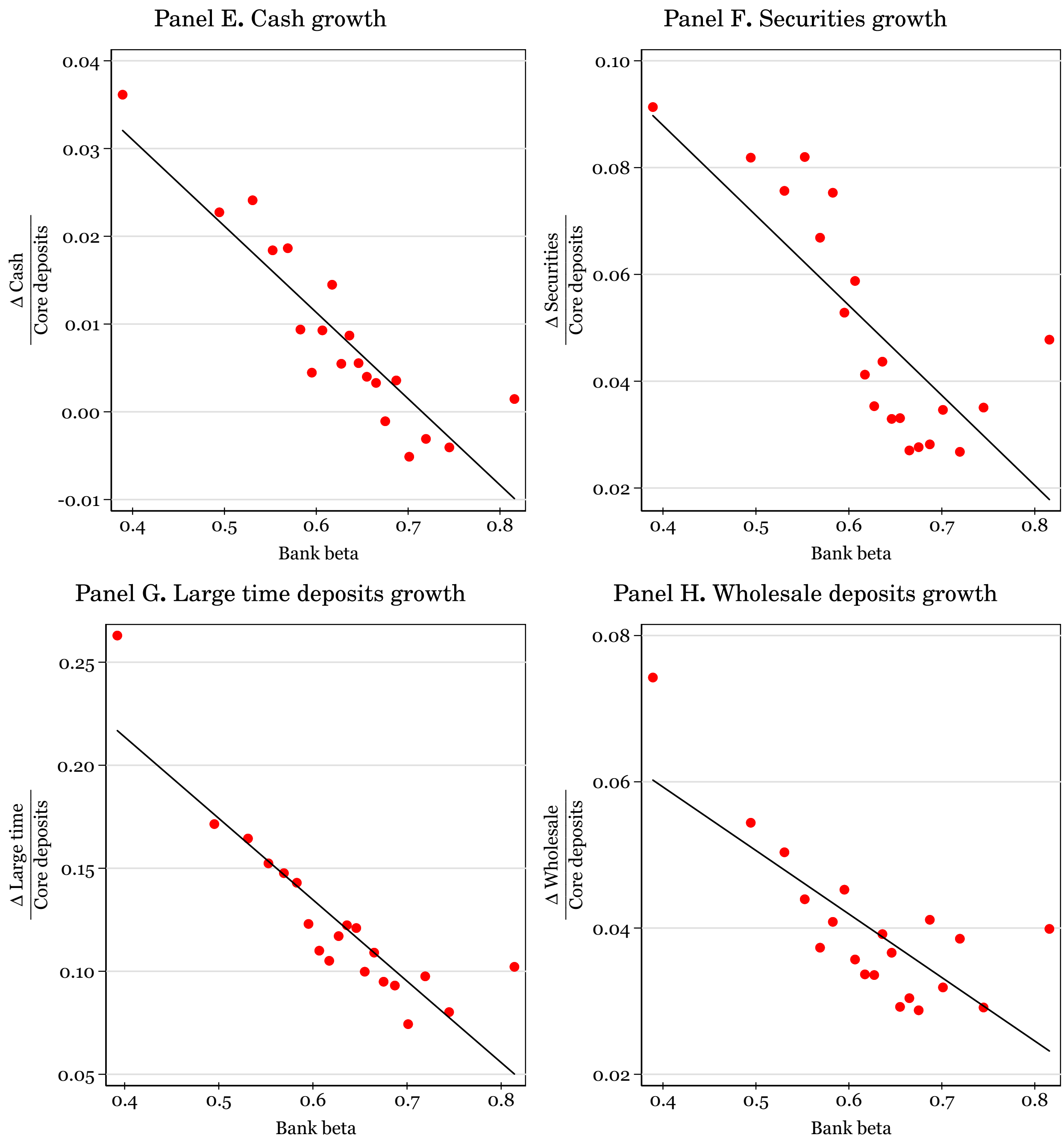

Fig. 6—continued.

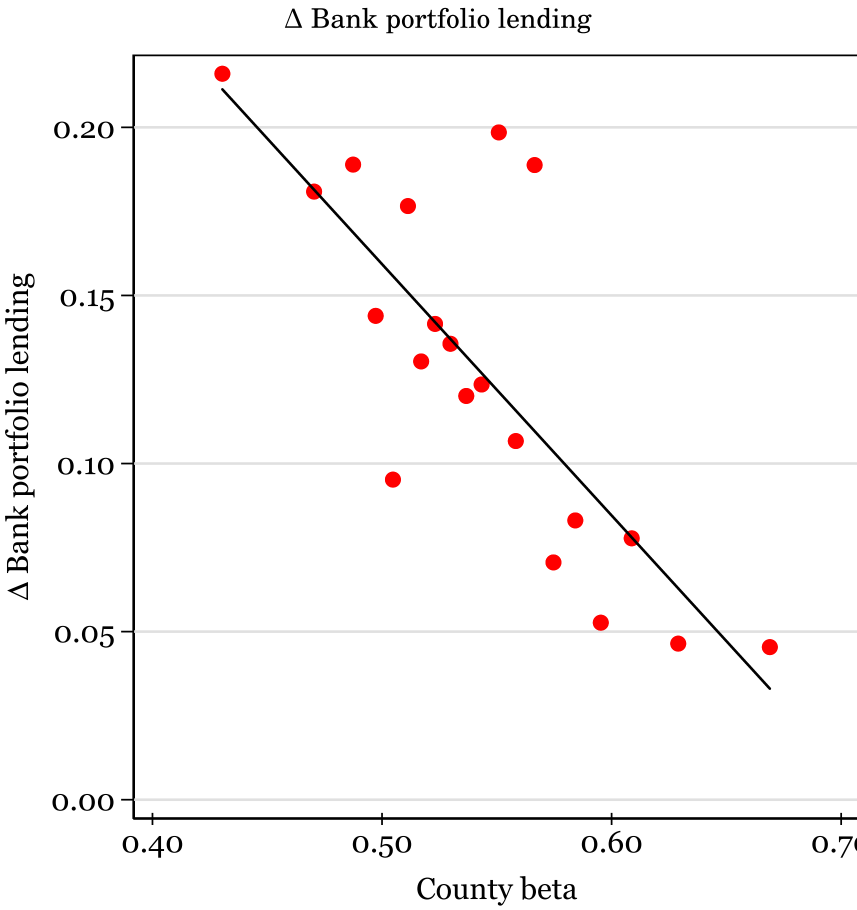

Fig. 7. Bank portfolio lending. This figure presents a binned scatter plot of the growth in bank portfolio lending from 2003 to 2006 against the county beta. The county beta is the average beta of all banks lending in the county, weighted by 2002 mortgage lending shares. Counties are sorted into 20 bins based on their county beta. The figure plots the average growth in bank portfolio lending for the counties in each bin.

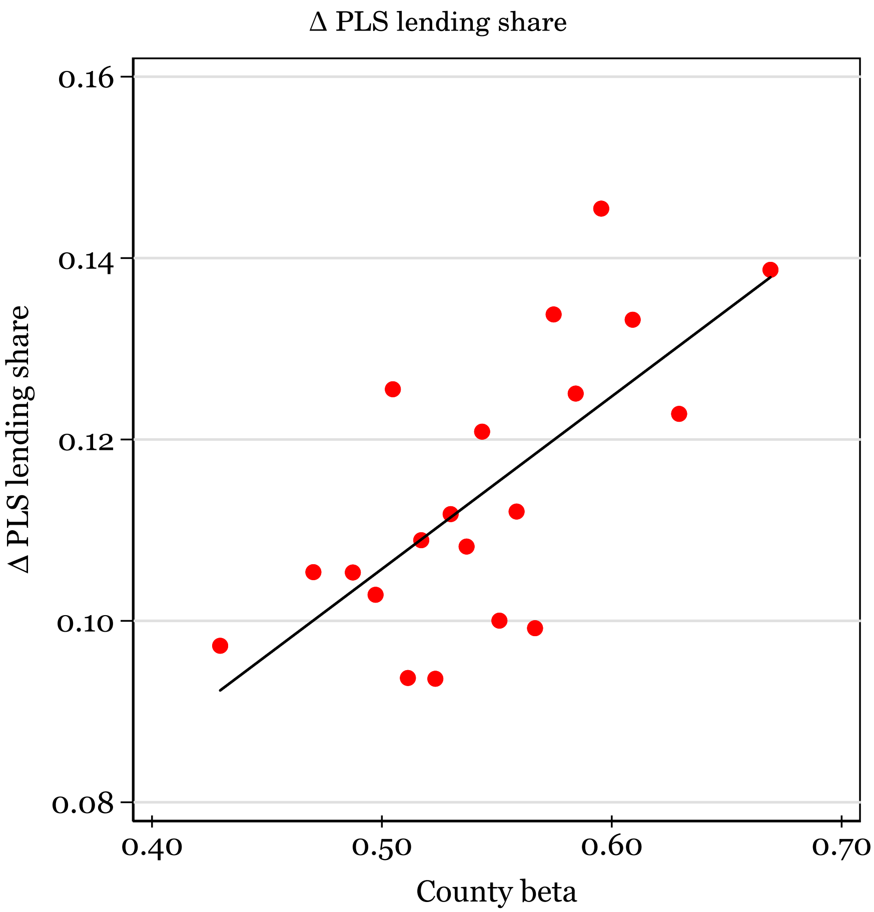

Fig. 8. PLS lending share. This figure presents a binned scatter plot of the change in the PLS lending share from 2003 to 2006 against the county beta. The county beta is the average beta of all banks lending in the county, weighted by 2002 mortgage lending shares. Counties are sorted into 20 bins based on their county beta. The figure plots the average change in the PLS lending share for the counties in each bin.

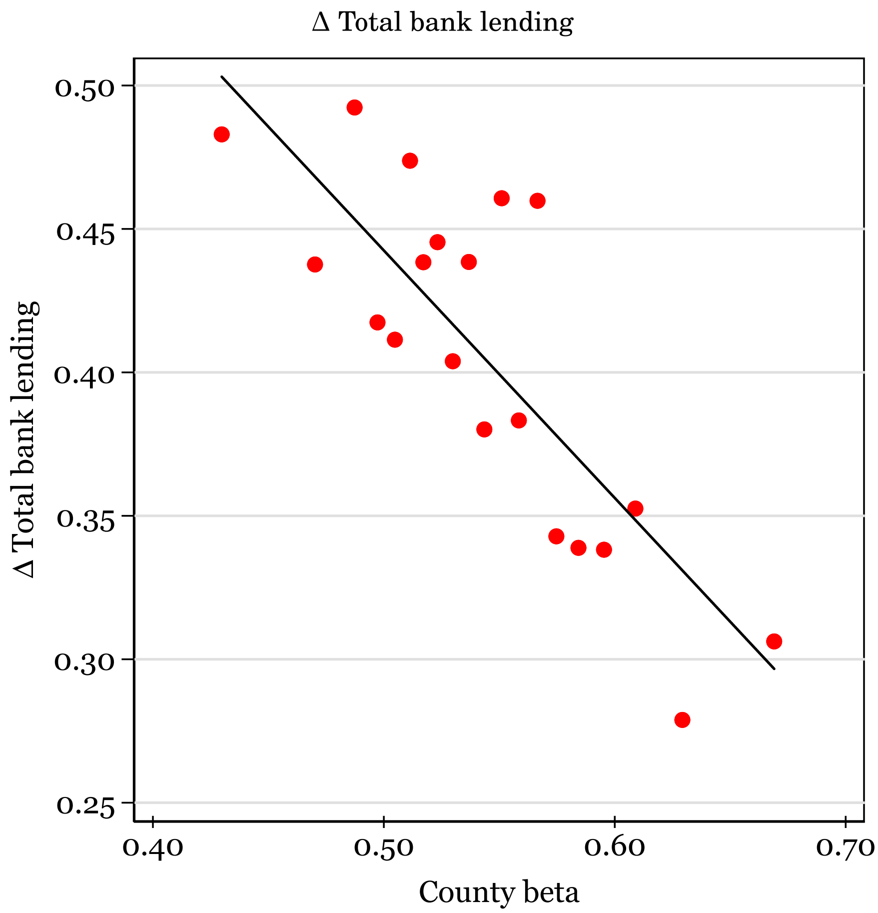

Fig. 9. Total bank lending. This figure presents a binned scatter plot of the growth in total bank lending from 2003 to 2006 against the county beta. The county beta is the average beta of all banks lending in the county, weighted by 2002 mortgage lending shares. Counties are sorted into 20 bins based on their county beta. The figure plots the average growth in nonbank lending for the counties in each bin.

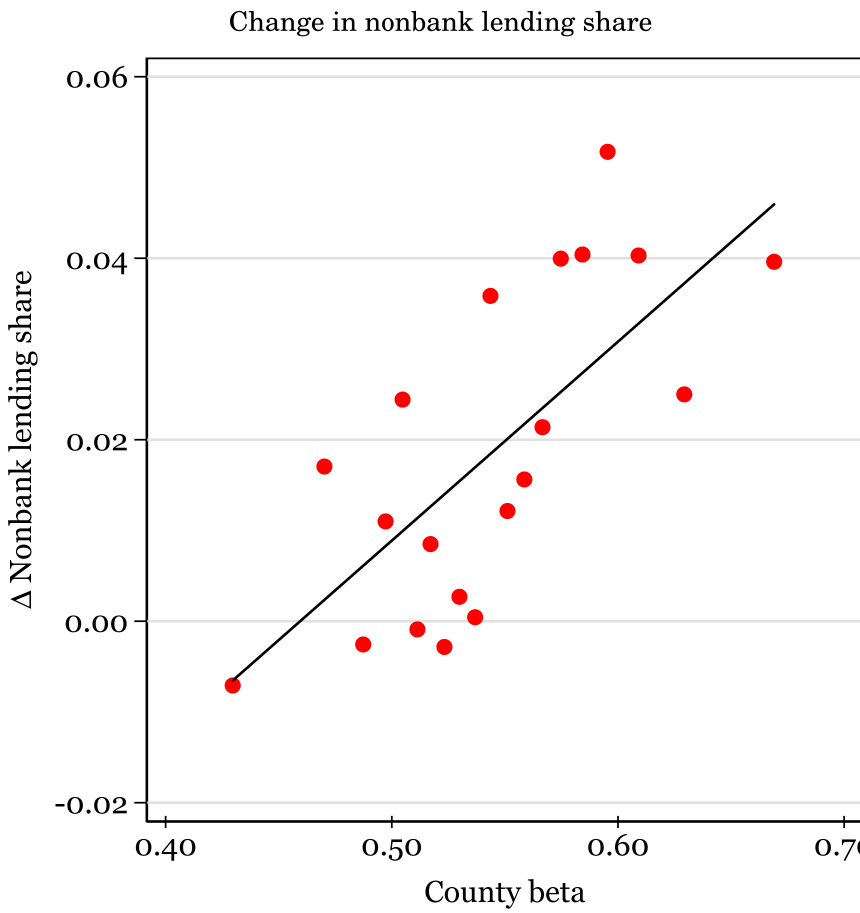

Fig. 10. Nonbank lending share. This figure presents a binned scatter plot of the change in the nonbank lending share from 2003 to 2006 against the county beta. The county beta is the average beta of all banks lending in the county, weighted by 2002 mortgage lending shares. Counties are sorted into 20 bins based on their county beta. The figure plots the average change in the nonbank lending share for the counties in each bin.

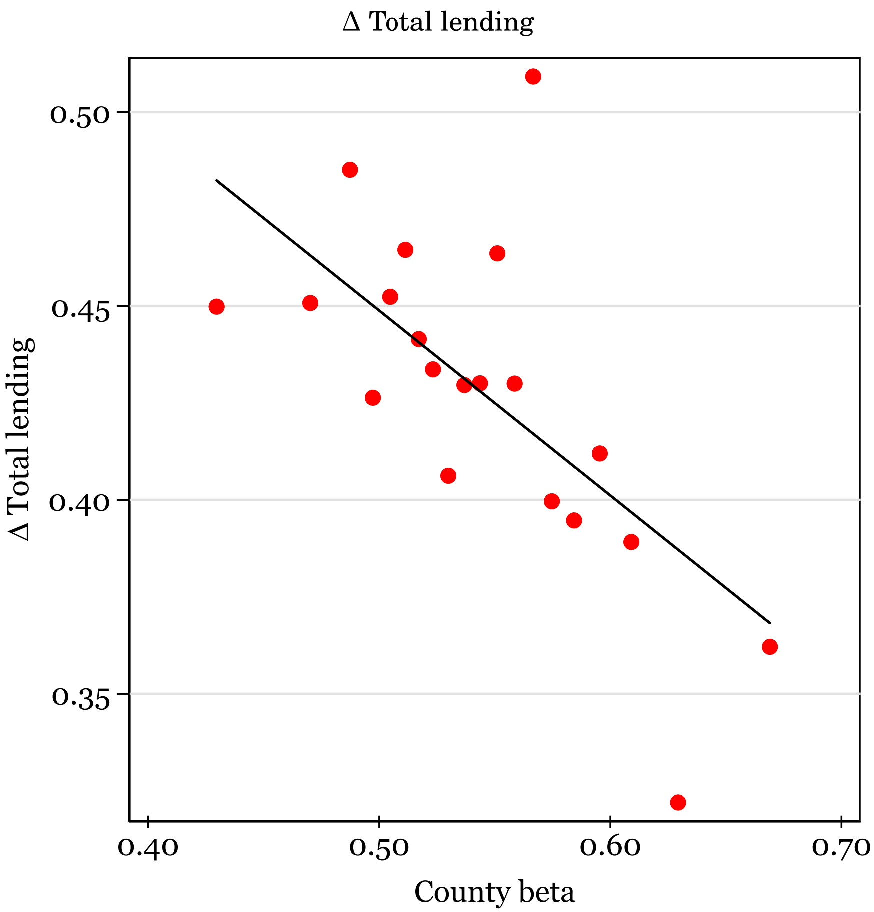

Fig. 11. Total lending. This figure presents a binned scatter plot of the growth in total non-GSE lending from 2003 to 2006 against the county beta. The county beta is the average beta of all banks lending in the county, weighted by 2002 lending shares. Counties are sorted into 20 bins based on their county beta. The figure plots the average growth in total non-GSE lending for the counties in each bin.

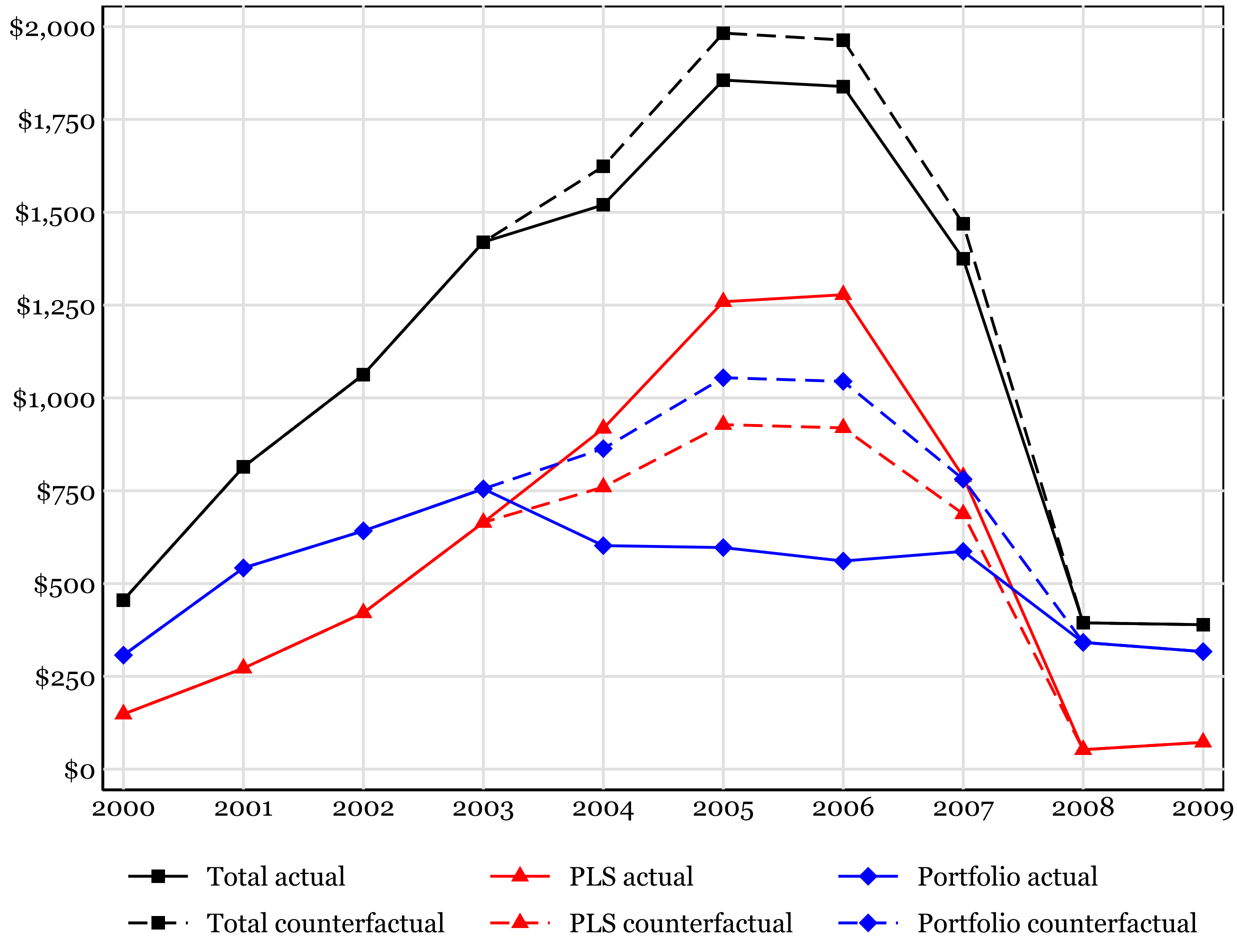

Fig. 12. Actual and estimated counterfactual originations. The figure shows actual (solid lines) and estimated counterfactual (dashed lines) aggregate originations of PLS (red triangles), bank portfolio loans (blue squares) and total non-GSE loans (black diamonds) from 2000 to 2009. The counterfactual originations remove the impact of Fed tightening through the deposits channel. This impact is based on our cross-sectional estimates, hence it does not account for potential spillovers. Actual PLS originations are from the Securities Industry and Financial Markets Association (SIFMA) and actual portfolio loans are from the Home Mortgage Disclosure Act (HMDA) dataset. Total loans are the sum of PLS and portfolio loans. See Section 5 for details and discussion.