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ABSTRACT

Small business lending by the four largest banks fell sharply relative to others in 2008 and remained depressed through 2014. We explore the dynamic adjustment process following this credit supply shock. In counties where the largest banks had a high market share, the aggregate flow of small business credit fell, interest rates rose, fewer businesses expanded, unemployment rose, and wages fell from 2006 to 2010. While the flow of credit recovered after 2010 as other lenders slowly filled the void, interest rates remain elevated. Although unemployment returns to normal by 2014, the effect on wages persists in these areas.

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"Small business owners feel that despite being creditworthy today, banks remain either wary or entirely unwilling to lend to them."

Mills and McCarthy (2014).

I. Introduction

The above quote from Karen Mills, the former head of the U.S. Small Business Administration, captures a concern expressed by many observers during the slow recovery from the 2007–2009 financial crisis and Great Recession: the possible existence of a small business "credit gap"—i.e., a reduction in the supply of credit to small firms.

In this paper, we ask whether such a credit gap did in fact open up in the post-crisis period, and what its economic implications may have been. Our point of departure, and the basis for our empirical strategy, is shown in Figure 1, which plots Community Reinvestment Act (CRA) data on small business loan originations by U.S. banks. While small business lending declined at all banks beginning in 2008, the four largest banks—those owned by Bank of America, Citigroup, JPMorgan Chase, and Wells Fargo—cut back significantly relative to the rest of the banking sector. By the trough in 2010, the annual flow of originations from the Top 4 banks stood at just 41% of its 2006 level, whereas the comparable figure for all other banks was 66%. Moreover, originations at the Top 4 banks remained depressed after 2010, hovering at roughly 50% of their pre-crisis level through 2014. By contrast, lending at other banks slowly recovered, approaching 80% of its pre-crisis level by 2014.

We begin by arguing that this differential decline in small business lending at the Top 4 banks reflects a differential contraction in credit supply. A natural alternative is that there was a differential shift in credit demand, perhaps because the Top 4 were disproportionately located in areas that were hardest hit by the Great Recession. Using CRA data at the bank-county level, we compare the small business loan growth of the Top 4 banks in a given county to other banks operating in the same county, thus sweeping away any local variation in loan demand. If anything, these within-county differences are slightly larger in absolute magnitude than the raw across-bank differences depicted in Figure 1, which is consistent with a supply-side rather than demand-side explanation for the differential decline in lending at the Top 4 banks.

A harder question is *why* the Top 4 banks cut their supply of small business loans more than other banks. Although we cannot answer this question definitively, we offer some hypotheses, which we flesh out in Section II. In brief, we think of the Top 4 loan supply shift as evolving in two distinct phases. First, the Top 4 pulled backed aggressively from small business lending in 2008 during the midst of the financial crisis. At this time, they were experiencing high charge-off rates on their small business portfolios, reinforcing their historical underperformance in a segment that they viewed as being peripheral to their overall business strategies. They also had to contend with large credit losses across a range of other products, threatening their solvency and leading to unprecedented wholesale funding pressures. Facing these challenges, managers at large banks chose to pull back from their non-core small business lending operations in order to focus on the task of managing through the crisis.

In the second phase, from 2010 to 2014, the Top 4 banks were slow to return to small business lending once the crisis had subsided, even as smaller banks, non-bank finance companies, and new online lenders began expanding in this market. This reluctance to re-enter seems to reflect a reassessment by the Top 4 banks of their comparative advantage in the small-business segment. And these concerns may have been amplified by several post-crisis changes in financial regulation that weighed most heavily on the largest banks, including new capital surcharges for systemically important institutions, the Federal Reserve's annual bank stress-testing regime, and the enhanced enforcement of anti-money-laundering rules.

To be clear, we do not attempt to estimate the causal impact of these individual channels, much less try to distinguish between them. Nevertheless, we believe that the above narrative makes it all the more plausible that the decline in Top 4 lending to small business that we document can be thought of as reflecting a systematic and sustained supply-side shift, rather than some sort of noise in the data.[1] With this observation in hand, the remainder of the paper then focuses on assessing the economic consequences of this shift in credit supply, using a difference-in-

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[1] In this regard, it is interesting to contrast our empirical strategy with that of Greenstone, Mas, and Nguyen (2015). They take a more atheoretic approach, inferring that a bank has experienced an inward shift in loan supply if it has a negative bank fixed effect in a regression of bank-county level loan growth on bank and county fixed effects. By contrast, we are effectively requiring that the negative bank fixed effect also be accompanied by some economically-grounded priors—i.e., by a plausible story for *why* the bank may have cut its supply. This is why we spend a good deal of effort trying to understand the forces underlying the Top 4 cutback in lending. The advantage of our approach is that we are less likely to pick up bank fixed effects that amount to measurement error from the standpoint of loan supply.

differences strategy that compares outcomes in counties where the Top 4 banks had a large initial market share to those in otherwise similar counties where they had a smaller share.

We are particularly interested in understanding the dynamic impact of this contraction in credit supply. Specifically, to the extent the pullback by the Top 4 was relatively persistent, one would naturally expect some degree of adjustment over time both by small businesses and by other suppliers of credit. With this dynamic perspective in mind, we first focus on county-level outcomes during the 2006–2010 period that covers the first phase of the Top 4's withdrawal from small-business lending. Compared to counties with a low initial Top 4 presence, we find that counties with a high initial Top 4 presence experience a decline in the annual flow of total small business lending, a decline in the fraction of business establishments that expand employment in a given year, slower employment growth, an increase in the unemployment rate, and slower wage growth. Thus, our results suggest that the credit supply shock from the Top 4 banks had a meaningful impact on labor market outcomes in affected counties in the immediate wake of the financial crisis.

We then explore how high Top 4 counties adapted from 2010 to 2014. We find that the annual flow of small business credit to affected counties begins to normalize after 2010 and has largely returned to trend by 2014. We also find that the differences in establishment expansion rates, employment growth, and unemployment rates between high and low Top 4 counties narrow after 2010 and largely disappear by 2014. However, we document a more persistent negative effect on county-level wage growth: the difference between high and low Top 4 counties remains economically and statistically significant through the end of our sample in 2014.

In order to shed more light on these persistent wage effects, as well as on adjustment by other lenders, we draw on proprietary data from a small business credit registry maintained by PayNet Inc. Using this data, we find that, beginning in 2008, small business borrowers in high Top 4 counties paid higher interest rates and obtained loans with shorter maturities. And, strikingly, these increases in the price of small business credit persist through 2014, consistent with the idea that small businesses have been forced to substitute towards higher cost providers of credit.

The persistence of these interest-rate effects helps to make sense of our results for employment and wages. Consider the consequences of a long-lived increase in the cost of credit in a setting where wages are sticky in the short run. Initially, higher loan rates will lead to a temporary spike in unemployment. Then as wages gradually adjust, the effect on unemployment will dissipate. However, if credit remains expensive, one would expect firms to become less capital intensive over time, leading to a lower marginal product of labor. Thus, the longer-run equilibrium involves a persistent negative impact on wages.

We next show that the composition of small business lenders in high Top 4 counties changes significantly from 2008 to 2014, potentially explaining why the cost of credit remains higher in these areas. As noted above, the annual flow of small business originations by all banks largely recovers in high Top 4 counties by 2014. This is in large part because small banks—those with assets less than $50 billion—grow their originations faster in affected counties from 2010 to 2014, filling some of the gap left by the Top 4 banks. Using the PayNet data, we also find that non-bank finance companies and alternative small business lenders—non-banks who lend via online web-based platforms—grow most rapidly in high Top 4 counties from 2010 to 2014. While these non-bank lenders are responding to a legitimate shortfall in credit supply, they may be relatively expensive marginal providers of credit, perhaps because they face higher funding costs than banks. Thus, the adjustment process in high Top 4 counties seems to be imperfect, involving a persistent impact on the cost of small business credit.

The validity of our difference-in-differences approach rests on a parallel trends assumption: outcomes in high Top 4 counties would have evolved similarly to those in otherwise similar low Top 4 counties had the former not been hit by a credit supply shock. In other words, we are assuming that, conditional on a large set of controls, a county's initial exposure to Top 4 banks is uncorrelated with local credit demand shocks, local credit supply shocks affecting non-Top 4 lenders, and any other omitted determinants of local labor market outcomes.

We offer several pieces of evidence in support of this assumption. First, we show that credit-market conditions and labor-market conditions evolved similarly in high and low Top 4 counties from 2000 to 2007, before diverging dramatically in 2008, precisely when the Top 4 began to aggressively pull back from small business lending. Second, we find that the initial decline in total small business lending in high Top 4 counties from 2006 to 2010 is entirely explained by the Top 4 banks: smaller banks in these areas were behaving similarly to smaller banks elsewhere. Third, we present a series of triple-difference results that zoom in further on the credit-supply mechanism. Looking within high Top 4 counties, we show that the employment effects are concentrated in industries that are most dependent on external finance, such as manufacturing. And, looking across high Top 4 counties, we find that the employment effects are more pronounced in the subset of counties that are most dependent on small business employers. Finally, our results using the proprietary PayNet data seem uniquely consistent with the idea that there was a credit supply shock from the Top 4 banks: the total volume of lending in high Top 4 counties declines, the cost of credit rises, and small business borrowers substitute towards non-Top 4 lenders. Taken together, we believe that this constellation of findings helps to buttress the validity of our basic empirical approach.

Our paper contributes to four strands of the literature. First, there is a large body of research that studies the real effects of credit supply shocks.[2] Relative to this work, our novel contribution is to focus less on the short-run impact of a shock, and more on the long-run dynamic adjustment process. Specifically, we document how labor-market outcomes like unemployment and wages respond over time to a persistent contraction in bank loan supply, as well as how this labor-market behavior is related to the entry of non-bank lenders. What we find most striking here is how, even after a number of years, the process of filling in the gap left by the Top 4 banks appears to be incomplete. This gradual adjustment process may reflect a slow-moving capital dynamic, whereby other lenders are not easily able to raise the equity needed to expand their lending (Myers and Majluf [1984]). Alternatively, it may point to the importance of information-intensive banking relationships that, once severed, are hard to rebuild (Rajan [1992]).

Second, there is a set of papers which argues that credit markets played a role in precipitating and amplifying the Great Recession.[3] Here our approach is particularly close to that of Bord, Ivashina, and Taliaferro (2017). They find that geographically diversified banks that were most exposed to declining house prices cut their small business lending relative to other less-exposed banks operating in the same counties, even in those counties where real estate prices did not fall. Thus, like us, they seek to identify a shock to small business credit supply using county-level data. One important distinction is that our strategy relies entirely on the differential behavior of Top 4 banks versus all others, whereas their results are robust to excluding the largest ten banks

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[2] Selected contributions include Bernanke (1983), Slovin, Sushka, and Polonchek (1993), Peek and Rosengren (2000), Ashcraft (2005), Khwaja and Mian (2008), Schnabl (2012), Benmelech, Bergman, and Seru (2015), and Rajan and Ramcharan (2015).

[3] See, for example, Ivashina and Scharfstein (2010), Almeida, Campello, Laranjeira, and Weisbenner (2011), Chodorow-Reich (2014), Mian, Rao, and Sufi (2013), Mian and Sufi (2014), Benmelech, Meisenzahl, and Ramcharan (2017), Greenstone, Mas, and Nguyen (2015), Duygan-Bump, Levkov, and Montoriol-Garriga (2015), Giroud and Mueller (2017), and Mondragon (2017).

from the analysis altogether. In this sense, the two papers study orthogonal components of the overall credit supply shock, and can be seen as complementary. It is useful to bear this complementarity in mind when thinking about the aggregate implications of both our results and those of Bord et al (2017). For example, while our identification strategy leads us to focus narrowly on the *relative* supply shift by the Top 4 banks, we know that small business lending by *all* banks fell dramatically in the wake of the financial crisis. If, based on evidence like that in Bord et al (2017), one believes that some of this drop reflects a more broad-based contraction in loan supply coming from other sources of variation, an extrapolation of our estimates and theirs would suggest that the small business credit gap may have contributed significantly to the severity of the Great Recession and the sluggish pace of the subsequent recovery.

Third, to the extent that regulation played a role in the Top 4 banks' reluctance to re-enter the small-business market once the crisis had subsided, our findings reinforce the view that one of the consequences of heightened bank regulation may be to drive activity to the less-regulated, non-bank sector.[4] In particular, it may be that some of the rapid growth of alternative, online lenders in recent years is due not only to the appeal of their web-based platforms, but also to a simple regulatory arbitrage: they can lend to small businesses without incurring much of the regulatory overhead that traditional banks must shoulder.[5]

Finally, and most speculatively, our findings may shed some light on the weak productivity growth in the decade since the crisis. Many authors have suggested that some of the productivity slowdown may be due to declining small business vibrancy.[6] While we would not want to claim that our results can account for the lion's share of the productivity phenomenon—much of which appears to be more secular in nature—it does seem possible that a contraction in bank credit supply to small business could have played a supporting role.

The plan for the rest of the paper is as follows. In Section II, we document that there was a large differential contraction in the supply of small business credit from the Top 4 U.S. banks

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[4] The potential for this unintended consequence of heightened regulation is emphasized by Acharya and Richardson (2009), Hanson, Kashyap, and Stein (2011), Acharya, Schnabl, Suarez (2013), and Begenau and Landvoigt (2016).

[5] Relatedly, Buchak, Matvos, Piskorski, and Seru (2017) show that non-bank lenders have also gained significant market share in residential mortgage lending since the financial crisis, and they present evidence linking the rise of non-bank mortgage lenders to the heightened regulations now faced by traditional banks.

[6] See, for instance, Decker, Haltiwanger, Jarmin and Miranda (2014), Hathaway and Litan (2014), Haltiwanger, Hathaway, and Miranda (2014), and Haltiwanger (2015).

beginning in 2008 and continuing through 2014; we also discuss some of the possible causes of this pullback. Section III explains our identification strategy for assessing the dynamic impact of this supply shock on local credit and labor markets. Section IV details the data sources we use in the analysis. Section V describes our principal empirical results, and Section VI offers some concluding remarks.

II. Contraction in the Supply of Small Business Loans from the Top 4 Banks

A. Identifying the relative shock to credit supply

As noted above, and as can be seen in Figure 1 and Panel A of Table 1, the Top 4 banks—those owned by Bank of America, Citigroup, JP Morgan, and Wells Fargo—significantly cut their small business lending relative to other U.S. banks beginning in 2008. We first demonstrate that this is truly a big bank effect: the reduction in lending by the Top 4 goes beyond what one would expect based on their other observable characteristics. To see this, Panel A of Table 2 presents bank-level, cross-sectional regressions of the form:

$$\%\Delta Loans_b = \alpha + \beta \times T4_b + \boldsymbol{\gamma}'\mathbf{x}_b + \varepsilon_b. \qquad (1)$$

The dependent variable in equation (1) is the percentage point change in bank *b*'s small business loan originations from 2006 to 2010. We are interested in the coefficient β on the indicator for Top 4 banks, denoted $T4_b$. Column (1) reports the coefficient from a univariate regression of 2006–2010 origination growth on the Top 4 indicator. The estimate implies that small business lending by the Top 4 fell by 31.6 percentage points ("p.p.") relative to other banks. In column (2), we control for a set of bank-level characteristics from the Call Reports, including a bank's funding mix (its fraction of deposit funding and its fraction of wholesale funding), pre-crisis asset growth, C&I charge-offs during the crisis, exposure to real estate loans, and initial equity capital ratios. The inclusion of these controls has only a small effect on the coefficient on the Top 4 indicator which falls to –26.4 p.p.

We next compare the Top 4 banks to "small banks"—those with assets under $50 billion in 2005—and "other larger banks" excluding the Top 4—those with 2005 assets between $50 billion and $500 billion. To do so, in columns (3) and (4), we include indicator variables for both the Top 4 and for other large banks $A50to500_b$, so small banks serve as the omitted category. The estimates in column (4) imply that, all else equal, the originations of the Top 4 shrank by 38.2 p.p. relative to small banks, while those of other large banks fell by 15.4 p.p. relative to small banks.

Furthermore, the 22.8 p.p. difference between the Top 4 and other large banks is large in magnitude and statistically significant at the 1% level. Thus, columns (3) and (4) suggest that while the contraction in small business lending is a function of bank size more generally, the very largest banks—the Top 4—withdrew by considerably more than even "super-regional" banks with assets between \$50 and \$500 billion.

What explains these differences? One possibility is that they reflect differences in loan demand, or in borrower creditworthiness, as opposed to differential changes in credit supply. For example, Figure 2 shows the geographic distribution of the Top 4 deposit share in a given market—denoted by $T4DS_c$—across counties in the lower 48 states. The population-weighted average county has a $T4DS_c$ of 30%. However, there are clear regional patterns in Top 4 presence, with $T4DS_c$ averaging 25% in the Northeast census region, 29% in the South, 15% in the Midwest, and 50% in the West. Since $T4DS_c$ is not randomly distributed across regions, our findings in Panel A of Table 2 could just be capturing the fact that the Top 4 operated in areas that were harder hit by the Great Recession and, therefore, experienced larger declines in loan demand.

To address this concern, in Panel B of Table 2, we use CRA data on small business loan originations at the bank-county level to estimate specifications of the form:

$$\%\Delta Loans_{bc} = \alpha_c + \beta \times T4_b + \boldsymbol{\gamma}'\mathbf{x}_b + \varepsilon_{bc}, \tag{2}$$

where $\%\Delta Loans_{bc}$ is the percentage point change in bank b's small business loan originations in county c. Because equation (2) includes county fixed effects, our estimates are now identified using only within-county variation in origination growth across banks. This means that our estimates are not influenced by differences in loan demand across counties.

Interestingly, the estimated coefficients on $T4_b$ in Panel B are similar to the raw across-bank estimates in Panel A and, if anything, are slightly larger in absolute magnitude. This suggests that the difference in loan growth between the Top 4 and other banks was indeed due to a relative supply shock, as opposed to differential exposure to negative demand shocks. And, as we emphasize below, the fact that the estimates in Panels A and B of Table 2 are similar helps to bolster the key parallel trends assumption that we make when we examine the economic consequences of the Top 4's pullback from small business lending.

B. Why did credit supply contract more at the Top 4 banks?

If we stipulate that there was indeed a relative shift in credit supply, *why* did the Top 4 cut their supply of small business loans more aggressively than other banks in 2008? And why didn't the Top 4 return to this market once the financial crisis subsided, even as other lenders did so? While we are not able to provide decisive answers to these questions, we are able to delineate a few hypotheses about the origins of the credit supply shock, based on our reading of various written accounts, as well as a series of conservations with bank executives, financial industry consultants, and policymakers.[7]

B.1. Phase 1: The initial pullback, 2008-2010

Observers offer a consistent story to explain the Top 4's withdrawal from small business lending in 2008. Prior to the crisis, this segment was only a modest portion of the Top 4's total loan portfolios. For instance, based on mid-2006 Call Report data, small business loans represented only 4% of total outstanding loans at the Top 4, compared to 9% of loans at other large banks with assets between $50 and $500 billion, and 22% of loans at small banks with assets under $50 billion. This pattern has been rationalized by noting that, relative to smaller banks, large banks are at a disadvantage in gathering and acting on the kind of non-quantitative, "soft" information that is so useful when assessing the creditworthiness of small firms (Stein [2002], Berger and Udell [2002], Berger, Miller, Petersen, Rajan, and Stein [2005], Liberti and Mian [2009], and Berger, Bouwman, and Kim [2017]).

However, from 2000 to 2007, large banks began relying more heavily on automated systems—similar to those used in consumer and residential mortgage lending—to underwrite small business loans based solely on quantitative, "hard" information (Carroll and Hoffman [2013], Mills and McCarthy [2014]). These automated underwriting systems combined information on the business owner's consumer credit score and, where available, a commercial credit score. The hope was that moving to an automated system would lower processing costs and improve underwriting quality. With the aid of these automated systems, the Top 4 banks gained

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[7] See, for example, "Big banks cut back on loans to small business," *Wall Street Journal*, November 26, 2015.

meaningful share in the small business market in the years leading up the crisis, going from approximately 20% of originations in 2000 to 33% in 2006.[8]

But as the U.S. economy decelerated from mid-2007 to late 2008, big banks experienced high charge-off rates on their small business loan portfolios. Furthermore, they realized that the transition to automated underwriting had not significantly lowered costs or improved underwriting quality.[9] For example, according to Mills and McCarthy (2014):

> *"Bank of America, which used credit scoring to make … loans of less than $150,000 through 2007, suffered significant losses in the recession and eventually exited that market segment due in part to poor loans underwritten largely based on credit score data."*

By late 2008, the Top 4 banks were facing huge losses in their core lending and capital markets divisions, threatening their solvency and leading to intense wholesale funding pressures. Executives at these banks needed to stabilize core business lines, rebuild equity capital buffers, and pass the U.S. government's May 2009 stress test. Facing these challenges, the large banks pulled back from small business lending—a non-core unit where they were already struggling—to focus on weathering the storm.[10] For example, according to Mills and McCarthy (2014):

> *"Some banks, particularly larger banks… significantly reduced or eliminated loans below a certain threshold, typically $100,000 or $250,000, or simply [would] not lend to small businesses with revenue of less than $2 million …."*

To illustrate the economic logic behind this sort of decision, consider a stylized example with two banks, where Bank A is a mid-size regional player primarily involved in traditional commercial banking activities, while Bank B is a Top 4 megabank that also is involved in a wide range of other capital markets and investment banking lines of business. Now suppose both banks see the profitability of their small-business lending unit decline by the same amount due to changes in the macroeconomic environment or increased regulation. Even in the face of this sort of symmetric shock, which bank might be expected to cut back on small business lending by more?

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[8] We calculate market share using CRA data. To ensure comparability over time, we adjust the historical series for all subsequent acquisitions by the Top 4 banks. Furthermore, since the bank asset size threshold for CRA reporting increased from $250 million in 2004 to $1 billion in 2005, we exclude banks with fewer than $1 billion in assets before 2005.

[9] Processing costs did not fall much because large banks only used automatic systems to decide the most obvious cases and continued to use a high-cost, manual process to decide the rest. And, underwriting quality did not improve because automated models were not particularly good at forecasting small business defaults (Carroll and Hoffman [2013]).

[10] Observers told us that the large banks mostly shut down their automated underwriting systems, routed all applications through their manual systems, and significantly tightened their underwriting standards.

Assuming that banks don't return capital to shareholders—so that their capital base is fixed in the short run—it should be megabank B. Megabank B has a broader set of other available opportunities in its internal capital market to which it can reallocate capital if it exits small business lending. By contrast, for the regional bank A, it is harder to exit small business lending if it wants to maintain its current size, because it faces a more limited set of opportunities in reallocating capital internally.

B.2. Phase 2: The slow rebound, 2010-2014

As shown in Table 1, small business lending at the Top 4 banks rebounded modestly after 2010, growing by 19% from 2010 to 2014. However, since the Top 4 had cut lending so aggressively from 2006 to 2010, one might have expected a stronger recovery. Indeed, originations grew by 34% from 2010 to 2014 at small banks with assets under $50 billion, even though they had cut lending by far less in the crisis.

Several factors may help to explain why the Top 4 did not jump back into small business lending once the crisis had passed. One possibility is that the rapid growth in small business lending at the Top 4 banks in the years prior to the crisis was a boom-time over-extension of credit—something akin to what occurred in the residential mortgage sector, albeit on a much smaller scale. And, having been disappointed with their ill-fated expansion into small business credit and particularly their foray into automated underwriting, the largest banks permanently re-evaluated their comparative advantage in this area following the crisis. In this telling, while perhaps painful, the post-2007 decline in small business lending at the Top 4 banks was a necessary corrective to these pre-crisis excesses.

Another possibility is that the slow rebound was in part a consequence of heightened post-crisis financial regulation. Even as late as 2014, a significant fraction of senior managers' time at the largest banks was being consumed by the need to comply with the array of heightened regulations that had gone into effect following the crisis—Basel III's new capital and liquidity rules, the Federal Reserve's annual bank stress tests, the preparation of so-called "living wills," to name but a few. This left less bandwidth to devote to the task of reimagining a struggling peripheral business line such as small business lending.

More directly, in the wake of the crisis, effective capital requirements have gone up not only in absolute terms, but also by more for the very largest banks. Those banks that are deemed to be globally systemically significant, such as the Top 4 banks, face capital surcharges, forcing them to maintain higher capital ratios against all risky assets relative to other banks.[11] Moreover, the implicit risk weights for small business loans in particular may have increased at large banks in recent years. This would be the case to the extent that the stress-testing regime that the Federal Reserve now applies to banks with assets over $50 billion makes relatively severe assumptions about the losses on small business loans in an economic downturn.[12] While heightened capital charges are arguably a well-justified component of the post-crisis efforts to reduce the systemic risk posed by the very largest banks, they may have some chilling effect on the amount of riskier lending—e.g., small business lending—done by these banks.

Finally, it is possible that Know Your Customer (KYC) regulations may have played a role as well. Loosely speaking, these rules require banks to verify their customers' identities and to monitor their activity for suspicious transactions, with the aim of reducing financial fraud and money laundering. Some observers have suggested that the enforcement of these rules, and the size of the associated penalties, have become tougher for big banks, in comparison to both the pre-crisis period and to smaller banks. KYC compliance costs are incurred when a bank enters into any relationship with a small business, and are not specific to just lending. Yet to the extent that they are meaningful, they might be expected to affect the economics of small business lending.

Given the short time series we are unable to distinguish between these competing explanations for the post-crisis decline in small business lending at the Top 4 banks. That is, we cannot say whether it was an unintended consequence of heightened regulation or a return to the normal, pre-boom state of affairs. However, we will argue that one particular aspect of the credit-boom story—that high Top 4 counties had a larger *aggregate* increase in small business lending than low Top 4 counties in the pre-crisis period—appears to be unsupported in the data.

[11] Specifically, since the Top 4 banks qualify as Global Systemically Important Banks (GSIBs), they are required to have additional Tier 1 common equity relative to risk-weighted assets. The current surcharges are 3.5% for JP Morgan, 3% for Citigroup, 3% for Bank of America, and 2% for Wells Fargo.

[12] An important qualification is that we cannot observe these stress-test loss assumptions separately for small business loans as opposed to the broader category of all commercial and industrial lending. See however The Clearing House (2017) for an analysis that attempts to indirectly infer the stress-test implied risk weights on small-business loans. Going further, several observers with ties to the financial industry have argued that the tougher bank capital regulations adopted in the wake of the crisis have contributed to the slow growth of small business lending, particularly at the largest banks, potentially helping to explain why employment growth at small firms has lagged behind that at larger firms during the post-crisis recovery. See, for example, The Clearing House (2017) and Strongin et al. (2014, 2015).

III. Assessing the Economic Consequences: Empirical Strategy and Predictions

To assess the impact of the credit supply shock on local credit and labor markets, we use a difference-in-difference strategy that compares outcomes in counties where the Top 4 banks had a larger initial market share to those in observably similar counties where they had a smaller share. This empirical strategy rests on two key identifying assumptions:

- **First stage assumption:** ***Because of the relative credit supply shift from the Top 4 banks, a county's initial Top 4 share is negatively related to the subsequent growth in aggregate small business lending in that county.***
- **Parallel trends / Exclusion restriction assumption:** ***Conditional on a set of county-level observables, a county's initial Top 4 share is uncorrelated with (i) local credit demand shocks, (ii) local credit supply shocks affecting other lenders, and (iii) omitted determinants of local real outcomes. Thus, credit and labor market outcomes in high and low Top 4 counties would have evolved similarly in the absence of the relative credit supply shock from the Top 4 banks.***

Assuming that these identifying assumptions hold, then our difference-in-difference estimates will have a valid causal interpretation.

We test four difference-in-difference (DD) predictions in the cross-section of U.S. counties:

- **Prediction DD1:** ***There is a negative relationship between a county's initial Top 4 share and the subsequent growth in total small business loan originations in that county.***
- **Prediction DD2:** ***There is a negative relationship between a county's initial Top 4 share and subsequent county-level labor-market outcomes, including employment and wage growth.***

Note that by combining Predictions DD1 and DD2, we can obtain an instrumental-variables (IV) estimate of the impact of a small business credit supply shock on local labor markets.

- **Prediction DD3:** ***There is a positive relationship between a county's initial Top 4 share and subsequent changes in interest rates on small business loans in that county.***

Combining Predictions DD1 and DD3 yields an IV estimate of semi-elasticity of loan demand with respect to interest rates. Although we primarily focus on results from reduced-form specifications, we take comfort from the fact that the corresponding IV estimate—the ratio of coefficients from the reduced-form and the first-stage specifications—implies a plausible semi-elasticity of demand for small business loans.

- **Prediction DD4:** ***There is a positive relationship between a county's initial Top 4 share and subsequent small business loan growth for other, non-Top 4 lenders in that county, including smaller banks, finance companies, and online lenders.***

Combining Predictions DD3 and DD4, we can obtain an IV estimate of the semi-elasticity of loan supply for these other lenders. And, as above, we will draw comfort from the fact that the implied semi-elasticity of loan supply seems plausible.

In addition, finding evidence consistent with Predictions DD3 and DD4 supports the view that any negative impact on local economic outcomes such as business growth and employment is due to a Top 4 credit supply shock rather than to a failure of the exclusion restriction. For example, suppose one is worried that a county's initial Top 4 share is correlated with negative shocks to local economic fundamentals and, thus, to loan demand, which could explain why Predictions DD1 and DD2 hold in the data. In this case, we would also expect to find a *decline* in interest rates and slower loan growth at other non-Top 4 lenders in high Top 4 counties.[13]

However, even if we do find evidence supporting each of Predictions DD1 through DD4, one may still ask whether exposure to the Top 4 banks impacts local labor market outcomes through a narrow small business credit supply channel of the sort we have in mind, or through a broader credit supply channel. The small business credit channel is the idea that an inward shift in the supply of credit to small businesses had a direct negative impact on local labor markets.[14] However, there may also be a broader credit channel because, while the Top 4 cut their lending to small businesses sharply beginning in 2008, their loan growth has also been stagnant in other categories, including residential mortgage and consumer lending. So a contraction in the supply of household credit from Top 4 banks may also have reduced consumer demand in affected counties, leading to adverse effects on local employment even in the absence of a direct small business credit channel.

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[13] When considering the impact on interest rates, it is important to hold expected default losses constant. Otherwise, if weak local fundamentals were associated with higher expected credit losses, one might expect a county with poor fundamentals to have both low loan growth and higher raw interest rates. Thus, we take care to control for loan credit quality (measured by the average credit score) in each county.

[14] Of course, the impact on labor markets is unlikely to be caused exclusively by an inward shift in the supply of business loans with amounts less than $1 million—the literal regulatory definition of small business loans. If the Top 4 are cutting back on their supply of business loans less than $1 million, then they are also likely to be cutting back on their supply of loans between $1 and $20 million to medium-sized businesses. Indeed, based on data on outstanding commercial loan balances from Call Reports, we find that commercial loan growth at the Top 4 has lagged significantly behind that at smaller banks—both for loans under $1 million and for loans over $1 million—since 2007.

To help distinguish between these stories, we use triple-difference specifications to test three further predictions that are unique to the narrower small business credit supply channel:

- **Prediction DDD1:** ***Looking <u>across</u> high Top 4 counties, the negative employment effects should be most pronounced in the subset of counties that were initially more dependent on small business employers.***
- **Prediction DDD2:** ***Looking <u>within</u> high Top 4 counties, the negative employment effects should be concentrated in industries that are more dependent on external finance.***

Importantly, Prediction DDD2 can be tested exploiting only *within*-county variation. This helps address any concerns about the failure of the exclusion restriction due to unobserved differential demand trends *across* counties.

Furthermore, since small firms in tradable industries such as manufacturing tend to be more reliant on external finance than small firms in non-tradable industries like retail and restaurants, this suggests that our employment results should be stronger in tradables:

- **Prediction DDD3:** ***Looking <u>within</u> high Top 4 counties, the negative employment effects should be stronger in tradable industries such as manufacturing.***

And given that employment in tradables is less exposed to shifts in local demand than employment in non-tradables (Mian and Sufi [2014]), finding evidence in favor of Prediction DDD3 would cut against an interpretation of our results in which credit-induced shifts in household demand play a major role.

IV. Data Sources

We carry out much of our analysis using a panel data set that consists of annual, county-level observations. This section describes the main data sources we use to construct this panel.

A. Small business lending data

Our data on small business loan originations in each U.S. county are derived from the Community Reinvestment Act (CRA) database. Any federally-regulated depository institution whose assets exceed $1 billion in 2005 dollars is required to file a CRA report. Small business loans are loans with an original amount of $1 million or less that are reported as either "commercial and industrial loans" or "loans secured by nonfarm or nonresidential real estate" on an institution's Call Report. The concept of originations in the CRA database includes renewals and refinancings as well as *de novo* originations. Furthermore, the data includes both term loans and credit line approvals. In the latter case, the origination amount equals the size of the credit line.

We obtain data on lending terms, as well as on lending volumes by non-bank finance companies and online lenders, from PayNet's proprietary loan-level database. PayNet maintains a private business credit registry that aggregates and analyzes data collected from over 300 member lenders, including banks and non-bank institutions. The PayNet database is the largest U.S. database of small business loans, leases, and credit lines, including over 23 million credit contracts and totaling more than $1.4 trillion in loans outstanding as of this writing.

The PayNet data consists of a loan-level panel that follows loan contracts over time, and a borrower-level panel dataset. The identities of individual borrowers and lenders were anonymized in the dataset used for this research. The loan-level panel includes the lender type—we know whether the lender is a bank, a finance company, or an online lender—and various loan characteristics, including the amount outstanding and maturity. For a smaller subset of loans, we are also able to infer the interest rate based on the loan's original principal amount and payment schedule. We infer the interest rate on each loan by computing an internal rate of return based on the initial principal amount and the schedule of promised loan repayments. The borrower-level panel includes the county where a borrower is located, a borrower's proprietary credit score from PayNet, and various proxies for borrower size based on its total borrowings in the PayNet database.

Since all of our regressions are run at the county-year level, the PayNet data is aggregated from the loan-quarter or borrower-quarter level to the county-year level by taking equal-weighted averages. To ensure comparability with the CRA data, which defines small business loans as those under $1 million, we restrict attention to borrowers whose total outstanding loans in the PayNet database (potentially across multiple loans) are less than $2 million at a given point in time.

B. Initial presence of Top 4 banks

Our main proxy for the initial presence of Top 4 banks in a given county is the *Top 4 Deposit Share* or $T4DS_c$. $T4DS_c$ is defined as the fraction of county c's total 2005 deposits that were held at depository institutions owned by Bank of America, Citigroup, JPMorgan, and Wells Fargo—i.e., we always aggregate bank-level data to the bank holding company level. $T4DS_c$ is constructed by aggregating branch-level data on deposits from the FDIC's Summary of Deposits (SOD) database to the county level. To ensure that our findings are driven by real changes in bank behavior as opposed to changes in the ownership structure of banks, we adjust both our CRA and SOD data for mergers.[15]

Because the CRA database contains bank-county level observations on small business loan originations, we can also measure the Top 4's initial presence in a county using their share of 2005 originations as opposed to their share of deposits. Naturally, the Top 4 loan and deposit shares are highly correlated across counties—the correlation is 0.75—and we obtain similar results if we use this alternative proxy for Top 4 presence.

Nonetheless, the Top 4 deposit share is our preferred measure for two reasons. First, because the FDIC's deposit data covers all depository institutions but the CRA loan data only covers those with assets over $1 billion, our deposit-based measure accounts for the market share of small community banks with assets less than $1 billion—a set of banks known to play an important role in small business lending (Berger and Udell [2006]). Second, the loan share variable may contain considerable transitory noise which would lead to measurement error in our key right-hand side variable. Indeed, the deposit share is more persistent than the loan share, both within counties and across counties.[16]

C. County-level labor market outcomes

We use four measures of county-level labor market activity: the establishment expansion rate, the unemployment rate, total employment, and wages. We obtain county-level data on establishment expansion rates—the fraction of business establishments that expand employment in a given year—from the Census's Bureau's Statistics on U.S. Businesses (SUSB) database.[17] Second, we obtain annual data on county-level unemployment rates and the size of a county's

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[15] We consider any depository institution that was acquired by one of the Top 4 banking firms between 2005 and 2014 to be a Top 4 bank in 2005. Thus, the wave of acquisitions that occurred during the 2008 peak of the financial crisis contributes to the Top 4 share. For example, both Wachovia's and Washington Mutual's 2005 deposits contribute to *T4DS* because the former was acquired by Wells Fargo and the latter was acquired by JPMorgan. The implicit assumption here is that these acquired banks were impacted by an organization-wide decision to pull back from small business lending after 2008.

[16] When we instead use the Top 4 loan share, our reduced form results are slightly weaker, consistent with the view that the loan share is a noisier measure of a county's exposure to the Top 4 than the deposit share. However, we obtain statistically strong and economically larger results if we use the deposit share as an instrument for the loan share. This approach is the natural solution to eliminating the attenuation bias resulting from the fact that the loan share is measured with error.

[17] The SUSB is carried out on March 12th each year. We call the expansion rate from March 12, YYYY to March 12, YYYY+1 the "year-YYYY expansion rate." The SUSB data is currently only available through 2012–2013.

civilian labor force from the Bureau of Labor Statistics' Local Area Unemployment (LAU) database. Our annual county-level LAU data reflect the annual average of 12 monthly surveys for each county. Third, we obtain annual data on county-level total private employment and wages from the BLS Quarterly Census of Employment and Wages (QCEW) database. Our annual county-level QCEW data on private employment reflect the annual average of four quarterly QCEW surveys for each county. Our wage variable is the annual average pay per employee, which the Census computes by dividing total annual wages by annual average employment in each county.

D. Additional county-level controls

Our difference-in-difference specifications control for a number of additional county-level variables. First, we use the QCEW data to compute the distribution of 2005 county-level employment across nine broad industries. We include these county-level employment shares as controls to ensure that our results are not driven by the possibility that counties with a high exposure to the Top 4 banks had different exposures to common industry shocks than other counties.

Second, to control for potential differences in local fundamentals linked to demographics, we obtain 2005 county-level demographic information from the American Community Survey (ACS), including the fraction of the population that is college-educated, the homeownership rate, the fraction of the population aged 25 years or older, and the fraction of the population over 65.

Finally, we control for county-level home price appreciation from 2002 to 2006, which we compute by taking a population-weighted average within each county of zip-code level home price data from Zillow. We control for 2002–2006 home price appreciation because those counties with the most rapid appreciation over this period subsequently saw the largest decline in house prices from 2006 to 2010 (Mian and Sufi [2016]), which in turn impacted local demand and economic activity via a household net worth channel as in Mian and Sufi (2014).

V. The Effect of the Small Business Credit Supply on Local Economic Activity

We now examine the economic consequences of the shock to the supply of small business loans from the Top 4 banks. Our basic empirical strategy is a difference-in-difference approach that compares economic outcomes in counties with a high Top 4 share to those in otherwise similar counties with a low Top 4 share. We first present baseline difference-in-difference estimates of the initial impact of this credit supply shock on local credit and labor markets from 2006 to 2010. To understand how affected counties have adjusted over time, we then trace out the dynamic impact over our full 2006 to 2014 sample. Next, we present three separate triple-difference specifications that help to isolate the underlying economic mechanism via which this credit supply shock impacted local labor markets. Finally, we use our data from PayNet to better understand how local credit markets have adjusted to the supply shock.

A. Baseline difference-in-difference results: Initial impact on affected counties

A.1. First stage estimates of the impact on loan volume

We begin with our first stage results, which show that, compared to otherwise similar counties, counties with a high initial Top 4 share experienced larger reductions in total small business loan originations from 2006 to 2010. Panel A of Figure 3 illustrates this result using a binned scatterplot. Specifically, the figure plots the percentage point change in loan originations in county c from 2006 to 2010 ($\%\Delta Loans_c$) versus the Top 4 Deposit Share in county c in 2005 ($T4DS_c$).[18] Table 3 presents these first-stage results more formally, reporting county-level cross-sectional regressions of the form:

$$\%\Delta Loans_c = \alpha_1 + \beta_1 \times T4DS_c + \boldsymbol{\gamma}_1' \mathbf{x}_c + \varepsilon_c . \tag{3}$$

In other words, equation (3) is a difference-in-difference specification that compares the change in small business lending between high and low Top-4 share counties. We estimate these regressions weighting each county by its 2005 population. We use population weights because households and firms, not counties, are the natural units of economic interest. (However, we obtain similar point estimates with similar levels of significance if we instead weight all counties equally.) Standard errors that are robust to residual clustering at the state level are shown in parentheses.

The first stage is strong in both economic and statistical terms. The coefficient of –21.7 in column (1) of Table 3 means that a county with a 100% Top 4 deposit share saw a 21.7 percentage point (p.p.) contraction in small business loan originations relative to a county in which the Top 4 banks had zero presence. Because the standard deviations of $T4DS_c$ and $\%\Delta Loans_c$ are 23.0% and

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[18] Counties are grouped into 40 bins based on $T4DS_c$ and the dots show the average level of $\%\Delta Loans_c$ in each bin. The solid line is the corresponding OLS coefficient estimate. Both $\%\Delta Loans_c$ and $T4DS_c$ are residualized using a set controls listed in Figure 3, so the figure corresponds to the multivariate specification in column (5) of Table 3.

18.4 p.p., respectively, this means that a one standard deviation increase in $T4DS_c$ is associated with a 0.27 (= 21.7 × 0.23 ÷ 18.4) standard deviation decline in county-level loan growth. The t-statistic on $T4DS_c$ is $t = 3.84$ in column (1) and the corresponding F-statistic is $F = 14.75$, exceeding the threshold of 10 below which Stock, Wright, and Yogo (2002) argue that weak instruments become a concern.

The next two columns of Table 3 add controls for other 2005 county-level observables. Specifically, column (2) adds our set of baseline controls: each county's 2005 population, average annual wages, labor force-to-population ratio, and unemployment rate as well as each county's industry mix (the fraction of 2005 county employment in nine broad industry groups). The addition of these controls has little effect on the coefficient of interest. Next, column (3) adds a set of controls from the 2005 American Community Survey (ACS): the fraction of college graduates, the fraction of home owners, the fraction of population aged 25 and over, and the fraction of population aged 65 and over. Since ACS data is only available for larger counties with populations exceeding 65,000, the sample size drops. However, the coefficient on $T4DS_c$ is virtually unchanged. In part, this is because our regressions weight counties by 2005 population. As result, the small counties that are dropped in column (3) receive little weight in columns (1) and (2). Column (4) adds controls for prior changes in county-level economic outcomes from 2002 to 2006, labeled *wage growth*, *labor force growth*, *Δunemployment rate*, and *home price growth*. Again, this has little impact on the $T4DS_c$ coefficient.

Overall, Table 3 shows that there is a strong and robust negative relationship between the initial presence of the Top 4 banks in a county and the growth in small business lending from 2006 to 2010, even in regressions estimated with a large battery of county-level controls.[19] Furthermore, in untabulated regressions, we verify that these results are robust to excluding a set of states such as California, Nevada, Arizona, and Florida that were particularly hard hit by the Great Recession.

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[19] Our baseline measure of county-level loan originations includes all small business loans with initial balances less than $1 million. The CRA database also contains data on loan originations to very small firms with annual revenues less than $1 million. We obtain nearly identical results using this narrower measure. For example, if we use this narrower measure, the coefficient on $T4DS_c$ in the specification corresponding to column (5) of Table 3 is $\beta_1 = -16.9$ with a t-statistic of 3.6.

A.2. Reduced-form and instrumental-variables estimates of impact on labor markets

We now turn to our reduced-form results, which show that counties with a higher initial Top 4 share also experienced more adverse labor market outcomes from 2006 to 2010. We begin by examining the impact on the expansion rate of business establishments, which is arguably our best measure of small business activity in a county because it counts all establishments equally. Indeed, small business owners report that a lack of access to credit primarily leads them to scale back the rate at which they are expanding their businesses (Mills and McCarthy [2014]).

The impact of the Top 4 credit supply shock on establishment expansion rates is shown in Panel B of Figure 3. As can be seen, there is a robust negative relationship between the change in a county's expansion rate from 2006 to 2010 and the county's Top 4 Deposit Share in 2005. The corresponding reduced-form regressions are reported in Panel A of Table 4. Specifically, we estimate county-level cross-sectional regressions of the form:

$$\Delta Expansions_c = \alpha_2 + \beta_2 \times T4DS_c + \boldsymbol{\gamma}_2'\mathbf{x}_c + \xi_c, \tag{4}$$

where $\Delta Expansions_c$ is the change in the county-level establishment expansion rate from 2006 to 2010. The coefficient on $T4DS_c$ of –1.59 in column (3) implies that a county with a 100% Top 4 share saw a 1.59 percentage point decline in the establishment expansion rate relative to a county with no Top 4 presence. Put differently, a one standard deviation increase in $T4DS_c$ is associated with a 0.158 (= 1.59 × 0.230 ÷ 2.31) standard deviation decline in the expansion rate.

Relative to column (1), columns (2) through (4) add the same batteries of controls that we introduced in Table 3. Column (5) in Table 4 adds the lagged outcome variable—the 2005 establishment expansion rate—as a control. Controlling for pre-trends in this way is an important robustness check in a difference-in-difference design. If the outcome variable is mean-reverting and the treated and untreated counties differ in their average initial level of the outcome variable, one might mistake mean reversion for a treatment effect (Ashenfelter [1978]). Hence, the parallel trends assumption is more credible when controlling for the lagged outcome, as we do in column (5). In summary, the estimates from columns (2) through (5) show that introducing a large battery of controls has little effect on the coefficient of interest.

Panel B of Table 4 presents the corresponding instrumental-variables (IV) estimates. We estimate cross-sectional regressions of the form:

$$\Delta Expansions_c = \alpha_{IV} + \beta_{IV} \times \%\Delta Loans_c + \boldsymbol{\gamma}_{IV}'\mathbf{x}_c + \omega_c, \tag{5}$$

using $T4DS_c$ as an instrument for $\%\Delta Loans_c$. Thus, the point estimates in Panel B of Table 4 are simply the ratio of the coefficients on $T4DS_c$ from the reduced form in Panel A and first stage in Table 3—i.e., $\beta_{IV} = \beta_2/\beta_1$. Focusing on column (3), our IV estimates suggest that a credit supply shock that leads to a one-standard deviation decline in $\%\Delta Loans_c$ leads to a 0.610 (=0.0766 × 18.4 ÷ 2.31) standard deviation fall in $\Delta Expansions_c$. These estimates support the view that credit supply shocks can have a meaningful impact on local small business activity.

The key identifying assumption underpinning our difference-in-difference estimates is that high and low Top 4 bank counties would have followed parallel trends in the absence of the credit supply shock from the Top 4 banks. To assess the plausibility this assumption, Figure 4 plots the time-series dynamics of annual loan originations and establishment expansion rates in high and low Top 4 counties. Figure 4 shows that loan originations and expansion rates in high and low Top 4 counties followed roughly parallel paths from 1999 through 2007. However, beginning in 2008, establishment expansion rates in high Top 4 counties fall significantly relative to those in low Top 4 counties—just as loan originations in high and low Top 4 counties diverge sharply.

Although the Top 4 banks were growing their small business lending more rapidly than other banks before 2008, Figure 4 shows that the growth in total small business lending by all banks was similar in high and low Top 4 counties prior to the crisis. This is because the Top 4 banks were rapidly gaining market share at the expense of other banks in these areas. Thus, judged relative to low Top 4 counties, it does not appear that aggregate small business lending conditions were overheated in high Top 4 counties before the crisis. To be sure, this fact does not allow us to conclude that the pre-crisis level of small business lending by the Top 4 was not excessive in some way; for example, it may have been excessive relative to their own underwriting capabilities in this segment. However, the evidence does cut against the view that high Top 4 counties experienced worse credit and labor market outcomes beginning in 2008 simply because the *aggregate quantity* of small business credit had been particularly over-extended in those areas and they were therefore experiencing a larger post-crisis correction.

Table 5 presents analogous results for three other county-level labor market outcomes: ΔUR_c, the change in the county-level unemployment rate from 2006 to 2010; $\Delta Emp_c - \Delta Pop_c$, the 2006–2010 employment growth rate minus the 2006–2010 population growth rate; and ΔW_c, the percentage change in county-level average annual wages from 2006 to 2010. Panel A of Table 5 presents the reduced form estimates and Panel B presents the IV estimates.

The impact on the unemployment rate (ΔUR_c) is shown in columns (1) through (3) of Table 5. The reduced form coefficient on $T4DS_c$ of 2.4 in column (2) of Panel A means that a county with a 100% Top 4 Deposit Share saw an additional 2.4 percentage point increase in unemployment relative to a county in which the Top 4 had zero presence. This implies that a one standard deviation increase in $T4DS_c$ leads to a 0.29 (= 2.4 × 0.23 ÷ 1.9) standard deviation increase in the unemployment rate.

The impact on relative employment growth ($\Delta Emp_c - \Delta Pop_c$) is shown in columns (4) through (6). The estimate of –5.52 in column (5) of panel A implies that that a county with a 100% Top 4 deposit share experienced a 5.52 percentage point decline in relative employment growth compared to a county in which the Top 4 had zero presence.

Finally, the results for 2006 to 2010 wage growth (ΔW_c) are presented in columns (7) through (9). The reduced-form estimate of –2.06 in column (8) of Panel A means that a county with a 100% Top 4 Deposit Share experienced an additional 2 p.p. decline in average annual pay per employee relative to a county with no Top 4 presence.

A.3. Aggregate implications

Looking across counties, the results in Tables 4 and 5 suggest that the shock to the supply of small business credit from the Top 4 banks had a significant initial impact on local labor markets from 2006 to 2010. Did this credit supply shock from Top 4 banks have a meaningful effect on the national unemployment rate from 2006 to 2010? While we cannot account for any potential general equilibrium effects stemming from the Top 4 bank credit supply contraction, we can offer a rough back-of-the-envelope calculation based on our cross-sectional micro-estimates. Since the population-weighted average level of $T4DS$ is 30%, our reduced-form estimates from column (3) of Table 5 Panel A suggest that exposure to the Top 4 banks directly contributed 0.3 p.p. (= 30% × 0.93 p.p.) to the rise in the national unemployment rate between 2006 to 2010. Because the unemployment rate rose by 5.1 p.p. over this period, this suggests that the Top 4 credit supply shock accounts for roughly 5% of the total increase.[20] Obviously, this calculation should be taken with a healthy grain of salt. However, it suggests that the Top 4 credit supply shock may have had non-trivial aggregate implications.

Going further, if one believes that part of the broader decline in the quantity of small business lending reflects a generalized contraction in bank loan supply, then an extrapolation of our difference-in-difference results suggests that the resulting small business credit gap may have contributed significantly to the severity of the Great Recession and the sluggish pace of the recovery. For instance, suppose that one believes that one-third of the overall 42 p.p. decline in small business lending from 2006 to 2010 was driven by a contraction in credit supply. Then our IV estimates from column (3) of Table 5 Panel B would suggest that the resulting small business credit gap could explain 14% (= 1/3 × –0.0525 × –42 ÷ 5.1) of the rise in the national unemployment over this period.[21]

B. Dynamics: How local economic activity adjusted to the Top 4 credit supply shock

Next, we explore the dynamic impact on local credit and labor market activity following the initial shock to Top 4 loan supply in 2008. What adjustment process might one expect to see if the Top 4 banks pulled back from small business lending and never really returned? Initially, the negative supply shock should lead to a small business credit crunch with attendant negative effects on local employment, just as we saw in the prior section. Over time, however, other lenders—either small banks or non-bank lenders—should be drawn into the market by the promise of greater returns, leading to a more normalized flow of credit in affected counties. However, to the extent that these new lenders were higher cost providers of credit than the Top 4 banks, then the supply shock might have a long-lasting impact on the cost of credit. Turning to the labor market, as the acute credit shortage eases and real wages slowly adjust downwards, one would expect the adverse effects on employment to dissipate. However, if the cost of small business credit remains elevated

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[20] Based on Table 1, on a population-weighted basis, the unemployment rose by 5.1 p.p. in the average county. This closely tracks the rise in the national unemployment rate of 4.9 p.p. from 4.4% in December 2006 to 9.3% in December 2010.

[21] If we instead use the somewhat larger estimates in column (2), we would calculate that exposure to the Top 4 banks directly contributed 0.7 p.p. (= 30% × 2.4 p.p.) to the rise in the national unemployment rate or roughly 14% of the total increase between 2006 and 2010. And our extrapolation based on our IV estimates would suggest that a broader small business credit gap could explain 37% (= 1/3 × –0.134 × –42 ÷ 5.1) of the total rise in unemployment.

in affected areas, small businesses in these areas might become less capital intensive, leading to persistently lower local wages.[22]

To trace out the cumulative response of county-level outcomes following the initial shock, Table 6 adapts our baseline difference-in-difference methodology. Specifically, for a given outcome variable Y_{ct}, we use a county-year panel from 2006 to 2014 and estimate regressions of the form:

$$Y_{ct} = \alpha_c + \alpha_t + \sum_{\tau=2007}^{2014} \beta_\tau \times T4DS_c \times 1_{\{t=\tau\}} + \boldsymbol{\gamma}'\mathbf{x}_{ct-1} + \varepsilon_{ct}. \qquad (6)$$

Because equation (6) includes both county and year fixed effects, each of the β_τ coefficients is analogous to a separate difference-in-difference estimate. Specifically, the coefficient β_τ reflects the difference between high and low *T4DS* counties in the *cumulative change* in the outcome variable from 2006 to year τ. As a result, the β_{2010} coefficients in Table 6 will be similar to the coefficient on *T4DS* in Tables 3 to 5.[23] Figure 5 plots these coefficients over time, effectively tracing out the cumulative impulse response from the Top 4 credit supply shock to local credit and labor market outcomes.

In columns (1) and (2) of Table 6, the dependent variable is $Y_{ct} = 100 \times (Loans_{ct} / Loans_{c2006})$ —i.e., the amount of small business originations in county c in year t scaled by the corresponding level in 2006. Thus, the β_τ coefficients reflect the cumulative percentage point decline in small business lending associated with the Top 4 supply shock. The first graph in Figure 5, which plots the annual β_τ coefficients from column (1) of Table 6, shows that counties with a high initial Top 4 presence experienced a prolonged small business credit crunch starting in 2008 and peaking in 2010. The plot also shows that the annual *flow* of small business credit to affected counties begins to turn around after 2010 and had largely returned to

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[22] Of course, in the very long-run, one would expect some combination of differential lender entry and labor mobility across regions to gradually eliminate any wage differentials due to initial geographical differences in cost of credit. However, it seems natural to think that this long-run convergence process may take many years (see, e.g., Ganong and Shoag [2016]).

[23] These coefficients are not exactly the same for two reasons. First, Table 6 uses dynamic lagged values of the control variables as opposed to the 2005 controls used in Tables 3 to 5. Second, the controls are assumed to have the same effect each year in Table 6. Because they absorb additional variation, the dynamic controls in Table 6 lead to coefficients that are similar but more precisely estimated than those in Tables 3 to 5. We have also estimated specifications that perfectly parallel those in Table 3—i.e., we use the same 2005 controls and interact these with a set of year dummies. This yields qualitatively similar results to those shown in Table 6, albeit with slightly diminished statistical significance in some specifications.

trend by 2014. As we will see below, the total annual flow of bank credit recovers because other banks have gradually stepped in to fill the gap left by the Top 4. Nonetheless, since the annual flow has only normalized in 2014, Figure 5 suggests that the Top 4 credit supply shock may have had a more permanent impact on the total *stock* of small business credit and physical capital in affected counties.

Columns (3) and (4) of Table 6 show an analogous set of specifications using $Expansions_{ct}$ as the dependent variable. Here, our county-year panel runs from 2006 to 2012. Again, the β_τ coefficients reflect differences in the cumulative change in the establishment expansion rate from 2006 to year τ between high and low *T4DS* counties. The estimates in column (3) of Table 6 are plotted in the second graph of Figure 5. The plot shows that differences in small business activity between high and low Top 4 counties emerge only in 2008, just when the Top 4 banks significantly cut their small business lending. Furthermore, these estimates suggest that the real effects of this credit supply shock are not confined to the depths of the financial crisis: Top 4 counties have lower business expansion rates even as late as 2011. Thus, our evidence sheds light on the factors affecting the *slow recovery* from the 2007–2009 financial crisis and recession, distinguishing our work from the literature that focuses primarily on the depths of the financial crisis (e.g., Chodorow-Reich [2014], Ivashina and Scharfstein [2010], Greenstone, Mas, and Nguyen [2015]).

Columns (5) and (6) of Table 6 present a parallel set of specifications for the county-level unemployment rate. Columns (7) and (8) repeat the exercise for the cumulative growth in employment relative to population growth. The coefficients from column (5) are shown in the third graph of Figure 5. Again, the estimates show that the differences in unemployment and relative employment growth between high and low Top 4 counties only begin to emerge in 2008 when the Top 4 banks cut their small business lending. The effect on unemployment peaks in 2010 and then dissipates slowly, vanishing only in 2013.

Finally, columns (9) and (10) show the results for county-level wages. Specifically, the dependent variable is average annual wages in county *c* in year *t* scaled by the corresponding level in 2006—i.e., $Y_{ct} = 100 \times (Wages_{ct}/\,Wages_{c2006})$. The fourth graph in Figure 5 plots the coefficients from column (9). Again, the wage effects only emerge in 2008. Interestingly, however, the impact on wages does not appear to dissipate over time. Instead, the estimates suggest that, even as late at 2014, cumulative wage growth in counties with *T4DS* = 100% was approximately 4 percentage points lower than in those with *T4DS* = 0%.

The natural interpretation of this set of findings is that real wages can only decline slowly due to nominal rigidities, leading to a temporary rise in unemployment following a negative shock. Once real wages have fully adjusted, employment returns to its long-run natural level. However, to the extent that small firms in affected counties have become less capital intensive because of a persistent increase in the cost of credit, one might expect to see longer-lived effects on the marginal product of labor and, hence, on equilibrium wages.

C. Isolating the mechanism

In this subsection, we assess the extent to which a county's initial Top 4 exposure influenced county-level employment through a narrow small business credit supply channel or through a broader credit supply channel. As we noted above, while the Top 4 banks' cutback in small business credit was especially pronounced, their loan growth has been stagnant in many categories since 2007. Thus, in addition to cutbacks in small business credit, a county's exposure to the Top 4 banks may have affected local labor markets because it reduced the supply of household credit, thereby crimping local consumer demand.[24] Although we cannot rule out the existence of this broader credit channel, we present three triple-difference specifications which collectively suggest that a narrower small business credit channel plays an important role in driving our baseline findings.

C.1. Differential effects based on the initial small business share of total employment

A first distinguishing prediction of the small business channel is that initial Top 4 exposure should have the largest impact on total employment in counties where small businesses account for a large fraction of initial employment. To test this hypothesis, we estimate cross-sectional specifications of the form:

$$\Delta Emp_c - \Delta Pop_c = \alpha + \beta \times T4DS_c + \delta \times SmallShare_c + \tau \times T4DS_c \times SmallShare_c + \boldsymbol{\gamma}'\mathbf{x}_c + \xi_c. \qquad (7)$$

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[24] Gete and Reher (2016) document that the Top 4 banks tightened their residential mortgage standards relative to other banks beginning in 2007, leading to a rise in rents and a decline in the homeownership rate in high Top 4 counties. Indeed, in untabulated results, we find that HMDA mortgage originations decline in high Top 4 counties relative to those in low Top 4 counties. Relatedly, D'Acunto and Rossi (2017) find that large banks reduced their mortgages to middle-income households but increased their jumbo mortgage lending from 2010 onwards.

In other words, we regress each county's relative employment growth from 2007 to 2010 on $T4DS_c$, the 2007 fraction of county employment at small firms (those with fewer than 500 employees), denoted $SmallShare_c$, and the interaction between these two variables, $T4DS_c \times SmallShare_c$.[25] Counties with a low initial fraction of small business employers serve as a placebo group in this triple-difference specification: the cutback in small business lending should lead to smaller declines in employment in those counties.

Table 7 presents the results from this exercise. Consider the estimates in column (3): when $SmallShare_c = 0\%$, the difference in relative employment growth between counties with $T4DS_c = 100\%$ and 0% is $\beta = 9.96$ percentage points (p.p.). Thus, in counties with no small businesses, $T4DS$ appears to have a small positive, but statistically insignificant effect on employment. However, when $SmallShare_c = 100\%$, the estimated difference in employment growth between counties with $T4DS_c = 100\%$ and 0% is -17.3 p.p. Thus, the triple-difference is $\tau = -27.3$ p.p. These findings suggest that the Top 4 credit supply shock is primarily working through a narrow small business channel.

C.2. Differential effects based on an industry's dependence on external finance

The small business credit supply channel also predicts that industries that are most reliant on external finance should be more adversely affected by the Top 4 credit supply shock. Thus, we next use data at the county-industry level and adopt the identification strategy of Rajan and Zingales (1998). Specifically, in Table 8, we estimate triple-difference regressions where industries with minimal external financing needs serve as the placebo group. Thus, our specifications take the form:

$$\Delta Y_{ic} = \alpha_i + \beta_1 \times T4DS_c + \beta_2 \times T4DS_c \times ExtFinUse_i + \boldsymbol{\gamma}'\mathbf{x}_c + \varepsilon_{ic}, \tag{8a}$$

and

$$\Delta Y_{ic} = \alpha_i + \alpha_c + \beta_2 \times T4DS_c \times ExtFinUse_i + \varepsilon_{ic}. \tag{8b}$$

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[25] Data on the county-level employment and the fraction of employees in firms under and over 500 employees is from the Census SUSB database. We use 2007 as the base year because this is the first year where employment by firm size is available.

In Panel A, ΔY_{ic} is $\Delta Expansions_{ic}$, the change in the establishment expansion rate in industry i and county c from 2006 to 2010. $ExtFinUse_i$ is a dummy variable that equals one if expanding firms in industry i required above-median use of external financial capital, according to the Census Bureau's 2007 Survey of Business Owners.[26] Industries are defined at the 2-digit NAICS level (20 industries). Each county-industry observation is weighted by the number of establishments or employment level in that cell from the 2005 cross-section. Equation (8a) includes a full set of industry fixed effects and equation (8b) includes both industry and county fixed effects. Thus, equation (8b) exploits only *within-county* variation, avoiding any potential concerns arising due to unobservable cross-county differences in local demand or other local factors.

Columns (1) to (3) of Table 8 Panel A show estimates of equation (8a). With our full set of controls in column (3), we find $\beta_1 = 0.66$ p.p., indicating that *T4DS* has essentially no impact on establishment expansion rates in industries with below-median reliance on external finance. However, we find $\beta_2 = -3.82$ p.p., suggesting that, in industries with above-median reliance on external finance, there are large differences in expansion rates between high and low Top 4 counties. Column (4) shows the estimate of equation (8b), which includes both industry and county effects. We find $\beta_2 = -3.51$ p.p., nearly identical to our estimates of β_2 in column (3).

It is also useful to compare the point estimates from Table 4 with those in Panel A of Table 8. Table 8 shows that there is a sizable effect for high external finance industries, but there is essentially zero effect for low external finance industries. Thus, the coefficients in Table 4, which reflect the effect on the average industry, are bracketed by the effect on low external finance industries $\beta_1 \approx 0$ and the effect on high external finance industries $\beta_1 + \beta_2 \approx \beta_2$.

Panel B of Table 8 presents an identical set of specifications in which the dependent variable is now $\Delta Y_{ic} = \Delta Emp_{ic} - \Delta Pop_c$, the employment growth in industry i and county c from 2006 to 2010 minus the population growth in county c from 2006 to 2010. Columns (1) to (3) in Panel B show estimates of specification (8a) for relative employment growth. In column (3) with all controls, we obtain $\beta_1 = -0.30$ p.p. and $\beta_2 = -7.28$ p.p. Column (4) shows the estimate of equation (8b) which includes both industry and county fixed effects. We find $\beta_2 = -8.19$ p.p. The

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[26] We define external capital to include bank and government loans, loans from family or friends, credit cards, venture capital investment or grants, and only consider employer firms in the Survey of Business Owners dataset.

results in Panel B show that the divergence in employment outcomes between high and low Top 4 counties is only present in industries that are reliant on external finance, supporting the view that the real impact from the credit supply shock primarily operates through a small business channel.

C.3. Differential effects: Employment in tradable versus non-tradable industries

Because small firms in tradable industries tend to be more reliant on external finance than small firms in non-tradable industries, the small business credit supply channel also suggests that our employment results should be stronger in tradable industries. Specifically, according to the 2007 Survey of Business Owners, 40% of expanding small businesses in tradable industries relied on some form of external financing; the corresponding figure for non-tradable industries was 31%. This difference is both economically and statistically significant.[27]

Table 9 presents results from triple-difference regressions that ask whether a county's initial exposure to the Top 4 banks had a larger impact on employment growth in tradable industries than in non-tradable industries. Specifically, in Table 9, we define industries at the 4-digit NAICS level and, following Mian and Sufi (2014), classify industries as tradable (e.g., manufacturing), non-tradable (e.g., restaurants and retail), or neither. The specifications in Table 9 take the same form in equations (8a) and (8b), but we replace $ExtFinUse_i$ with $Tradable_i$—a dummy variable equal to one for tradable industries—and restrict attention to tradable and non-tradable industries. As in Panel B of Table 8, the dependent variable in Table 9 is $\Delta Y_{ic} = \Delta Emp_{ic} - \Delta Pop_c$.[28]

Across all columns in Table 9, the coefficient on the key interaction term $T4DS_c \times Tradable_i$ is negative and significant, indicating that the Top 4 supply shock had a more negative impact on employment in tradable industries than in non-tradable industries. In this way, the results in Table 9 help to distinguish our findings from those in Mian and Sufi (2014), who argue that the large drop in household net worth during the Great Recession had a negative effect on household

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[27] We can also measure average external finance dependence using Compustat data from 1990 to 2006, restricting attention to small, mature firms, following Cetorelli and Strahan (2006). For these small firms, we find that firms in tradable industries are, on average, more dependent on external finance than firms in non-tradable industries.

[28] Since almost all tradable industries are classified as being dependent on external finance in Table 8 (and vice-versa for non-tradable industries), the only major differences between Table 8 Panel B and Table 9 is that the latter works with industries at the 4-digit NAICS level (as opposed to the 2-digit level) and drops industries that are neither classified as tradable or non-tradable by Mian and Sufi (2014).

demand. Specifically, exploiting geographic variation across counties, they find that larger home price declines from 2007 to 2009 led to larger declines in local employment in non-tradable industries, which are highly exposed to shifts in local consumption demand but had little impact on local employment in tradable industries, which are less exposed to local demand.[29] By contrast, our findings in Table 9 suggest that the Top 4 small business credit supply shock had a bigger impact on local employment in tradable industries. Not only is this finding distinct from the housing-related effect documented in Mian and Sufi (2014), but, because small firms in tradable industries are more reliant on external finance, it also supports the small business credit supply channel interpretation of our findings. Furthermore, Table 9 suggests that our findings cannot be readily explained by a broader credit channel in which shocks to household credit plays a major role. Indeed, per the logic in Mian and Sufi (2014), a negative shock to the supply of household credit should have a larger impact on local employment in non-tradable industries, which are most exposed to local consumption demand.

D. How the small business lending market adjusted to the Top 4 credit supply shock

Finally, we investigate how local credit markets have adjusted to the supply shock from the Top 4 banks. First, we examine how the shock impacted the cost of credit in affected counties. We then show how other lenders—both smaller banks and non-bank lenders—have gradually stepped in to fill the credit gap left by the Top 4 banks.

D.1. Loan terms

In Table 10, we use data from PayNet to explore how the Top 4 shock has impacted the pricing of small business loans. As in Table 6, we construct a county-year panel that runs from 2006 to 2014 and estimate specifications of the form:

$$Y_{ct} = \alpha_c + \alpha_t + \sum_{\tau=2007}^{2014} \beta_\tau \times T4DS_c \times 1_{\{t=\tau\}} + \boldsymbol{\gamma}'\mathbf{x}_{ct-1} + \varepsilon_{ct}, \qquad (9)$$

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[29] Thus, in columns (2), (3) and (5) of Table 9, we control for both 2002 to 2006 home price growth and the interaction of prior home price growth and a dummy variable for tradable industries. We do so because counties with the largest home price appreciation from 2002 to 2006 subsequently experienced the largest decline in house prices from 2006 to 2010 (Mian and Sufi [2016]). And, as Mian and Sufi (2014) show, these subsequent price declines impacted local consumption demand and employment in non-tradables due to the household net worth channel. Indeed, this same effect emerges in our county-industry panel. Nonetheless, introducing these controls has almost no impact on the coefficient on $T4DS_c \times Tradable_i$.

where Y_{ct} is either the average loan interest rate or the average loan maturity of small business loans originated in county c and year t in the PayNet database.

Columns (1) to (2) of Table 10 show the results when the outcome variable is the loan interest rate measured in percentage points. For a subset of loans in the PayNet database, we can infer the loan rate. For each county-year cell, we then compute the average rate on these newly originated loans. To isolate the impact of a supply shock holding fixed credit quality, we control for the average PayNet borrower credit score in each county-year. The estimates in column (2) imply that, by 2012 and 2013, firms in counties with a $T4DS_c$ of 100% paid interest rates that were roughly 1.1 percentage points higher than firms in counties with a $T4DS_c$ of 0%. This an economically meaningful effect judged relative to the mean (13.5 p.p.) and standard deviation (5.3 p.p.) of rates. Columns (3) and (4) show the analogous results when the dependent variable is the loan maturity measured in months.[30] The coefficients in column (4) imply that firms in counties with a $T4DS_c$ of 100% received loans with maturities that were 1.9 to 2.7 months shorter than firms in counties with a $T4DS_c$ of 0%. This can be judged relative to a mean and standard deviation of loan maturity of 45.3 and 4.2 months, respectively.

Furthermore, the effects on interest rates and maturities in Table 10 have not dissipated over time, even though employment has gradually recovered in high *T4DS* counties. These longer-lasting effects on loan pricing are consistent with the view that the smaller banks and non-bank lenders who have stepped in to fill the gap are higher-cost credit providers than the Top 4 banks (Carroll and Hoffman [2013] and Mills and McCarthy [2016]).[31] Thus, even though the annual flow of credit recovered, this persistent pricing difference suggests that a small business credit gap may have still existed in high Top 4 counties as late as 2014. In summary, the results in Table 10

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[30] Our loan-level data contains the maturity for each new loan origination. To construct the outcome variable, we first collapse the data to the lender-county-year level by taking equal-weighted averages. To purge the loan maturity variable of any variation due to different loan types across lenders in the database, we next run a panel regression of the lender-county-year average loan terms on lender fixed effects and retain the residuals. Finally, we average these residuals to create county-year average loan maturities. The results are similar using unresidualized average county-year loan maturities.

[31] According to Mills and McCarthy (2016), online lenders often charge interest rates of 25 percent or more. On the other hand, as of November 2014, the Federal Reserve's Survey of Terms of Business Lending indicates that the weighted average interest rate on bank C&I loans under $1 million was below 4%. Furthermore, the STBL suggests that interest rates on small business loans at small banks are higher than those at large banks. Obviously, however, we cannot make definitive comparisons using the STBL data because we are unable to control for differences in borrowers across bank types.

suggest that small businesses in affected counties paid a higher price to obtain credit. In combination with our prior findings that the quantity of credit fell, this strongly suggests that high Top 4 counties experienced a relative contraction in credit supply.

Combining the estimates in Table 10 with the specifications in Table 2, we can obtain an instrumental variables (IV) estimate of the semi-elasticity of demand for small business credit. Here, the structural equation of interest is $\%\Delta Loans_c = \alpha + \beta \times \Delta r_c + \boldsymbol{\gamma}'\mathbf{x}_c + \varepsilon_c$. We estimate this equation using two-stage least squares on the cross-section of differences from 2006 to 2010, with $T4DS_c$ serving as instrument for the change in interest rate Δr_c. Thus, the cross-sectional analogue to Table 10 is the first stage regression, and the regression in Table 2 is the reduced form. Estimating this semi-elasticity provides another sanity check on the analysis: we want to know whether a plausible semi-elasticity of demand can be used to reconcile our findings on loan quantities with our findings on prices.

Columns (1) and (2) of Table 11 present these results. In column (1), we estimate that the semi-elasticity of loan demand is $\beta = -19.8$ p.p. In other words, a 100 basis point increase in the cost of credit leads to a 20 p.p. decline in demand. The estimates are imprecise, which is hardly surprising given the large number of other changes in credit markets over this time period as well as the coarseness of the data. However, the magnitude of the estimated semi-elasticity of demand seems reasonable, suggesting that the decline in lending volumes we observe can plausibly be tied to the increased cost of credit.

D.2. The response of other banks

In order to study the response of other banks to the pullback in small business lending by the Top 4 banks, we decompose total county loan growth by all banks (A) into a component from the Top 4 banks ($T4$), from other big banks (B) with 2005 assets between \$50 and \$500 billion, and from small banks (S) with 2005 assets under \$50 billion:

$$\begin{aligned}\frac{\Delta L_{A,1}}{L_{A,0}} &= \frac{\Delta L_{T4,1}}{L_{A,0}} + \frac{\Delta L_{B,1}}{L_{A,0}} + \frac{\Delta L_{S,1}}{L_{A,0}} \\ &= \frac{L_{T4,0}}{L_{A,0}}\frac{\Delta L_{T4,1}}{L_{T4,0}} + \frac{L_{B,0}}{L_{A,0}}\frac{\Delta L_{B,1}}{L_{B,0}} + \frac{L_{S,0}}{L_{A,0}}\frac{\Delta L_{S,1}}{L_{S,0}}.\end{aligned} \tag{10}$$

In other words, the percentage growth in small business loan originations in county c from time 0 to time 1 can be decomposed into the sum of three components: a contribution from the Top 4, a contribution from other large banks, and a contribution from small banks. By definition, each group's contribution to total origination growth is their initial share of originations at time 0 multiplied by their origination growth from time 0 to 1.

Panel A of Table 12 shows estimates of the impact of *T4DS* on these different components of total bank loan origination growth from 2006 to 2010. (The regressions in Table 12 include our full suite of county-level controls and correspond to the regression in column (5) of Table 3.) The first row shows that a county with a *T4DS* of 100% had origination growth that was 17.9 p.p. lower than an otherwise comparable county with *T4DS* of 0%. The remaining columns show that the entire contraction in small business lending from 2006 to 2010 is explained by the contribution of the Top 4 banks. The second row shows that from 2010 to 2014 a county with a *T4DS* of 100% rebounded sharply, with loan origination growth 26.6 p.p. greater than a similar county with a *T4DS* of 0%. However, the remaining columns show that the majority of this 2010 to 2014 rebound is due to other large banks and small banks. The third row shows that, over the full 2006 to 2014 period, there is little difference in loan growth between high and low *T4DS* counties, because more rapid loan growth at non Top 4 banks from 2010 to 2014 has offset the initial 2006 to 2010 decline from the Top 4.

Panel B of Table 12 looks at the group-level growth rates in the second line of equation (10). In column (1), we find that the Top 4 banks cut their lending by somewhat less in places where they had a larger initial market share. This is precisely what one should expect if county-level loan demand is downward sloping. Specifically, since, in equilibrium, total loan quantities fall more and interest rates rise more in counties with a higher initial exposure to the Top 4 banks, the Top 4 should find it most attractive to continue their own lending in those counties where they previously had the largest market share.

Columns (2) and (3) of Panel B show that lending by other large non-Top 4 banks and small banks grew much faster in high *T4DS* counties from 2010 to 2014. Yet, these other banks did not grow much in high *T4DS* counties from 2006 to 2010. Thus, it appears to take several years for other banks to fill the gap left by the Top 4. This may be because many of these other banks were also highly constrained from 2008 to 2010 at the height of the financial crisis. And their gradual entry after 2010 may reflect external financing frictions (Myers and Majluf [1984]), whereby they are not easily able to raise the equity capital needed to expand their lending in affected counties. Moreover, new lenders might face adverse selection when extending credit to borrowers whose previous banking relationships have been severed (Rajan [1992]).[32]

As above, we can also obtain an instrumental variables (IV) estimate of the semi-elasticity of non-Top 4 banks' loan supply. We do so by considering the cumulative change in interest rates from 2006 to 2013 along with the other banks' supply response from 2010 to 2013. These IV estimates are shown in columns (5) and (6) of Table 11. For example, in column (5) we estimate the semi-elasticity of supply for other banks to be 22 p.p. Again, these estimates are imprecise. However, the magnitude seems reasonable, hinting that the rising lending volumes from other banks that we observe since 2010 can plausibly be linked to the increased cost of credit in affected counties.

D.3. The response of non-bank lenders

Finally, in Table 13, we ask whether the credit supply shock from the Top 4 has led to substitution towards non-bank lenders. Because these non-bank lenders are not included in the CRA data, we use proprietary PayNet data.[33] Table 13 shows that traditional non-bank lenders have higher loan growth rates from 2010 to 2014 in high Top 4 counties relative to low Top 4 counties. We also find that, as of 2014, new alternative non-bank lenders, who only lend via an online platform, have the greatest presence in high Top 4 counties. As in Kashyap, Stein, and Wilcox [1993], this substitution towards non-bank lenders further supports the view that the declining bank loan originations in high Top 4 counties are due to a reduction in small business credit supply as opposed to a decline in credit demand.

More specifically, columns (1) to (3) of Table 13 present the results from cross-sectional specifications in which we regress the percentage point change in small business loan originations by traditional non-bank lenders from 2010 to 2014 in county c, denoted $\%\Delta NBLoans_c$, on $T4DS_c$.

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[32] Berger, Bouwman, and Kim (2017) find that small businesses in areas served by large banks reported being more financially constrained during the crisis, but that a greater local presence of small community banks (those with assets under $1 billion) helps to offset this effect.

[33] Although lender identities are anonymized in the PayNet data we use for this analysis, the lenders are classified into four categories: banks, independent finance companies, captive finance companies, and alternative lenders. We group independent finance companies and captive finance companies together as "traditional non-bank lenders." Captive finance companies are the financing subsidiaries of equipment manufacturers who offer customers loans and leases to finance equipment purchase from their parent manufacturer (Edgerton [2012]). Independent finance companies are stand-alone non-bank business lenders. Alternative lenders are lenders that lend only via an online web-based platform.

The estimate in column (2) means that non-bank small business lending grew by 47 percentage points more in a county with a 100% Top 4 share than a county with no Top 4 presence.

Columns (4) to (6) examine lending by the new online small business lenders who have gained prominence in recent years. Data on lending by alternative lenders is only available in 2014. Therefore, we measure alternative lending in per capita terms: we examine dollar origination by alternative lenders in 2014 divided by 2005 population. We present cross-sectional specifications in which we regress 2014 alternative lender originations per capita in county c, denoted $AltLoans_c$, on $T4DS_c$. For example, the coefficient in column (5) implies that per capita originations by these alternative online lenders are \$1.84 higher in counties with a 100% Top 4 share compared to counties with no Top 4 banks. This can be judged relative to the mean and standard deviation of alternative loans per capita of \$4.00 and \$2.62, respectively. (By way of comparison, per capita bank loan originations from the CRA database are approximately \$650 in 2014.)

Again, we can combine the estimates in Table 13 with those in Table 10 to obtain instrumental variable estimates of the semi-elasticity of loan supply from traditional non-bank finance companies. These IV estimates are shown in columns (3) and (4) of Table 11. In column (3), we estimate the semi-elasticity of supply for non-bank finance companies to be 26 p.p., similar to our estimate of the semi-elasticity of supply for non-Top 4 banks.

In summary, counties with a larger initial Top 4 bank share experienced larger increases in the cost of small business credit after 2008, faster small business loan growth by both smaller banks and non-bank finance companies from 2010–2014, and a larger presence of new online lenders by 2014.

VI. Conclusion

We have shown that, beginning in 2008 and continuing through 2014, there was a large contraction in the supply of small business lending by the Top 4 banks. From 2008 to 2010, this credit supply shock had a significant impact on small business activity and employment in those counties that were most exposed to the Top 4 banks. Moreover, what we find particularly striking is the gradual nature of the subsequent adjustment process—the fact that it took several years for smaller banks and non-bank lenders to pick up the slack. And, while the total flow of small business credit to affected counties largely recovers by 2014, the cost of credit remains elevated, perhaps because these other lenders are higher-cost providers. Thus, while the impact on employment in affected counties dissipates by 2014, the negative impact on local wages persists. More generally, due to protracted nature of the adjustment process in credit markets, our findings suggest that a large credit supply shock from a subset of lenders can have surprisingly long-lived effects on real activity.

However, the precise array of forces that led to this particular supply shock remains unclear. Our reading of the evidence suggests that, from 2008 to 2010, the pullback by the Top 4 reflects a response to the financial crisis and a reassessment of their comparative advantage in small business lending. But there are also hints that heightened post-crisis regulation may help explain why the Top 4 were slow to return to small business lending after 2010, even as smaller banks and non-bank lenders were rapidly expanding in this segment. Going forward, it will be useful to better disentangle the causes of this shock. For example, if regulation played an important role from 2010 to 2014, then understanding the specific rules that contributed the most would be helpful from a policy perspective. We hope to investigate these questions in future work.

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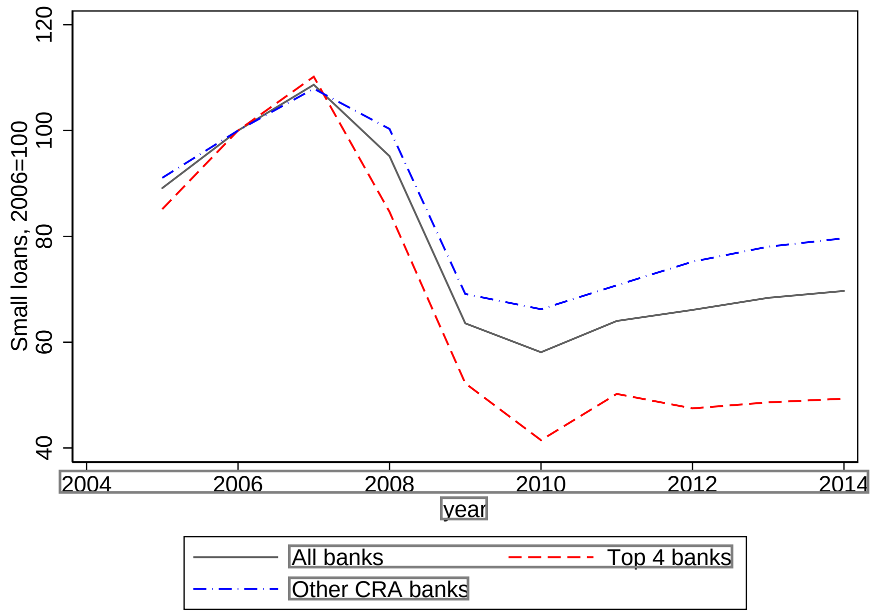
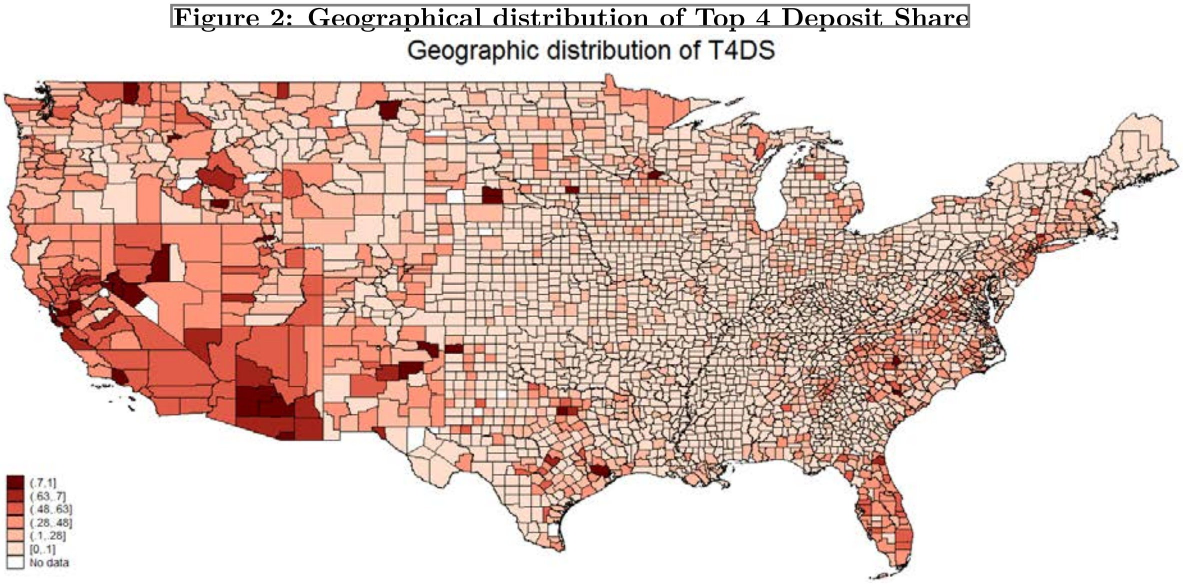
Figures

Figure 1: Annual originations of small business loans by Top 4 U.S. banks vs. all other banks



Notes: Data on small business loan originations is from Community Reinvestment Act filings. Small business loans are business loans with an initial balance less than \$1 million. The historical originations data for each of the Top 4 banks are adjusted for mergers by including all originations from banks they acquired prior to the end of 2014. Other CRA banks include all non-Top 4 banks, which includes approximately all banks with assets greater than \$1B from 2005 onwards.

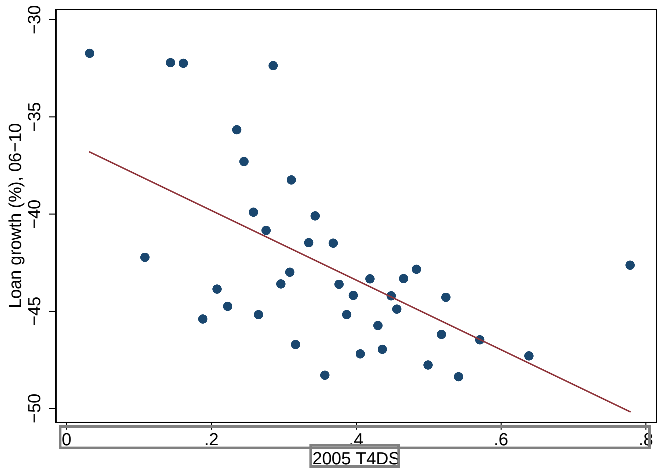
Figure 2: Geographical distribution of Top 4 Deposit Share



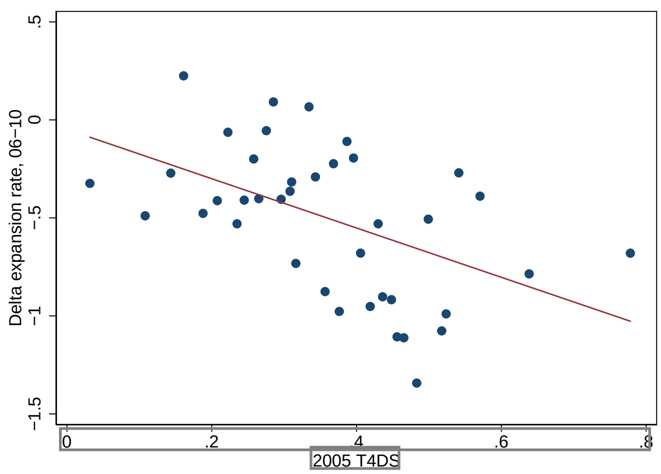
Notes: Top 4 Deposit Share represents the fraction of total bank deposits in a county accounted for by Top 4 banks in 2005. The deposits data for each of the Top 4 banks are adjusted for mergers by including all deposits from banks they acquired prior to the end of 2014. Data on bank deposits is from the Summary of Deposits.

Figure 3: Cross-sectional population-weighted impact of 2005 Top 4 bank share on 2006-2010 loan growth and change in expansions

PANEL A: Impact of 2005 Top 4 bank share on 2006-2010 Loan Growth



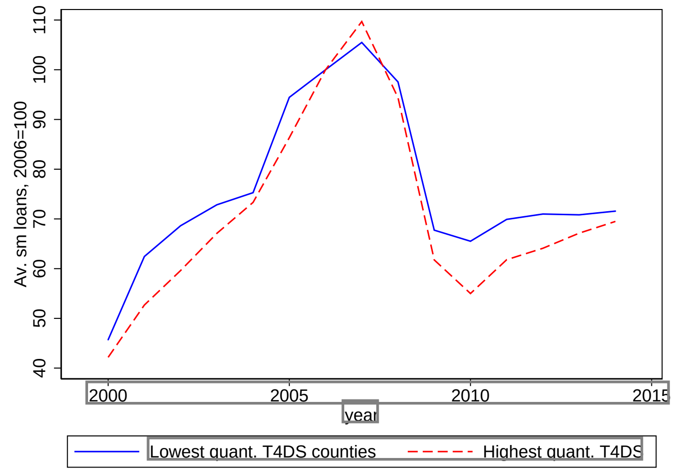
PANEL B: Impact of 2005 Top 4 bank share on 2006-2010 change in expansion rates



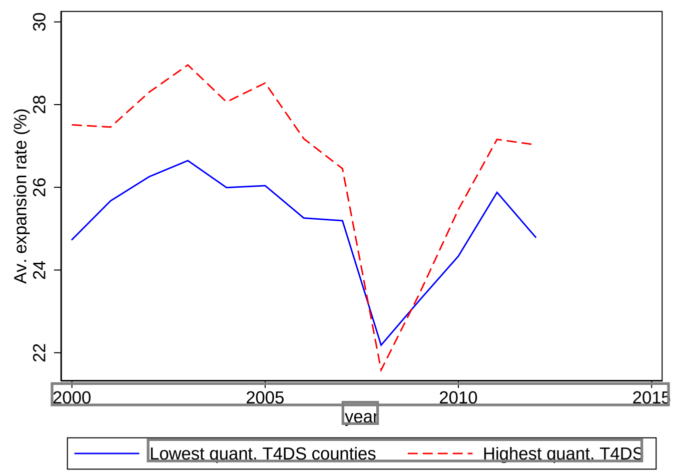
Notes: The first plot corresponds to the regression specification in column (5) of Table 3, and the second plot corresponds to the regression specification in column (5) of Table 4, Panel A. The residualized control variables include 2005 population, average county wages, labor force-to-population fraction, unemployment rate, expansion rate, the 2005 fraction of county employment in 9 broad industry classes, the 2005 fraction of college graduates, fraction of home owners, fraction of population aged 25+, fraction of population aged 65+, as well as the 2002-2006 wage growth, labor force growth, home price growth, and change in unemployment rate. The number of observations is 616.

Figure 4: Time-series of small business loans and expansion rates by 2005 Top 4 bank deposit share quantile

PANEL A: Small business lending originations, scaled by 2006 levels

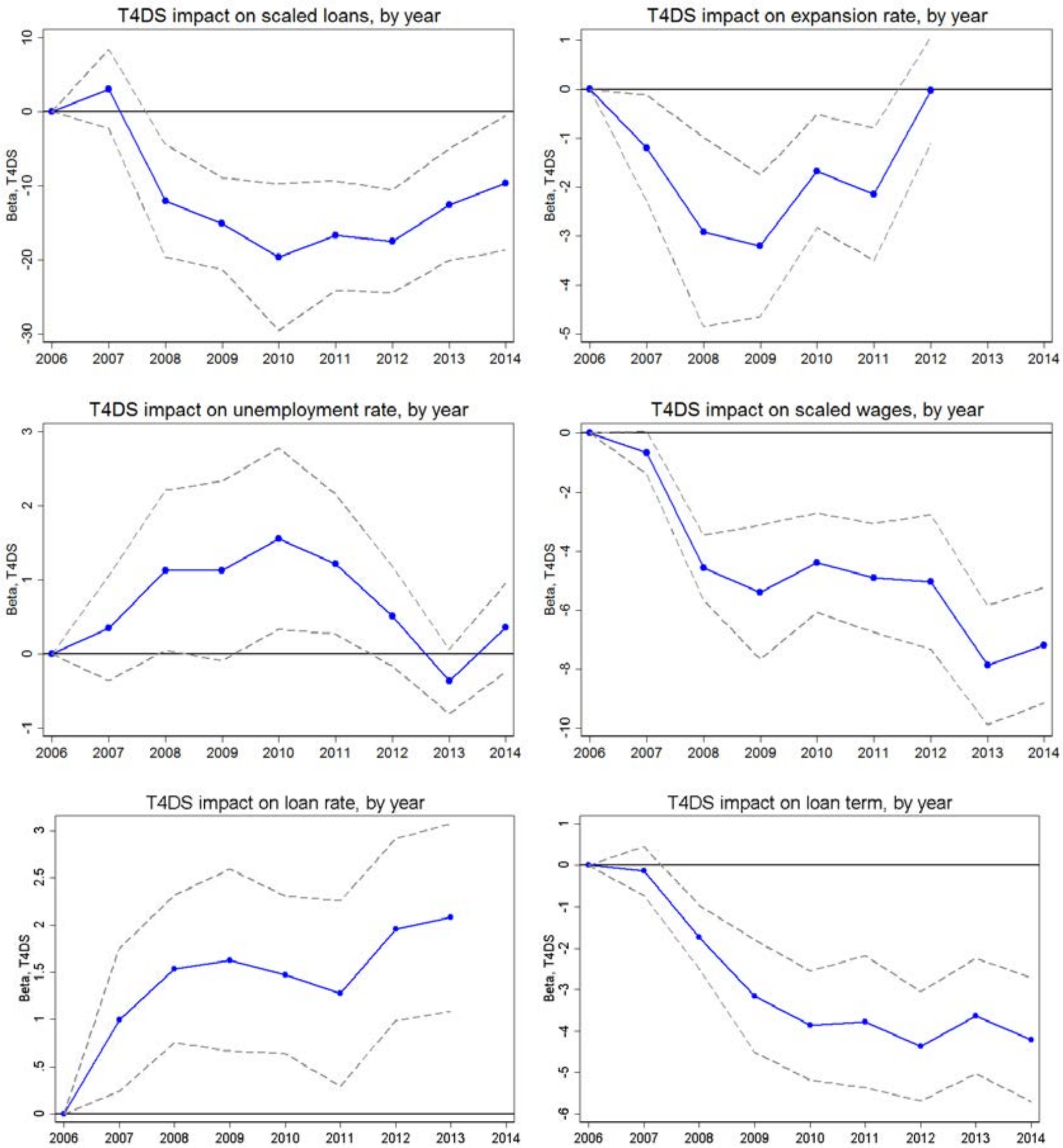


PANEL B: Business expansion rates



Notes: Small business loan originations data is calculated using Community Reinvestment Act filings. Average annual establishment expansion rates for counties are calculated with data from the U.S. Census Bureau, Statistics of U.S. Businesses database. $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits.

Figure 5: Estimated impact of Top 4 bank deposit share variable on outcomes over time



Notes: The graphs in Figure 5 plot the cofficients and confidence intervals on $T4DS_c \times Year_t$ as reported in panel regression specifications (1), (3), (5), and (9) of Table 6, as well as specifications (1) and (3) of Table 9, estimating

$$Y_{ct} = \alpha_c + \alpha_t + \beta \times T4DS_c \times Year_t + \gamma' \mathbf{x}_{ct} + \epsilon_{ct}.$$

The outcome variables Y_{ct} are: 1) $Loans_{ct}$, the total small loans in county c in year t scaled by 2006 total small loans in county c, 2) $Expansions_{ct}$, the establishment expansion rate in county c in year t, 3) ur_{ct}, the unemployment rate in county c in year t, 4) $wage_{ct}$, the annual average pay in county c in year t scaled by the annual average pay in county c in 2006, 5) $Loan\,Term_{ct}$, the average loan term in months in county c in year t, residualized by lender fixed effects, from PayNet data, and 6) $Loan\,rate_{ct}$, the inferred loan rate in county c in year t for a smaller set of the PayNet data. $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits, $Year_t$ is an indicator variable for year t for all years in the panel (except 2006). All specifications are run with year and county fixed effects. All specifications include as controls: lagged year average county wages, labor force size, unemployment rate, private employment, and fraction of county employment in nine broad industry classes. Gray dashed lines report 95% confidence intervals (standard errors clustered by state).

Tables

Table 1: Summary Statistics on Annual Small Business Loan Originations and Other Variables

PANEL A: Annual small business loan originations ($B)

	All banks	Top 4 banks	All other banks	50B+, not Top 4 banks	Under 50B banks
2006	302.27	98.12	204.15	79.80	124.35
2007	327.78	108.13	219.66	76.19	143.47
2008	286.50	83.05	203.45	70.58	132.87
2009	191.62	51.24	140.37	52.58	87.79
2010	174.82	40.70	134.12	52.16	81.96
2011	192.45	49.28	143.17	52.73	90.44
2012	198.64	46.58	152.06	51.61	100.45
2013	204.13	47.68	156.44	51.04	105.40
2014	208.01	48.38	159.63	49.60	110.03
2006-2010, growth	-42%	-59%	-34%	-35%	-34%
2010-2014 growth	19%	19%	19%	5%	34%
2006-2014, growth	-31%	-51%	-22%	-38%	-12%

PANEL B: Summary statistics for baseline county-level regression variables (population-weighted)

Variable	**Mean**	**Standard Deviation**	***N***
Top 4 Bank deposit share, 2005	0.300	0.230	3112
Loan growth, 2006-2010 (%)	-41.1	18.4	3134
ΔExpansion rate, 2006-2010 (ppt)	-0.631	2.31	3135
Expansion rate, 2010 (%)	26.1	2.1	3135
Wages, 2005	38,487	9,647	3135
Labor force / Population, 2005 (fraction)	0.503	0.045	3127
Δunemployment rate, 2006-2010 (ppt)	5.061	1.905	3127
Employment growth - pop growth, 2006-2010 (%)	-9.2	7.3	3111
Wage growth, 2006-2010 (fraction)	0.096	0.041	3134
Unemployment rate, 2005	5.172	1.403	3127
Wage growth, 2002-2006 (fraction)	0.153	0.045	3134
Labor force growth, 2002-2006 (fraction)	0.044	0.063	3127
Δunemployment rate, 2002-2006 (ppt)	-1.146	1.087	3127
Home price index growth, 2002-2006 (fraction)	0.506	0.354	998
Population, 2005 (M)	1.071	1.899	3135
Percent college+ educated, 2005	29.265	9.488	775
Percent homeowners, 2005	65.340	10.773	775
Percent age 25+, 2005	65.286	3.544	775
Percent age 65+, 2005	11.603	3.136	775

Notes on Panel A: Data on small business loan originations is from Community Reinvestment Act filings. Small business loans are business loans with an initial balance less than $1 million. The historical originations data for the Top 4 banks (Bank of America, Citigroup, JP Morgan Chase, Wells Fargo), as well as other banks, are adjusted for mergers by including all originations from banks they acquired prior to the end of 2014. Non Top 4 banks are limited to those in the CRA sample which includes all banks with assets greater than approximately $1 billion.

Table 2: Did Top 4 banks decrease small business bank loans more from 2006 to 2010? Bank and county-bank level analysis

Panel A of this table displays results from running bank-level cross-sectional regressions of the form:

$$\%\Delta Loans_b = \alpha + \beta \times T4_b + \gamma' \mathbf{x}_b + \epsilon_b.$$

Each bank observation is weighted by its 2005 assets. $\%\Delta Loans_b$ is the 2006-2010 growth in small business loan originations for bank b, winsorized at 1%. $T4_b$ is an indicator for a top 4 bank (Bank of America, Citigroup, JP Morgan Chase, Wells Fargo), and $\mathbf{x}_b$ is a vector of 2005Q4 bank-level control variables, including an indicator for a bank with total commercial banking assets between \$50B and \$500B in 2005. In Panel A, robust standard errors are reported. The row "Top 4 = 50-500B Banks" reports the p-value from a test of equality of the Top 4 bank coefficient and the 50-500B banks coefficient in that specification.

Panel B of this table displays results from running county-bank-level cross-sectional regressions of the form:

$$\%\Delta Loans_{bc} = \alpha_c + \beta \times T4_b + \gamma' \mathbf{x}_b + \epsilon_{bc}.$$

Each county-bank observation is weighted by the 2006 level of deposits. County fixed effects are included. $\%\Delta Loans_{bc}$ is the 2006-2010 growth in small business loan originations for bank b in county c, winsorized at 1%. $T4_b$ is an indicator for a Top 4 bank (JP Morgan Chase, Bank of America, Citi, Wells Fargo), and $\mathbf{x}_b$ is a vector of 2005Q4 bank-level control variables, including an indicator for a bank with total commercial banking assets between \$50B and \$500B in 2005. In Panel B, standard errors are clustered by bank. $*p < 0.1, **p < 0.05, ***p < 0.01$

	Panel A: Bank level				Panel B: County-bank level			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta Loans_b$	$\Delta Loans_b$	$\Delta Loans_b$	$\Delta Loans_b$	$\Delta Loans_{bc}$	$\Delta Loans_{bc}$	$\Delta Loans_{bc}$	$\Delta Loans_{bc}$
Top 4 bank	-31.60***	-26.35***	-42.46***	-38.24***	-36.63***	-24.28***	-59.70***	-49.95***
	(5.889)	(6.326)	(5.945)	(7.907)	(6.583)	(8.360)	(10.74)	(10.72)
50-500B Banks (05)			-17.02**	-15.37**			-37.01***	-33.26***
			(7.399)	(7.066)			(11.58)	(12.48)
Whsale Fund / assets		-28.83		-21.66		-29.56		-13.28
		(29.88)		(26.47)		(59.88)		(49.02)
05-07 Asset Gr		33.56		35.10		-44.27		-42.34
		(23.07)		(22.38)		(48.83)		(45.96)
Deposits / assets		-38.32		-50.69		48.25		26.22
		(37.86)		(37.74)		(99.18)		(86.20)
Real Estate / assets		31.26		20.64		-8.382		-39.83
		(28.54)		(27.47)		(45.16)		(51.56)
08-09 CnI chargeoffs		-250.9*		-339.4**		-208.5		-421.6**
		(130.1)		(133.1)		(161.0)		(182.0)
Book cap ratio (05)		-364.5**		-316.5**		-388.8**		-230.6
		(142.0)		(131.6)		(174.4)		(180.8)
Top 4 = 50-500B Banks?			0.001	0.006			0.001	0.049
County FE					Yes	Yes	Yes	Yes
Observations	377	376	377	376	10358	10153	10358	10153
R^2	0.247	0.390	0.277	0.412	0.209	0.240	0.217	0.245

Table 3: Impact of 2005 Top 4 bank share on the 2006 to 2010 growth in small business loan originations

The table displays results from running county-level cross-sectional regressions of the form:

$$\%\Delta Loans_c = \alpha_1 + \beta_1 \times T4DS_c + \gamma_1 \mathbf{x}_c + \epsilon_c.$$

Each county observation is weighted by its 2005 population level. $\%\Delta Loans_c$ is the 2006-2010 growth in small business loan originations for county c, $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits, and $\mathbf{x}_c$ is a vector of county-level control variables. Baseline controls includes 2005 population, average county wages, the labor force-to-population fraction, the unemployment rate, as well as the 2005 fraction of county employment in ten broad industry classes. ACS controls include variables from the 2005 American Community Survey, including the fraction of college graduates, the fraction of home owners, the fraction of population aged 25+, and the fraction of population aged 65+. Labor force growth, wage growth, home price growth controls are measured from 2002 to 2006, and Δunemployment rate represents the 2002-2006 percentage point change. Standard errors are clustered by state. $*p < 0.1, **p < 0.05, ***p < 0.01$

	(1)	(2)	(3)	(4)	(5)
	Δ Loans	Δ Loans	Δ Loans	Δ Loans	Δ Loans
T4DS, 05	-21.67***	-17.99***	-20.80***	-17.64***	-17.91***
	(5.648)	(6.276)	(6.720)	(5.986)	(5.789)
Labor force growth				-34.77***	-43.75***
				(12.58)	(11.82)
Wage growth				29.05	25.44
				(24.13)	(22.84)
Δ Unemp rate				-0.503	-0.515
				(1.060)	(0.965)
Home price growth				-13.61***	-13.63***
				(3.218)	(2.770)
Expansions rate, 05					140.2***
					(32.40)
Baseline Controls	No	Yes	Yes	Yes	Yes
ACS Controls	No	No	Yes	Yes	Yes
Observations	3112	2828	769	616	616
R^2	0.075	0.129	0.263	0.363	0.391

Table 4: Impact of 2005 Top 4 bank share on the 2006 to 2010 change in establishment expansion rate

The table displays results from running county-level cross-sectional regressions of the form:

$$\Delta Expansions_c = \alpha_2 + \beta_2 \times T4DS_c + \gamma_2^{'} \mathbf{x}_c + \xi_c,$$

in Panel A, and county-level cross-sectional instrumental variable regressions of the form:

$$\Delta Expansions_c = \alpha_{IV} + \beta_{IV} \times \%\Delta Loans_c + \gamma_{IV}^{'} \mathbf{x}_c + \omega_c,$$

in Panel B. Each county observation is weighted by its 2005 population level. $\Delta Expansions_c$ is the 2006-2010 difference in establishment expansion rates for county c, winsorized at 1%; $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits; $\%\Delta Loans_c$ is the 2006-2010 growth in small business loan originations for county c instrumented by $T4DS_c$. $\mathbf{x}_c$ is a vector of county-level control variables. Baseline controls includes 2005 population, average county wages, the labor force-to-population fraction, the unemployment rate, as well as the 2005 fraction of county employment in nine broad industry classes. ACS controls include variables from the 2005 American Community Survey, including the fraction of college graduates, the fraction of home owners, the fraction of population aged 25+, and the fraction of population aged 65+. $\Delta 02-06$ controls include the 2002-2006 growth in wages, growth in labor force, and change in unemployment rate. Standard errors are clustered by state. $*p < 0.1, **p < 0.05, ***p < 0.01$

	(1)	(2)	(3)	(4)	(5)
	Δ Expansions	Δ Expansions	Δ Expansions	Δ Expansions	Δ Expansions
Panel A: Reduced Form Estimates					
T4DS, 05	-1.206**	-1.855***	-1.594**	-1.318**	-1.258**
	(0.577)	(0.571)	(0.617)	(0.573)	(0.527)
Home price growth				0.831**	0.836***
				(0.316)	(0.270)
R^2	0.014	0.118	0.210	0.344	0.418
Panel B: Instrumental Variable Estimates					
Δ Loans	0.0557*	0.103**	0.0766**	0.0747*	0.0702**
	(0.0288)	(0.0499)	(0.0381)	(0.0389)	(0.0326)
Home price growth				1.847**	1.793***
				(0.720)	(0.622)
Baseline Controls	No	Yes	Yes	Yes	Yes
ACS Controls	No	No	Yes	Yes	Yes
Δ 02-06 Controls	No	No	No	Yes	Yes
05 Exp. rate	No	No	No	No	Yes
Observations	3112	2828	769	616	616

Table 5: Impact of 2005 Top 4 bank share on the 2006 to 2010 change in unemployment rates, relative employment growth, and wage growth

The table displays results from running county-level cross-sectional regressions of the form:

$$\Delta y_c = \alpha_2 + \beta_2 \times T4DS_c + \gamma_2^{'}\mathbf{x}_c + \xi_c,$$

in Panel A, and county-level cross-sectional instrumental variable regressions of the form:

$$\Delta y_c = \alpha_{IV} + \beta_{IV} \times \%\Delta Loans_c + \gamma_{IV}^{'}\mathbf{x}_c + \omega_c,$$

in Panel B. Each county observation is weighted by its 2005 population level. Δy_c is either the 2006-2010 difference in unemployment rate, the 2006-2010 growth in private employment minus the 2006-2010 growth in population for county c, or the 2006-2010 growth in wages for county c, $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits, $\%\Delta Loans_c$ is the difference in small business loan originations in 2010 and 2006 for county c (divided by 2006 originations) instrumented by $T4DS_c$. $\mathbf{x}_c$ is a vector of county-level control variables. Baseline controls includes 2005 population, average county wages, the labor force-to-population fraction, the unemployment rate, as well as the 2005 fraction of county employment in nine broad industry classes. ACS controls include variables from the 2005 American Community Survey, including the fraction of college graduates, the fraction of home owners, the fraction of population aged 25+, and the fraction of population aged 65+. $\Delta 02-06$ controls include the 2002-2006 growth in wages, growth in labor force, and change in unemployment rate. Standard errors are clustered by state. $*p < 0.1, **p < 0.05, ***p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δ Unemp rate	Δ Unemp rate	Δ Unemp rate	Δ Emp - Δ Pop	Δ Emp - Δ Pop	Δ Emp - Δ Pop	Δ Wages, pct	Δ Wages, pct	Δ Wages, pct
T4DS, 05	2.796**	2.404**	0.926	-3.444	-5.520***	-2.639*	-2.184***	-2.061***	-1.801*
	(1.241)	(1.121)	(0.974)	(2.451)	(1.742)	(1.340)	(0.777)	(0.735)	(1.042)
Home price growth			2.639***			-4.417***			-0.397
			(0.745)			(1.428)			(0.922)
R^2	0.114	0.352	0.651	0.012	0.331	0.529	0.015	0.129	0.225
Panel B: Instrumental Variable Estimates									
Δ Loans	-0.129***	-0.134***	-0.0525	0.158	0.307***	0.150**	0.101**	0.115**	0.102
	(0.0487)	(0.0495)	(0.0472)	(0.101)	(0.0976)	(0.0625)	(0.0409)	(0.0462)	(0.0646)
Home price growth			1.925*			-2.382			0.992
			(1.110)			(1.739)			(1.091)
Baseline Controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
ACS Controls	No	No	Yes	No	No	Yes	No	No	Yes
Δ 02-06 Controls	No	No	Yes	No	No	Yes	No	No	Yes
Observations	3104	2828	616	3090	2821	616	3111	2827	616

Table 6: Yearly impact of Top 4 bank share on outcomes in panel regression

The table displays results from running 2005 county-year panel regressions from 2006 to 2014 of the form:

$$Y_{ct} = \alpha_c + \alpha_t + \sum_{\tau=2007}^{2014} \beta_\tau \times T4DS_c \times 1_{\{t=\tau\}} + \gamma' \mathbf{x}_{ct-1} + \epsilon_{ct}.$$

Each county-year observation is weighted by the 2005 population level of the county. Y_{ct} is either 1) $Loans_{ct}$, the total small loans in county c in year t scaled by its 2006 total small loans, multiplied by 100, 2) $Expansions_{ct}$, the establishment expansion rate in county c in year t (in percent), 3) ur_{ct} is the unemployment rate in county c in year t (in percent), 4) $(Emp - Pop)_{ct}$, the difference between the private employment in county c in year t scaled by its private employment in 2006, and population in county c in year t scaled by its 2006 population, multiplied by 100, or 5) $wage_{ct}$, the annual average pay in county c in year t scaled by its average pay in 2006, multiplied by 100. $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits, $Year_t$ is an indicator variable for year t, $\mathbf{x}_{ct-1}$ is a vector of county-year control variables. Baseline controls includes lagged year average wages, unemployment rate, scaled private employment, and scaled population, as well as the lagged year fraction of county employment in nine broad industry classes. House prices are the lagged year house price index, scaled by its 2006 level. Standard errors are clustered by state. $*p < 0.1, **p < 0.05, ***p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Sm loans	Sm loans	Exp. rate	Exp. rate	Unemp rate	Unemp rate	Emp - Pop	Emp - Pop	Wages	Wages
T4DS X 2007	3.027	6.266**	-1.204**	-0.927	0.348	0.413	-0.731	-0.837	-0.664*	-0.324
	(2.710)	(3.103)	(0.555)	(0.561)	(0.360)	(0.389)	(0.825)	(0.904)	(0.371)	(0.433)
T4DS X 2008	-12.02***	-9.618**	-2.916***	-2.179*	1.128**	1.181**	-2.304**	-2.083	-4.558***	-3.366***
	(3.871)	(4.408)	(0.987)	(1.110)	(0.551)	(0.582)	(1.120)	(1.254)	(0.560)	(0.539)
T4DS X 2009	-15.09***	-13.26***	-3.194***	-3.030***	1.121*	1.338**	-3.575***	-3.382**	-5.389***	-3.831***
	(3.158)	(3.297)	(0.739)	(0.879)	(0.617)	(0.661)	(1.200)	(1.316)	(1.161)	(1.297)
T4DS X 2010	-19.64***	-16.29***	-1.670***	-2.491***	1.554**	1.915***	-0.433	-1.426	-4.385***	-2.587***
	(5.028)	(5.499)	(0.588)	(0.788)	(0.621)	(0.664)	(1.578)	(1.718)	(0.861)	(0.945)
T4DS X 2011	-16.72***	-12.78***	-2.142***	-2.802***	1.211**	1.475***	-2.160**	-2.280**	-4.907***	-3.106***
	(3.769)	(4.195)	(0.692)	(0.875)	(0.481)	(0.529)	(0.994)	(1.065)	(0.939)	(0.946)
T4DS X 2012	-17.49***	-11.65***	-0.0224	-0.964	0.509	0.598	-0.864	-0.815	-5.037***	-2.878**
	(3.535)	(3.505)	(0.553)	(0.751)	(0.343)	(0.404)	(0.773)	(0.756)	(1.161)	(1.196)
T4DS X 2013	-12.55***	-6.816*			-0.368	-0.181	0.105	-0.0136	-7.861***	-5.239***
	(3.842)	(3.678)			(0.221)	(0.270)	(0.862)	(0.879)	(1.030)	(1.045)
T4DS X 2014	-9.606**	-0.799			0.354	0.591*	-0.0799	-0.291	-7.186***	-4.569***
	(4.632)	(3.673)			(0.305)	(0.343)	(1.194)	(1.204)	(1.001)	(0.895)
House prices		10.93***		-3.920***		0.743***		-0.974		3.240***
		(3.949)		(0.782)		(0.256)		(1.138)		(0.959)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25346	8790	19720	6838	25346	8790	25333	8788	25345	8790
R^2	0.655	0.845	0.723	0.829	0.916	0.929	0.803	0.865	0.893	0.914

Table 7: Differential impact of 2005 Top 4 bank share on employment in areas with high small firm employment share

The table displays results from running county-level cross-sectional regressions of the form:

$$\Delta Emp_c - \Delta Pop_c = \alpha + \beta \times T4DS_c + \delta \times SmallShare_c + \tau \times T4DS_c \times SmallShare_c + \gamma' \mathbf{x}_c + \xi_c.$$

Each county observation is weighted by its 2005 population level. $\Delta Emp_c - \Delta Pop_c$ is the difference between the 2007-2010 growth in total private firm employment for county c and the 2007-2010 population growth for county c. $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits, $SmallShare_c$ is the 2007 fraction of employment in county c accounted for by firms with fewer than 500 employees, and $\mathbf{x}_c$ is a vector of county-level control variables. Baseline controls includes 2005 population, average county wages, the labor force-to-population fraction, the unemployment rate, as well as the 2005 fraction of county employment in nine broad industry classes. ACS controls include variables from the 2005 American Community Survey, including the fraction of college graduates, the fraction of home owners, the fraction of population aged 25+, and the fraction of population aged 65+. $\Delta 02-06$ controls include the 2002-2006 growth in wages, growth in labor force, and change in unemployment rate. Standard errors are clustered by state. $*p < 0.1, **p < 0.05, ***p < 0.01$

	(1)	(2)	(3)
	Δ Emp - Δ Pop	Δ Emp - Δ Pop	Δ Emp - Δ Pop
T4DS, 05	6.980	12.53	9.956
	(5.953)	(7.977)	(7.216)
T4DS X Sm. share (07)	-24.31**	-36.04**	-27.31**
	(10.47)	(14.11)	(12.98)
Small share (07)	7.413***	8.945*	2.866
	(2.618)	(5.306)	(4.648)
Home price growth			-4.018***
			(1.007)
Baseline Controls	Yes	Yes	Yes
ACS Controls	No	Yes	Yes
Δ 02-06 Controls	No	No	Yes
Observations	2814	769	616
R^2	0.329	0.478	0.515

Table 8: Differential impact of Top 4 bank share on external finance dependent industries' expansion and employment growth

The table displays results from running industry-county-level cross-sectional regressions of the form:

$$\Delta Y_{ic} = \alpha_i + \beta_1 \times T4DS_c + \beta_2 \times T4DS_c \times ExtFinUse_i + \gamma' \mathbf{x}_c + \epsilon_{ic},$$

and in column (4) of the form

$$\Delta Y_{ic} = \alpha_i + \alpha_c + \beta_2 \times T4DS_c \times ExtFinUse_i + \epsilon_{ic}.$$

In Panel A, ΔY_{ic} is $\Delta Expansions_{ic}$, the 2006-2010 difference in establishment expansion rates for industry i in county c, winsorized at 1%. In Panel B, ΔY_{ic} is $\Delta Employment_{ic}$, the 2006-2010 growth in average annual employment for industry i in county c, minus the 2006-2010 population growth in county c. Each industry-county observation is weighted by its 2005 number of establishments (Panel A) or its 2005 employment level (Panel B). $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits, $ExtFinUse_i$ is an indicator for above-median use of non-personal finance for expansion capital in industry i according to 2007 Survey of Business Owners data, and $\mathbf{x}_c$ is a vector of county-level control variables. Baseline controls includes 2005 population, average county wages, the labor force-to-population fraction, and the unemployment rate. ACS controls include variables from the 2005 American Community Survey, including the fraction of college graduates, the fraction of home owners, the fraction of population aged 25+, and the fraction of population aged 65+. $\Delta 02-06$ controls include the 2002-2006 growth in wages, growth in labor force, growth in home prices, and change in unemployment rate. Standard errors are clustered by state. $*p < 0.1, **p < 0.05, ***p < 0.01$

	(1)	(2)	(3)	(4)
Panel A: Expansions				
	Δ Expansions	Δ Expansions	Δ Expansions	Δ Expansions
T4DS, 05	-1.063	0.183	0.661	
	(0.637)	(0.601)	(0.611)	
T4DS X Ext Fin hi	-3.395***	-3.765***	-3.821***	-3.513***
	(0.590)	(0.652)	(0.637)	(0.584)
Expansions rate, 05			-7.809**	
			(3.008)	
Observations	54899	18443	12152	55094
R^2	0.0653	0.134	0.187	0.187

Panel B: Employment				
	Δ Employment	Δ Employment	Δ Employment	Δ Employment
T4DS, 05	-2.168	0.609	-0.298	
	(1.885)	(1.581)	(1.560)	
T4DS X Ext Fin hi	-8.323***	-7.483***	-7.283***	-8.192***
	(1.833)	(2.192)	(2.214)	(1.847)
Employment (M), 05			-17.96*	
			(9.606)	
Industry FE	Yes	Yes	Yes	Yes
County FE	No	No	No	Yes
Baseline Controls	Yes	Yes	Yes	No
ACS Controls	No	No	Yes	No
Δ 02-06 Controls	No	Yes	Yes	No
Observations	38112	15292	10907	38230
R^2	0.145	0.148	0.147	0.183

Table 9: Differential impact of Top 4 bank share on tradable vs. non-tradable industry employment growth

The table displays results from running industry-county-level cross-sectional regressions of the form:

$$\Delta Y_{ic} = \alpha_i + \beta_1 \times T4DS_c + \beta_2 \times T4DS_c \times Tradable_i + \gamma' \mathbf{x}_c + \epsilon_{ic},$$

and in columns (4) and (5) of the form:

$$\Delta Y_{ic} = \alpha_i + \alpha_c + \beta_2 \times T4DS_c \times Tradable_i + \epsilon_{ic},$$

where all observations are restricted either to tradable goods industries or non-tradable goods industries, as classified by Mian and Sufi (2014), ΔY_{ic} is $\Delta Employment_{ic}$, the 2006-2010 growth in average annual employment for industry i in county c, minus the 2006-2010 population growth in county c. Each industry-county observation is weighted by its 2005 employment level. $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits, $Tradable_i$ is an indicator for industry i being a tradable goods industry, and $\mathbf{x}_c$ is a vector of county-level control variables. Baseline controls includes 2005 population, average county wages, the labor force-to-population fraction, and the unemployment rate. ACS controls include variables from the 2005 American Community Survey, including the fraction of college graduates, the fraction of home owners, the fraction of population aged 25+, and the fraction of population aged 65+. $\Delta 02-06$ controls include the 2002-2006 growth in wages, growth in labor force, growth in home prices, and change in unemployment rate. Standard errors are clustered by state. $*p < 0.1, **p < 0.05, ***p < 0.01$

	(1)	(2)	(3)	(4)	(5)
	Δ Employment	Δ Employment	Δ Employment	Δ Employment	Δ Employment
T4DS, 05	-5.146**	-3.759*	-3.186		
	(2.259)	(2.151)	(2.113)		
T4DS X tradable	-6.180**	-5.729**	-5.326*	-6.057**	-5.996**
	(2.953)	(2.737)	(2.693)	(2.682)	(2.794)
Employment (M), 05			7.647		
			(15.68)		
Industry FE	Yes	Yes	Yes	Yes	Yes
County FE	No	No	No	Yes	Yes
Baseline Controls	Yes	Yes	Yes	No	No
ACS Controls	No	No	Yes	No	No
Δ 02-06 Controls	No	Yes	Yes	No	No
Δ Home price X tradable	No	Yes	Yes	No	Yes
Observations	28736	18557	16324	28548	18592
R^2	0.252	0.287	0.298	0.323	0.340

Table 10: Impact of Top 4 bank share on loan term length and loan rates

The table displays results from running county-year panel regressions from 2006 to 2014 of the form:

$$Y_{ct} = \alpha_c + \alpha_t + \sum_{\tau=2007}^{2014} \beta_\tau \times T4DS_c \times 1_{\{t=\tau\}} + \gamma' \mathbf{x}_{ct-1} + \epsilon_{ct}.$$

Y_{ct} is either the residual average loan term (in months) in county c in year t from PayNet data (obtained by regressing Y_{lct} on a full set of lender l fixed effects, and defining the residuals from that regression as Y_{ct}), or the inferred loan rate in county c in year t for a smaller set of the PayNet data, $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits, $Year_t$ is either an indicator variable for year t, $\mathbf{x}_{ct-1}$ is a vector of county-year control variables. For regressions with residual average loan term as outcome that use the full PayNet data, each county-year observation is weighted by the 2005 population level of the county; regressions with loan rate as outcome weight each county-year observation by the 2006 number of loans in that county with rate data. Baseline controls includes lagged year average county wages, unemployment rate, scaled private employment, and scaled population, as well as the lagged year fraction of county employment in nine broad industry classes. Standard errors are clustered by state. $*p < 0.1, **p < 0.05, ***p < 0.01$

	(1)	(2)	(3)	(4)
	Loan rate	Loan rate	Loan term	Loan term
T4DS X 2007	0.942**	0.468	0.0314	0.452
	(0.388)	(0.388)	(0.287)	(0.309)
T4DS X 2008	1.424***	1.026***	-1.408***	-0.632
	(0.381)	(0.370)	(0.400)	(0.450)
T4DS X 2009	1.510***	1.176***	-2.812***	-1.278
	(0.444)	(0.405)	(0.714)	(0.843)
T4DS X 2010	1.285***	0.680*	-3.512***	-1.903*
	(0.399)	(0.388)	(0.737)	(0.971)
T4DS X 2011	0.990**	0.381	-3.315***	-1.990*
	(0.432)	(0.395)	(0.840)	(1.037)
T4DS X 2012	1.614***	1.076**	-3.840***	-2.698***
	(0.453)	(0.433)	(0.724)	(0.880)
T4DS X 2013	1.811***	1.181***	-3.006***	-1.824*
	(0.463)	(0.413)	(0.759)	(0.910)
T4DS X 2014			-3.599***	-2.689***
			(0.774)	(0.909)
House prices, sc		-0.0460		1.005
		(0.303)		(0.957)
Av credit score	-0.0211***	-0.0149***		
	(0.00342)	(0.00401)		
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Baseline Controls	Yes	Yes	Yes	Yes
Observations	11242	6493	25329	8790
R^2	0.700	0.813	0.484	0.598

Table 11: Estimates of demand and supply semi-elasticities

The table displays results from running county-level cross-sectional instrumental variable regressions from 2006 to 2013 (or 2010 to 2013) of the form:

$$\%\Delta Loans_c = \alpha_{IV} + \beta_{IV} \times \Delta rate_c + \gamma'_{IV}\mathbf{x}_c + \omega_c,$$

where the first stage of the regression is

$$\Delta rate_c = \alpha + \beta \times T4DS_c + \gamma'\mathbf{x}_c + \epsilon_c.$$

In columns (1) and (2), $\%\Delta Loans_c$ is the 2006-2010 growth in total loans in county c; in columns (3) and (4), $\%\Delta Loans_c$ is the 2010-2013 growth in non-bank total loan volume from the PayNet data in county c; in columns (5) and (6), $\%\Delta Loans_c$ is the 2010-2013 growth in non-Top 4 bank small business loans in county c. $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits. $\Delta rate_c$ is the difference in the inferred loan rate in county c from the PayNet data, and $\mathbf{x}_c$ is a vector of county-level control variables. In columns (1) and (2), $\Delta rate_c$ is the 2006-2010 difference in loan rates. In columns (3) through (6), $\Delta rate_c$ is the 2006-2013 difference in loan rates. Each county-year observation by the 2006 number of loans in that county with rate data. Baseline controls includes 2005 population, average county wages, the labor force-to-population fraction, the unemployment rate, as well as the 2005 fraction of county employment in nine broad industry classes. ACS controls include variables from the 2005 American Community Survey, including the fraction of college graduates, the fraction of home owners, the fraction of population aged 25+, and the fraction of population aged 65+. Standard errors are clustered by state. $*p < 0.1, **p < 0.05, ***p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Tot loans	Δ Tot loans	Δ Nonbank	Δ Nonbank	Δ Non-T4 bank	Δ non-T4 bank
Δ rate (10-06)	-19.81*	-27.59				
	(11.09)	(20.07)				
Δ rate (13-06)			26.02*	15.46	22.03	26.09
			(13.93)	(13.93)	(14.47)	(18.07)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
ACS Controls	No	Yes	No	Yes	No	Yes
Observations	1342	729	1301	727	1301	727

Table 12: Impact of Top 4 bank share on loan growth at Top 4, other Large, and Small Banks
The table displays results from running county-level cross-sectional regressions of the form:

$$\Delta Y_c = \alpha + \beta \times T4DS_c + \gamma' \mathbf{x}_c + \epsilon_c. \quad (1)$$

Each county observation is weighted by its 2005 population level. ΔY_c is the growth in small business loan originations for a specific pair of years for all banks (L_A), top 4 banks only (L_{T4}), other large banks with \$50B+ in total commercial bank assets in 2005 (L_B), or small banks with under \$50B in assets (L_s). Initial year is denoted time 0, and ending year is time 1. The identity relating total loan growth to bank group loan growth is:

$$\frac{\Delta L_{A,1}}{L_{A,0}} = \frac{\Delta L_{T4,1}}{L_{A,0}} + \frac{\Delta L_{B,1}}{L_{A,0}} + \frac{\Delta L_{S,1}}{L_{A,0}}$$
$$= \left(\frac{L_{T4,0}}{L_{A,0}}\right)\left(\frac{\Delta L_{T4,1}}{L_{T4,0}}\right) + \left(\frac{L_{B,0}}{L_{A,0}}\right)\left(\frac{\Delta L_{B,1}}{L_{B,0}}\right) + \left(\frac{L_{S,0}}{L_{A,0}}\right)\left(\frac{\Delta L_{S,1}}{L_{A,0}}\right).$$

$T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits, and $\mathbf{x}_c$ is a vector of county-level control variables. Each specification includes the same controls as in the regression in column (5) of Table 3. These controls include 2005 population, average county wages, labor force-to-population fraction, and unemployment rate, the 2005 expansion rate, the 2005 fraction of county employment in nine broad industry classes, the fraction of college graduates, fraction of home owners, fraction of population aged 25+, fraction of population aged 65+ , as well as the 2002-2006 wage growth, labor force growth, home price growth, and change in unemployment rate. Standard errors are clustered by state. $*p < 0.1, **p < 0.05, ***p < 0.01$

PANEL A: Estimates of β from (1), over different years, where ΔY_c is the contribution to total loan growth due to banks of a specific group

	All banks	T4 banks	Large banks	Small banks
	$\beta(T4DS, \frac{\Delta L_{A,1}}{L_{A,0}})$	$\beta(T4DS, \frac{\Delta L_{T4,1}}{L_{A,0}})$	$\beta(T4DS, \frac{\Delta L_{B,1}}{L_{A,0}})$	$\beta(T4DS, \frac{\Delta L_{S,1}}{L_{A,0}})$
2006-2010	-17.91***	-21.80***	-0.70	4.59
2010-2014	26.63**	6.84	7.22**	12.57**
2006-2014	-4.94	-19.59***	4.66	10.00**

PANEL B: Estimates of β from (1), over different years, where ΔY_c is the growth of loans by banks of a specific group

	T4 banks	Large banks	Small Banks
	$\beta(T4DS, \frac{\Delta L_{T4,1}}{L_{T4,0}})$	$\beta(T4DS, \frac{\Delta L_{B,1}}{L_{B,0}})$	$\beta(T4DS, \frac{\Delta L_{S,1}}{L_{A,0}})$
2006-2010	12.22*	-26.27***	-10.42
2010-2014	19.65	35.61*	45.81***
2006-2014	12.75***	-3.30	16.32*

Table 13: Impact of 2005 Top 4 bank share on 2010 to 2014 non-bank loan growth

The table displays results from running county-level cross-sectional regressions of the form:

$$\Delta NBLoans_c = \alpha_1 + \beta_1 \times T4DS_c + \gamma_1 \mathbf{x}_c + \epsilon_c,$$

and also of the form

$$AltLoans_c = \alpha_2 + \beta_2 \times T4DS_c + \gamma_2 \mathbf{x}_c + \epsilon_c.$$

Each county observation is weighted by its 2005 population level. $\Delta NBLoans_c$ is the 2010 to 2014 growth in non-bank loan origination dollar volume in county c from PayNet data winsorized at 5%, $AltLoans_c$ is the dollar volume of 2014 alternative lender originations in county c from PayNet data (normalized by the 2005 population of county c). $T4DS_c$ is the fraction of total deposits in county c accounted for by Top 4 banks in 2005 according to the Summary of Deposits, and $\mathbf{x}_c$ is a vector of county-level control variables. Baseline controls includes 2005 population, average county wages, the labor force-to-population fraction, the unemployment rate, as well as the 2005 fraction of county employment in nine broad industry classes. ACS controls include variables from the 2005 American Community Survey, including the fraction of college graduates, the fraction of home owners, the fraction of population aged 25+, and the fraction of population aged 65+. $\Delta 02-06$ controls include the 2002-2006 growth in wages, growth in labor force, growth in home prices, and change in unemployment rate. Standard errors are clustered by state. $*p < 0.1, **p < 0.05, ***p < 0.01$

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Nonbank	Δ Nonbank	Δ Nonbank	Alt loans	Alt loans	Alt loans
T4DS, 05	64.69***	46.62**	24.44	1.990***	1.836***	1.669***
	(22.59)	(21.46)	(24.35)	(0.364)	(0.379)	(0.434)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
ACS Controls	No	Yes	Yes	No	Yes	Yes
Δ 02-06 Controls	No	No	Yes	No	No	Yes
Observations	2824	769	616	2827	769	616
R^2	0.162	0.236	0.269	0.321	0.434	0.445