No Risk, No Growth: The Effects of Stress Testing on Entrepreneurship and Innovation*

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Abstract

This paper shows that post-crisis financial regulation reduces bank credit to young firms and leads to a decline in entrepreneurship and innovation. I provide evidence that banks subject to stress tests strongly cut small businesses lending, in particular lending secured by real estate collateral. Lower credit supply leads to a relative decline in the number and share of entrepreneurs during the recovery in counties with high exposure to stress tested banks, relative to counties with low exposure. Since real estate collateral is an important source of financing for young firms, the decline in entrepreneurship is stronger in sectors with a higher share of firms using home equity financing, i.e. where the reduction in credit hits hardest. Counties with higher exposure also see a decline in innovation: patent applications by young firms fall significantly, but not by old. As young firms contribute disproportionately to aggregate growth, my findings suggest that financial regulation reduces dynamism and innovation in the U.S. and contributes to the post-crisis productivity slowdown. Results are robust to controlling for unobservable local and industry characteristics through granular fixed effects and an instrumental variable approach that predicts county exposure with a gravity model of bank expansion.

Keywords: stress tests, small business lending, entrepreneurs, innovation, productivity slowdown

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1 Introduction

Recoveries are times of renewal. Incumbent unproductive firms exit while new firms enter and fuel growth. Every U.S. recovery since 1970 has shown a V-shaped pattern in employment by young firms. Following a collapse during the crisis, it quickly rebounds (Figure 1a). The Great Recession stands out as the exception to the rule. During the crisis gross job creation by young and old firms fell to a similar extent – but young firms never recovered (Figure 1b). This is all the more striking since equity and housing markets surpassed pre-crisis levels quickly and unemployment fell to historic lows. What explains the conspicuous absence of churning and persistent decline in entrepreneurship?

This paper argues that anemic growth of young firms reflects more stringent financial regulation. Following the financial crisis, regulators sought to increase the banking sector's resilience. Higher capital requirements and annual stress tests were introduced in a bid to reduce risk and foster macroeconomic stability. While a growing literature shows that stress tests are effective at reducing banks' risk-taking, a crucial question is whether the shift in bank behavior has adverse economic effects. Existing research analyzes the consequences of financial regulation on credit supply, but has not been able to establish a clear link to the slow recovery and disappointing performance of entrepreneurs. At the same time, macroeconomic literature identifies declining dynamism and weak growth among young firms as key forces behind declining growth in the U.S. economy, but has not related it to changes in supply and allocation of credit.[1]

[Figure 1 about here]

I show that regulation alters lending incentives and hurts banks' ability to channel funds to young and dynamic firms. Large banks subject to post-crisis stress tests strongly reduce lending to small businesses during the recovery, especially to firms pledging real estate collateral. The contraction in loan supply hurts the real economy. Since the majority of young firms (or entrepreneurs, I will use both terms interchangeably) is small, counties in which stress tested banks have a higher pre-crisis market share see a relative decline in young firm employment. As real estate is an important source of collateral for entrepreneurs, the decline is stronger in industries in which more firms use home equity financing to start a business, i.e. where the reduction in lending hits hardest. The dearth of young firms due to the contraction in loan supply is economically large. Moving a county from the 25^{th} to the 75^{th} percentile in terms of market share of stress tested banks reduces the employment share of young firms during the recovery by 0.8 percentage points, or one one-third of the average decline in entrepreneurship since 2007.

[1] For literature on stress tests and bank lending, see Bassett and Berrospide (2017); Acharya, Berger and Roman (2018); Bordo and Duca (2018); Cortés, Demyanyk, Li, Loutskina and Strahan (2018); Pierret and Steri (2018). Studies addressing declining dynamism and growth are Haltiwanger (2015); Decker, Haltiwanger, Jarmin and Miranda (2016a,b, 2017, 2018); Fernald (2016); Foster, Grim and Haltiwanger (2016); Alon, Berger, Pugsley and Dent (2018). A notable exception are Blattner, Rebelo and Farinha (2018), who show for Portugal that changing capital requirements lead to misallocation of credit and hurt aggregate productivity growth.

Since young firms contribute disproportionately to innovation and growth, I find that financial regulation is an important factor behind declining dynamism and the feeble recovery. Counties with higher exposure to stress tested banks have fewer patent applications by young firms, relative to the pre-crisis period. The decline is more pronounced when I adjust for the quality of innovation and weigh patents by their citations. There is no effect of exposure on patenting by old firms. Moving a county from the 25^{th} to the 75^{th} percentile in terms of exposure reduces patent applications by young firms by 16 %. I also provide suggestive evidence that the decline in entrepreneurship and innovation contributes to the productivity slowdown. Counties with higher exposure see significantly weaker labor productivity and wage growth during the recovery, reflecting the outsized importance of young firms for aggregate productivity.

My empirical analysis begins by showing that banks subject to stress tests cut small business lending. Following the financial crisis, regulators introduced the Dodd-Frank Wall Street Reform and Consumer Protection Act (Dodd-Frank Act or DFA) with the objective to improve financial stability and consumer protection. An important aspect of DFA are annual 'stress tests' that monitor investment portfolios of systemically relevant banks. If banks fail these tests, they have to adjust their equity and cannot distribute capital over the following quarters. The primary objective of stress testing is to enhance financial stability and reduce risky bank lending. However, a common complaint of small business owners is that stress testing reduces their credit supply by large banks (Bordo and Duca, 2018).[2] Figure 2, panel (a), shows that total small business lending declined by around 20 % relative to its pre-crisis peak. Total commercial lending has recovered and stands at 40 % above its pre-crisis level. Panel (b) shows that the decline is especially pronounced for stress tested banks (blue solid line), whose small business lending is still close to its crisis trough by 2016.

[Figures 2 and 3 about here]

To estimate the effect of stress tests on loan supply, I compare lending by stress tested to non-stress tested banks during the pre- and post-crisis period in a difference-in-difference setting. Regression results show that stress tested banks cut small business loans by around 30 % more than non-stress tested banks. The reduction in loan volume reflects a contraction in credit supply. Granular Community Reinvestment Act data on the bank-county level allow me to control for local unobservable county characteristics through time-varying fixed effects at the borrower-county level. Since loan demand by small businesses is predominately dependent on the state of local business cycles, fixed effects isolate the variation in lending due to changes in banks' loan supply.

However, panel (a) in Figure 3 shows that stress tested banks did not cut small business lending uniformly. While unsecured loans (red dashed line) saw a modest decline and surpassed their pre-crisis peak by 2013, secured loans (blue solid line) collapsed by over 45 % relative to their peak.

[2] For examples, see "How Dodd-Frank Stole The Recovery By Killing Small-Business Growth" (Investor's Business Daily), "How the Dodd-Frank Act hurts small businesses" (The Washington Post), and "Dodd-Frank has made banks safer but slowed economy, data show" (Financial Times).

Panel (b) plots the share of secured to total small business loans and shows that the shift in banks' portfolios since the crisis is limited to stress tested banks (blue solid line), while non-stress tested banks did not cut either category differentially. Regressions show that the strong decline in secured small loans by stress tested banks, relative to non-stress tested banks, is highly significant and robust to alternative specifications. The fall in secured lending suggests a disproportionate contraction in credit to entrepreneurs: young firms are opaque and inherently risky, and often use home equity or personal assets to secure a loan (Steijvers and Voordeckers, 2009).

I argue that stress tests are responsible for the decline in bank lending. Since the post-crisis period is riddled with regulatory initiatives and government programs, I undertake additional tests to isolate the role of stress tests. First, I show that there are no differential pre-trends across groups, and cross-sectional and difference-in-difference specifications yield similar results. Second, I exploit the staggered introduction of stress testing of 19 banks in 2009, and another set of 11 banks in 2014. Banks in the 2009-stress tested sample reduce their secured small business lending from 2009 on, while banks in the 2014 sample only do so by 2014. Third, within the sample of stress tested banks, the subgroup of banks that failed stress tests has significantly lower growth of secured small business lending, relative to stress tested banks that passed. Fourth, results are robust to the inclusion of bank*time fixed effects, so unobservable time-varying bank characteristics are not confounding effects. Consequently, unless contemporaneous changes in regulation affect the subset of stress tested banks (and those that did not pass) at the same time and in the same direction as stress tests, they are unlikely to explain my findings. The importance of stress tests for lending is in line with a recent survey by the MIT Golub Center, in which senior officers of large banks report that post-crisis financial regulation, and in particular stress tests, are the main determinants of changes in their post-crisis risk management practices.[3]

After establishing that stress tested banks reduce lending to small firms, I analyze the consequences of the decline in credit supply for the real economy. For each U.S. county, I define pre-crisis exposure to stress tested banks as the share of county deposits held in branches of stress tested banks.[4] Exposure reflects geographic variation in the importance of stress tested banks in local markets across the U.S. Using detailed county by industry by age employment data on firms, I find that the contraction in lending to small firms leads to a relative decline in employment among young firms. Counties with high exposure see a significant decline in employment and share of young firms during the post-crisis period, relative to counties with low exposure.[5]

Bank-level regressions show that stress tested banks cut back especially on small business lending secured by real estate collateral, an important source of financing for entrepreneurs (Steijvers and

[3] See MIT GCFP and GrantThompson (2017): "The risk management function of the future".

[4] In robustness checks, I define exposure based on the share of small business loans in each county, using Community Reinvestment Act data.

[5] An important assumption is that young firm are small, a common finding in the literature. More than 90 % of start-ups have less than 20 employees (Haltiwanger, 2015). In the SBO 2007, more than 99 % of young firms have less than 1mn in revenue.

Voordeckers, 2009). I exploit this finding to further shed light on the mechanism of how bank lending affects entrepreneurs. Using the 2007 Survey of Business Owners I compute the industry share of young firms that use home equity or personal assets to finance operations. I find that the decline in entrepreneurship is particularly strong in home equity intensive industries. Within industries in the top tercile of home equity usage, the negative effect of exposure on entrepreneurs is almost four times as large as for industries in the bottom tercile. Inclusion of granular county*time and industry*time fixed effects that absorb common shocks affecting firms within each county and industry over time do not change effect size and significance. In line with findings on the bank level, the stability of coefficients to controlling for demand shows that exposure reflects a contraction in loan supply. The decline is large in magnitude: in home equity-intensive industries, counties at the 75^{th} percentile of exposure see a 0.8 % stronger decline in the share of young firm employment, relative to counties at the 25^{th} percentile. For the average county, the share of young firm employment out of total employment declined by 2.1 % relative to the pre-crisis period, so exposure to stress tested banks explains around one-third of the average cross-sectional decline.

Since entrepreneurs have an outsized effect on the aggregate economy, I show that the contraction in financing of entrepreneurs hurts innovation. Using data on U.S. patents aggregated to the county level, I define 'young firms' as firms (assignees) that did not file a patent application more than five years ago. County exposure has a strong and significantly negative effect on innovation by young firms. Over the post-crisis period, counties at the 75^{th} percentile of exposure see a 16 % decline in patent applications by young firms, relative to counties at the 25^{th} percentile. There is no change in patenting activity of old firms. When I account for the importance of patents and weigh by citations, the negative effect of exposure more than doubles in magnitude. The increase in effect size suggests that innovative entrepreneurs are hit disproportionately.[6]

In light of recent literature establishing that young firms contribute disproportionately to productivity growth (Haltiwanger, 2015; Alon, Berger, Pugsley and Dent, 2018) and the debate on the post-crisis productivity slowdown (Teulings and Baldwin, 2014; Fernald, 2016), my results raise the question whether regulation exacerbates these macroeconomic trends. I provide suggestive evidence that stress tests negatively affect labor productivity and wage growth during the recovery, and contribute to the decline in growth: A one standard deviation increase in exposure reduces county labor productivity growth by 0.9 % during the recovery, or one-third of its average total increase from 2010 to 2016. Similar to findings for young firm employment on the county-industry level, wages (a common proxy for labor productivity) decline significantly more in industries with higher reliance on home equity financing. My results suggest that stress testing, through its effect on loan supply and entrepreneurship, contributes to the anemic recovery and weak growth since the recession − a finding in line with work on the importance of declining dynamism for growth (Decker, Haltiwanger, Jarmin

[6]Industries with the highest share of home equity intensive usage (i.e. those hit hardest by the contraction in loan supply) are manufacturing and information − precisely the industries most important for patenting and innovation. This can explain the increased effect size when accounting for innovation quality.

and Miranda, 2017).

The key challenge for identification is to control for unobservable shocks that affect young firms and are correlated with county exposure to stress tested banks. I overcome this issue by including granular fixed effects. County*industry fixed effects exploit variation within the same county-industry pair over time and control for unobservable and time-invariant county and industry heterogeneity. County*time fixed effects allow shocks to affect each county at each point in time heterogeneously. Thereby I control for unobservable time-varying county fundamentals (such as house prices or unemployment). Industry*time fixed effects absorb common time-varying shocks to industries, for example the secular decline in manufacturing. Essentially, I am comparing employment by young firms in the same county and same industry for different levels of exposure, exploiting only the within variation of each county-industry pair (Jiménez, Ongena, Peydró and Saurina, 2014). Adding the battery of fixed effects does not affect estimated coefficients in a statistically meaningful way.

In addition, I use an instrumental variable (IV) approach, which predicts changes in exposure with a gravity model of bank expansion, combined with staggered state-level deregulation of interstate banking from 1994 to 2005 (Goetz, Laeven and Levine, 2013, 2016). Building on a large literature highlighting the importance of distance in banking (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010), in a first step I predict banks' geographic distribution of deposits across counties. I employ a gravity model based on the distance between banks' headquarter and branch county, as well as relative market size. In a second step, I re-scale predicted deposits with an index of staggered interstate banking deregulation developed in Rice and Strahan (2010). Re-scaling takes into account that states restricted out-of-state banks from entering to different degrees. Computing exposure based on predicted deposits yields an instrument for observed exposure with a strong first stage. IV regressions confirm OLS estimates and show that higher exposure significantly reduces young firm employment, innovation, and labor productivity. IV coefficients are similar in terms of sign and significance to OLS, but slightly larger in magnitude.

I take further steps to bolster identification. First, I restrict the sample to adjacent counties bordering state lines, which allows me to absorb any common shocks to county-pairs that lie across state borders through border-pair fixed effects. Although R^2 quadruples when including fixed effects, the coefficient on exposure is almost identical across specifications with and without fixed effects. This suggests that exposure is orthogonal to a wide selection of unobservable and observed characteristics (Altonji, Elder and Taber, 2005; Oster, 2017). Second, I run regressions in which I include time-varying county and industry shocks that affect firms in different age groups heterogeneously. This specification accounts for different sensitivities of young firms to local and sector shocks. Main results remain unaffected. Third, difference-in-difference specifications for bank and county regressions show no differential trend in the pre-treatment period before the crisis, but a steadily increasing effect during the recovery. Taken together, the stability of coefficients across specifications suggests that higher exposure to stress tested banks exerts a negative effect on employment and innovation due to changes in bank loan supply.

A battery of auxiliary regressions ensures the robustness of my findings. On the bank level, I show that effects of stress testing on loan supply are similar when I use nearest neighbor matching and when I restrict the sample to banks of comparable size. Also, within the sample of stress tested banks, those that fail stress tests reduce their secured lending significantly more than banks that do not fail tests. Within-bank comparisons under specifications with bank*time fixed effects show that stress tested banks reduce secured small business lending significantly more than unsecured small business lending. This finding holds when controlling for unobservable aggregate shocks to secured and unsecured small business lending separately through loan type*time fixed effects.

On the county level, I show that neither the pre-crisis housing boom, the decline of house prices during the recession, nor variation in home ownership across counties explain results. As results are robust to factors related to the housing market, this rules out demand-driven explanations based on the collateral channel. Multivariate descriptive statistics show that counties with higher exposure are in general larger and more urban, while most other differences in pre-crisis county characteristics are statistically insignificant. Further controlling for differential effects of county size and urbanity on industries increases baseline coefficients. Additionally, I restrict the sample to counties with a population above 100,000 or to counties that saw no change in the presence of large banks from 2000 to 2007. Results are similar across specifications, which further mitigates concerns that larger banks operate in more populous counties or that the contraction in lending by stress tested banks simply reflects a correction of excessive entry and lending in the pre-crisis period. Splitting the sample into tradable and non-tradable industries yields a stronger negative effect of exposure on young firm employment in tradable sectors, suggesting that local demand does not explain results.

In line with bank-level results, county regressions hence confirm that the negative effects of exposure reflect changes in loan supply, and not unobservable county or industry characteristics. I also show that exposure is different from local competition in the banking market, in the sense that controlling for deposit concentration in local markets does not affect results. Finally, I provide suggestive evidence that borrowers are unable to substitute the decline in bank lending with alternative sources of financing. Using data on peer-to-peer business loans, I find a positive effect of exposure on non-bank lending. Yet, aggregate statistics suggest that the increase in non-bank lending is too small, and non-bank financing too costly, to compensate for the decline in bank lending.

Literature and Contribution This paper speaks to literature in finance and macroeconomics, first and foremost to work on the consequences of financial regulation and the decline in economic dynamism. The main contribution lies in providing an explanation for the persistent decline in entrepreneurship and feeble recovery since the crisis. I thereby highlight a quantitatively important channel through which financial regulation affects the real economy: it prevents young firms from getting credit and thereby hurts aggregate innovation and growth.

My paper connects to recent work that analyzes the effects of regulation, in particular stress testing, on loan supply and risk taking. Bordo and Duca (2018) and Cortés, Demyanyk, Li, Loutskina and

Strahan (2018) show that stress tested banks reduce credit supply and raise interest rates on small business loans, while Bassett and Berrospide (2017) find that the Federal Reserve's Comprehensive Capital Analysis and Review does not affect banks' loan growth in general. Focusing on large borrowers and syndicated loans, Acharya, Berger and Roman (2018) and Pierret and Steri (2018) show that banks act more prudent when subject to stress tests and reduce risky lending. Chen, Hanson and Stein (2017) and Bord, Ivashina and Taliaferro (2018) show that there was a persistent shift in portfolios of large banks since the crisis period and provide suggestive evidence that it contributed to weak growth among small firms.[7] In contrast, this paper provides micro-evidence on the effect of stress testing on the real economy. Bank lending, in particular secured lending, is a crucial form of financing for young and constrained firms.[8] I show that stress tests reduce credit supply to entrepreneurs, as well as innovation and productivity. More generally, my results suggest that higher capital requirements have severe side effects through a reallocation of credit at the extensive margin.

I also speak to literature highlighting the decline in entrepreneurship. Siemer (2016); Moreira (2017) and Bassetto, Cagetti and De Nardi (2015) show that the decline of young firm employment during the Great Recession can have lasting effects on growth. They relate to work by Decker, Haltiwanger, Jarmin and Miranda (2016a,b, 2017, 2018) that shows a secular decline in business dynamism, and papers by Aghion and Howitt (2014); Aghion (2017), and Decker, Haltiwanger, Jarmin and Miranda (2014) that focus on the importance of creative destruction arising from entry and exit of firms. The long-run decline in dynamism and fall in entrepreneurship during the crisis created considerable attention. I provide an explanation for the anemic recovery from the Great Recession based on cross-sectional evidence and show that changes in bank lending hurt start-ups above and beyond the immediate effects during the crisis.

Finally, this paper provides a supply-side explanation for the post-crisis productivity slowdown (Teulings and Baldwin, 2014; Fernald, 2016).[9] Young firms contribute around one-third to aggregate productivity and have an outsized effect on growth (Haltiwanger, 2015; Alon, Berger, Pugsley and Dent, 2018; Pugsley, Sedlacek and Sterk, 2017), but Foster, Grim and Haltiwanger (2016) and Chodorow-Reich and Wieland (2018) provide evidence that the Great Recession had no cleansing effect, as job creation by new firms disappointed. By showing how changes in the allocation of credit across borrower classes affect aggregate growth, this paper relates to work on zombie lending and misallocation (Caballero and Hammour, 1994; Acharya, Eisert, Eufinger and Hirsch, 2017; Schivardi,

[7] For further papers on regulation and bank resolution, see Gambacorta and Mistrulli (2004); Aiyar, Calomiris, Hooley, Korniyenko and Wieladek (2014); Fraisse, Lé and Thesmar (2015); Jiménez, Ongena, Peydró and Saurina (2017); Granja and Leuz (2017); Gropp, Rocholl and Saadi (2017); Celerier, Kick and Ongena (2018); De Jonghe, Dewachter, Mulier, Ongena and Schepens (2018); Gropp, Mosk, Ongena and Wix (2018); Shapiro and Zeng (2018).

[8] See Carpenter and Petersen (2002); Lusardi and Hurst (2004); Jensen, Leth-Petersen and Nanda (2014); Robb and Robinson (2014); Adelino, Schoar and Severino (2015); Corradin and Popov (2015); Harding and Rosenthal (2017); Schmalz, Sraer and Thesmar (2017).

[9] For papers on the slowdown in investment and productivity growth, see Fernald (2014); Byrne, Fernald and Reinsdorf (2016); Fernald (2016); Fernald and Wang (2016); Gutiérrez and Philippon (2017a,b). The slowdown also led to a debate on whether we entered a period of secular stagnation, see Summers (2015); Gordon (2015); Bloom, Jones, Van Reenen and Webb (2017); Fernald, Hall, Stock and Watson (2017).

Sette and Tabellini, 2017).[10] Blattner, Rebelo and Farinha (2018) show that higher capital requirements hurt productivity growth through zombie lending in Portugal. Banks subject to changes in capital requirements increase lending to financially distressed and inefficient firms. Literature on zombie lending shows that inefficient firms get credit, although they should not. I show that entrepreneurs who need credit do not get it. These 'ghost entrepreneurs', i.e. entrepreneurs that could not start a business because of a lack in credit, cannot contribute to innovation and growth, so the decline in young firm employment has sizeable effects on the local economy.[11] To this end, my paper highlights the inherent trade-off between financial stability and growth, a theme well-explored for developing countries (Loayza, Ranciére, Servén and Ventura, 2007; Loayza, Ouazad and Ranciere, 2017).

The paper proceeds as follows. Section 2 explains main variables and provides descriptive statistics. Section 3 lays out empirical strategy and reports main regression results for the bank and county level. Section 4 links financial regulation to the productivity slowdown and Section 5 provides additional robustness checks. Section 6 concludes.

2 Data and Descriptive Statistics

This section first provides background information on post-crisis financial regulation and stress testing. It then explains data construction and provides descriptive statistics for main bank and county variables.

Stress Testing Following the recent financial crisis in the U.S., regulators introduced stress tests for the largest financial institutions. The first stress test was carried out in 2009 under the Supervisory Capital Assessment Program (SCAP) and they became regular exercises under the Comprehensive Capital Analysis and Review (CCAR) in 2011. Their goal is to asses whether banks are able to withstand adverse shocks, including rising unemployment and falling house prices. Regulators provide banks with three scenarios: *baseline*, *adverse*, and *severely adverse*. Each scenario simulates an increasingly hostile economic environment. For example, the severely adverse scenario in 2014 stress tests assumes a rise in the unemployment rate to 12 % and a fall in house prices by 35 %. Banks have to develop annual capital plans and maintain adequate capital to weather these scenarios. They submit their capital plans to the regulator for review, including planned capital issuance and distributions.

[10] On misallocation, i.e. the importance of the allocation of capital and labor across firms for aggregate productivity, see Restuccia and Rogerson (2008); Hsieh and Klenow (2009); Pagés (2010); Syverson (2010); Decker, Haltiwanger, Jarmin and Miranda (2017); Gopinath, Kalemli-Ozcan, Karabarbounis and Villegas-Sanchez (2017); Restuccia and Rogerson (2017); Chakraborty, Goldstein and MacKinlay (2018); Restuccia (2018). Other papers that link productivity to changes in loan supply are Duval, Hong and Timmer (2017); Manaresi and Pierri (2017); Doerr, Raissi and Weber (2018). They provide evidence that credit supply shocks reduce firm productivity through adjustment frictions and a reduction in productive investment. These papers focus on changes in within-firm productivity in response to contractions in lending.

[11] In a related paper, Huber (2018) shows that a contraction in bank lending has aggregate effects by depressing local demand of firms connected to a bank in distress, which has spillover effects on non-connected firms in the same area.

Based on internal models, the Federal Reserve decides whether banks passed or failed tests.[12]

The outcome of the decision is publicly disclosed in the CCAR summary report. If banks fail to meet supervisory criteria, they are not allowed to make any capital distribution in the following quarters. In essence, stress tests are forward-looking capital requirements with the goal to ensure that banks have sufficient capital and reduce their risk-taking. In 2009, 19 institutions with assets exceeding \$ 100 billion were part of the stress tests. By 2014, tests included smaller institutions with assets over \$ 50 billion and covered a total of 32 banks.[13] The thresholds were chosen such that they cover the largest and systemically relevant financial institutions in the U.S. banking system. Stress tests are seen as effective in altering banks' lending behavior to reduce risk. A survey by the MIT Golub Center states that both regulators and senior officers of large banks agree that "a large portion of [why banks implemented risk management practices after the financial crisis] is driven by [...] regulations" and that "stress tests were effective, but costly".[14]

However, small businesses and banks have complained that stress tests reduce banks' ability to supply credit to small and risky firms. The Clearinghouse, a banking association and payments company that is owned by the largest commercial banks, argues that "the Federal Reserve's CCAR stress test is imposing dramatically higher capital requirements on [...] small business loans" (Clearinghouse, 2017a). In a similar vein, the National Small Business Association states that "lending is much harder than it was before the great recession". There are two main reasons why small business loans are particularly sensitive to stress tests. First, small business is pro-cyclical and depends on local demand, which makes it sensitive to changes in unemployment and hence riskier under adverse scenarios. Since banks can loosen their capital requirement by reducing risk in their loan portfolio, small business lending becomes more expensive for stress tested banks. (Cortés, Demyanyk, Li, Loutskina and Strahan, 2018). Second, young and small firms are risky and opaque with no credit history. To overcome asymmetric information about borrower quality, banks require them to post collateral (Carpenter and Petersen, 2002; Berger, Espinosa-Vega, Frame and Miller, 2011; Berger and Bouwman, 2013; Berger, Imbierowicz and Rauch, 2016).[15] Stress tests model a strong decline in house prices (collateral values) in addition to rising unemployment (weak local demand). Secured small business lending is thus not only inherently risky, but subject to both declining demand and falling collateral values, which implies high capital requirements and makes it less profitable for stress tested banks.[16]

[12]Since 2013, the Federal Reserve can give an objection, a conditional non-objection, or a non-objection to a bank's capital plans. Stress tests rest on a scenario and model that applies to all banks to a similar extent. What differs is the underlying composition of banks' assets.

[13]The decision to include smaller institutions was made in 2012. Since these smaller banks were stress tested by 2014, I chose 2014 as starting date for the second group of banks.

[14]See MIT GCFP and GrantThompson (2017): "The risk management function of the future".

[15]Additionally, Agarwal, Benmelech, Bergman and Seru (2012); Cole and White (2012) and Acharya, Berger and Roman (2018) argue that commercial loans secured by real estate are particularly risky.

[16]Publications by The Clearing House argue that stress testing reduces small business loan growth and imposes up to 45 % higher capital requirements on small business loans. (Clearinghouse, 2016, 2017a,b).

Bank Data The bank level analyzes how stress tested banks change their loan supply to small businesses, in particular when loans are secured by real estate collateral. The Federal Deposit Insurance Corporation (FDIC) provides detailed bank balance sheet data at quarterly frequency in its Statistics on Depository Institutions (SDI). I define small business loans as loans outstanding with origination amount less or equal to $1,000,000. Secured commercial loans are defined as "Nonresidential loans (excluding farm loans) primarily secured by real estate held in domestic offices", and exclude loans for construction purposes.[17] Each bank (identified by its certificate number) is assigned a dummy with value one if its bank holding company (BHC) is mandated to undergo stress tests (see list 15 in Appendix B). To control for differences in bank characteristics, I collect data on banks' residential mortgage lending, lending for the purpose of construction of new structures, total assets, Tier 1 capital ratio, non-interest and total income, total investment securities, overhead costs (efficiency ratio), unused commitments, return on assets, interest expense on deposits, and total deposits. All controls and growth rates are trimmed at the 0.5^{th} and 99.5^{th} percentile. I also remove outliers that are at least five standard deviations above or below the mean. Since information on small business lending pre-2009 is only available for the second quarter of each year, for consistency I also drop all other quarters in later years.

Since SDI provide data on the bank-quarter level, controlling for loan demand is imperfect. For example, stress tested banks could lend to counties with lower demand for loans in general, in which case it is difficult to disentangle the effect of regulation on loan supply from loan demand. Therefore, I collect detailed data on the bank-county-year level on small business loans, provided by the Community Reinvestment Act (CRA). CRA provides data on banks' small business loan origination in each county. Any depository institution that is federally-regulated and has assets of at least $1 billion in 2005 dollars is required to file a CRA report. I define loans smaller $1,000,000 as small business loans and combine CRA loan data with bank balance sheet data by SDI.[18] I restrict the sample to bank-county pairs with at least three loans over the sample period.

Table 1 reports mean and standard deviation (Std. Dev.) plus additional statistics for key bank variables across the full sample of 10,151 banks from 2002-2016. The share of secured small business loans equals 53 % on average, with significant variation of 0.24 as standard deviation. Table 2 provides multivariate descriptive statistics of pre-crisis (2007) bank characteristics with stress tested dummy as dependent variable. Column (1) uses the full sample, column (2) adds state fixed effects, column (3) MSA fixed effects (all at the bank headquarters level). Columns (4)-(5) restrict the sample to BHCs

[17] Unsecured commercial loans are defined as "Commercial and industrial loans. Excludes all loans secured by real estate, loans to individuals, loans to depository institutions and foreign governments, loans to states and political subdivisions and lease financing receivables."

[18] CRA defines small business loans as loans with origination amount of $1 million or less. Additionally, it provides a further breakdown for loans smaller $100,000 and loans with origination amount between $\$100,000 - 250,000$. Loans are classified as business loans if they are reported as "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.

with total assets between 10bn and 500bn, and 10bn and 150bn. Finally, column (6) restricts the sample to stress tested banks and uses dummy *failed* as dependent variable, which takes on value one if a bank failed any stress test. Stress tested banks are significantly larger, but extend a smaller share of secured small business loans. They also have lower securities over total assets and lower interest expenditure on deposits. Adding fixed effects and narrowing the sample in reduces significance of explanatory variables, a fact I will exploit in robustness tests. In terms of aggregate sample statistics, stress tested banks cover 65 (58) % of total bank assets (loans), 35 (31) % of total (secured) small business loans, and 50 % of CRA loans (all values as of 2008).

[Tables 1 and 2 about here]

County Data The county-level analysis examines how county exposure to stress tested banks affects entrepreneurship and innovation during the post-crisis period. To calculate county exposure to stress tested banks, I use data by the FDIC's Summary of Deposits (SOD), which provide yearly information on bank deposits in each county. I compute exposure as of 2007 as

$$exposure_{c,07} = \sum_{b=1}^{B} \frac{deposits_{c,b}}{deposits_c} \times \mathbb{1}(stress\ tested_b), \tag{1}$$

where $deposits_{c,b}$ denotes bank b's deposits in county c in year 2007, and $\mathbb{1}(stress\ tested_b)$ is an indicator with value one if bank b belongs to a stress tested bank holding company. High exposure implies that a large share of county deposits is held in offices of stress tested banks, while low exposure implies that deposits are held in offices of non-stress tested banks. $exposure$ ranges from $[0, 1]$. Equation (1) rests on two main assumptions. First, the share of deposits is a valid proxy for the importance of a bank in the local economy. The online appendix shows that the correlation between banks' deposits and assets (CRA loans) across counties is high and results are quantitatively and qualitatively similar when exposure is based on CRA loans. Second, stress tested banks reduce lending in areas where they have a stronger pre-crisis presence. I provide direct evidence in support of this assumption in bank-county-year level regressions.

To shed light on the role of young firms, I use data on the county-industry-year level on end-of-quarter employment by firm age groups, provided by the Quarterly Workforce Indicators (QWI). I follow the literature and define young firms or entrepreneurs as firms aged zero to one (Gourio, Messer and Siemer, 2016; Curtis and Decker, 2018). For each two digit industry in each county, I use 4^{th} quarter values. QWI are the only publicly available data set that provides information on county employment by firm age.[19] Yearly patent applications are provided by PatentsView. I assign patents

[19] For other papers using QWI data on firm age, see Adelino, Ma and Robinson (2017); Curtis and Decker (2018). Note that the data classifies subsidiaries of existing firms as start-ups whenever they are formed as separate legal entities. "For example, a new McDonalds franchisee opening her first McDonald's location is classified as a startup, whereas a new location opened by an existing franchisee, or by corporate headquarters, would be an expansion" (Adelino, Ma and Robinson, 2017).

to the county of the inventor, and define young firms as assignees (organizations) that patented at most five years ago for the first time (see Appendix B for detailed variable construction). The average sample share of patents by young firms out of total county patents equals 21 %, which is close to the aggregate value of 25.3 % (Goldschlag and Perlman, 2017).

To calculate county labor productivity, I use data on GDP by state from BEA's regional economic accounts and calculate county GDP by weighing state GDP by county personal income shares within each state (provided by BEA's local area personal income).[20] I define labor productivity as county GDP over employment. Labor productivity is available only on the county level. For more granular analysis I use data on average wages on the county-industry-year level, provided by the Quarterly Census of Employment and Wages (QCEW). Wages are a common proxy for labor productivity (Chen, Hanson and Stein, 2017). For each two-digit NAICS industry, I obtain wage data for the 4^{th} quarter of each year. Finally, I sum CRA data on small business loans to the county level to construct aggregate county-level small business lending. Baseline county controls include log population, the share of black population and share of population older than 65 years, labor force participation rate, unemployment rate, and house prices. I also collect data on county household debt-to-income ratios and per capita income.[21]

As I will show, stress tested banks reduce small business lending to firms that secure loans by real estate collateral. Young firms often use home equity and personal assets to finance expansion of operations (Jensen, Leth-Petersen and Nanda, 2014; Adelino, Schoar and Severino, 2015; Harding and Rosenthal, 2017; Schmalz, Sraer and Thesmar, 2017; Bahaj, Foulis and Pinter, 2018). Hence, firms in industries that rely more on collateral should be harder hit by the contraction in lending against real estate collateral.[22] To this end, I use data from the 2007 Public Use Survey of Business Owners (SBO). It provides firm-level data on sources of business start-up and expansion capital, broken down by two-digit NAICS industries. For each industry i I compute the average fraction of young firms f that reports using home equity financing or personal assets (*home equity* henceforth) to start or

[20] Although labor productivity does not reflect capital intensity and investment, Fernald, Hall, Stock and Watson (2017) show that the decline in labor productivity growth is almost entirely due to a slowdown in total factor productivity growth. Hence, during the recovery labor productivity is a reasonable proxy for total factor productivity.

[21] Data sources (in order): Census Bureau's Population Estimates, BLS LAUS, FHFA House Price Index (HPI), Federal Reserve's Enhanced Financial Accounts, and BEA LAPI.

[22] I build on a large literature that establishes the importance of collateral for firms' access to finance, in particular for young and small firms (see (Hubbard, 1998; Beck, Demirgüç-Kunt, Laeven and Levine, 2008; Berger, Espinosa-Vega, Frame and Miller, 2011; Liberti and Petersen, 2017) and Gan (2007); Chaney, Sraer and Thesmar (2012); Cvijanovic (2014)). Young firms and start-ups are often opaque and harder to monitor, and have no credit history; hence they are financially constrained To overcome information asymmetry about the quality of borrowers, banks require small firms to pledge collateral (see Jiménez, Salas and Saurina (2006); Benmelech and Bergman (2008); Bolton, Freixas, Gambacorta and Mistrulli (2016); Hollander and Verriest (2016); Stroebel (2016); Degryse, Karapetyan and Karmakar (2017); Prilmeier (2017)). This makes collateral crucial for small and young firms' access to finance (Carpenter and Petersen, 2002). For a recent survey on financing of small business, see Hoffer, Miller and Wille (2017). For example, recent surveys show that insufficient credit history is the 2^{nd} most cited reason for credit denial among small firms (*Small Business Credit Survey 2016*, Federal Reserve (2017)). The Federal Reserve's 2003 Survey of Small Business Finances states that 45 % of small business loans are collateralized by real estate

expand their business:[23]

$$home\ equity_{i,07} = \frac{\sum_{f=1}^{F_i} \mathbb{1}(uses\ home\ equity_f)}{\sum_{f=1}^{F_i} 1} = \%\text{ of firms using home equity in industry i.} \quad (2)$$

Tables 3 and 4 provides summary statistics for main county variables for the full sample and by county exposure to stress tested banks. Table 3 reports mean and standard deviation (Std. Dev.) plus additional statistics for key county variables across the full sample of 2,644 counties from 2002-2016. Panel (a) reports summary statistics for the county-year level, panel (b) for the county-industry-year level. Since QWI reports missing values for several industries, the number of observations is lower than for wages provided by QCEW. Table 4 provides multivariate descriptive statistics of pre-crisis county characteristics with exposure as dependent variable. Column (1) uses the full sample, column (2) adds state fixed effects. Columns (3)-(4) restrict the sample to counties with total population above 100,000 and 200,000. Column (5) only includes counties in the medium tercile in terms of change in exposure from 2000 to 2007. High exposure counties are on average larger and more urban than counties with low exposure. Across most specifications, their characteristics are not different in a statistical sense.

Figure 4 provides details on county exposure, as defined in equation (1). Panel (a) shows its distribution, panel (b) mean and standard deviation (black bars) across the full sample (left bar) and within states (weighted by state population). Panel (c) shows a map of U.S. counties, where darker areas indicate higher exposure. There is significant variation in county exposure across the full sample, as well as within individual states. 805 counties have zero exposure to stress tested banks. Figure 5, panel (a), shows the share of firms that report using home equity financing to start or expand operations, as defined in equation (2) by industry. There is significant variation across industries.

[Figures 4-5 and Tables 3-4 about here]

3 Empirical Strategy and Results

This section lays out empirical strategy and reports main results for the bank and county level. The empirical argument follows three steps, visualized in Table 12. First, I establish that stress tested banks reduce lending to small businesses, building on the fact that stress tests increase banks' costs of lending to small firms (Acharya, Berger and Roman, 2018; Cortés, Demyanyk, Li, Loutskina and Strahan, 2018). In a second step, I show that the reduction in credit supply to small businesses hurts entrepreneurs: counties with higher exposure to stress tested banks see a weaker recovery of young firm

[23] The underlying assumption is that sector-wide financing needs are unrelated to local county-specific changes during the recovery. This is similar in spirit to a Rajan and Zingales (1998) approach, who argue that industries' needs for external finance are determined by technology. The online appendix shows that the correlation of the share of firms using home equity to expand operations between the 2007 and 2012 SBO is high and that every single industry in the top (bottom) tercile of $home\ equity_{i,07}$ is also in the top (bottom) tericle in 2012. The same holds for the share of firms using bank financing. Consequently, results are similar when I use 2012 values.

employment, because entrepreneurs lack credit. This step build on the assumptions that a) almost all young firms are small; b) young firms rely on bank financing and collateral; and c) they are unable to substitute into other forms of lending. These assumptions are well-established in the literature (Steijvers and Voordeckers, 2009; Decker, Haltiwanger, Jarmin and Miranda, 2014), and I will also provide direct evidence for assumption c).[24] Finally, I show that the decline in young firms due to the contraction in loan supply negatively affects innovation and productivity. I build on a vast literature that establishes the importance of entrepreneurs for disruptive innovation and aggregate productivity (Haltiwanger, 2015; Aghion, 2017).

3.1 Stress Tests and Bank Lending

I first establish on the bank-county-year level that stress tested banks reduce small business lending by more than non-stress tested banks. I then show on the bank-year level that the contraction in small business lending is stronger for loans secured by real estate collateral. To estimate how stress tested banks adjust their lending relative to other banks during the recovery, I run the following panel specification from 2002 to 2016:

$$log(CRA)_{b,c,t} = \gamma^{cra}\ stress\ tested_{b,t} + controls_{b,t-1} + \theta_b + \tau_{c,t} + \epsilon_{b,t}, \tag{3}$$

where $log(CRA)_{b,c,t}$ denotes log volume of small business CRA lending by bank b to county c in year t. *stress tested* is a dummy with value one for each year a bank is undergoing stress tests, and zero otherwise. For example, banks that were stress tested from 2009 on get value one for each stress tests on from 2009, while banks that were added to the group of stress tested banks by 2014 get value zero for all years prior to 2014, and value one from then on. Bank controls include log total assets, return on assets, investment securities to total assets, deposits to total assets, tier 1 capital ratio, overhead costs, interest expense on deposits over total deposits, and the share of non-interest income, all lagged by one period. Standard errors are clustered on the bank holding company (BHC) level. After including controls, as well as bank (θ_b) and time (τ_t) fixed effects, coefficient $\gamma^{cra} < 0$ indicates that stress tested banks reduce lending by more than non-stress tested banks, relative to their respective pre-crisis trends. To compare results in bank-county regressions with aggregate regressions on the bank level, regressions are weighted by the average pre-crisis share of loans by bank b in county c.

Coefficient γ^{cra} in regression equation (3) reflects changes in banks' loan supply, but also loan demand. In counties where stress tested banks have higher loan exposure, small firms could demand less credit for reasons unrelated to stress testing. For example, a rise in local uncertainty due to nearing elections or a natural disaster could reduce loan demand and small business lending, irrespective of

[24] More than 90 % of start-ups have less than 20 employees (Haltiwanger, 2015). Carpenter and Petersen (2002) show that small firms are financially constrained, and Steijvers and Voordeckers (2009) report that 53 % of loans granted to small firms use personal collateral, that the share is even higher for young and risky firms, and that young firms have limited outside financing options.

bank performance. Disaggregated bank-county data allow me to include county*time fixed effects ($\tau_{c,t}$) that absorb any unobserved changes in borrower characteristics across counties.[25] In other words, with county*time fixed effects I compare lending by bank b to the same county. Under the assumption that small businesses depend on local demand, including county*time fixed effects isolates changes in loan supply. Comparing coefficients with and without county fixed effects thus provides insights on magnitude and direction of the bias arising from imperfectly controlling for county characteristics.

Table 5, column (1), shows that stress tested banks reduce small business lending by 24.1 % more during the post-crisis period, relative to non-stress tested banks. Effects are conditional on bank controls, bank and year fixed effects. To isolate changes in credit supply, column (2) introduces county*time fixed effects to account for changes in unobservable county characteristics. The coefficient of interest keeps sign and significance, which suggests that stress tested banks reduce their loan *supply* to small businesses. The increase in coefficient size suggests that stress tested banks lend to counties with generally (weaker) stronger loan demand during the (pre) post crisis period. It also implies that coefficients on the aggregate bank-year or county-year level (where it is not possible to control for bank-specific demand shocks) will be downward biased. Note that the coefficient is equally precisely estimated in both specifications. In column (2), stress tested banks reduce small business lending by 34.5 %.

[Table 5 about here]

To further shed light on the role of stress testing, I exploit the staggered addition of banks to the stress test sample in 2009 and 2014 and estimate

$$\begin{aligned} log(CRA)_{b,c,t} = {} & \delta_1 \; stress\ tested\ 09_b + \delta_2 \; stress\ tested\ 14_b + \delta_3 \; post\ 09_t + \delta_4 \; post\ 14_t \\ & + \delta_5 \; stress\ tested\ 09_b \times post\ 09_t + \delta_6 \; stress\ tested\ 09_b \times post\ 14_t \\ & + \delta_7 \; stress\ tested\ 14_b \times post\ 09_t + \delta_8 \; stress\ tested\ 14_b \times post\ 14_t \\ & + controls_{b,t-1} + \theta_b + \tau_c, t + \epsilon_{b,c,t}, \end{aligned} \tag{4}$$

where *post 09 (14)* is a dummy with value one for years 2009-2013 (2014-2016). *stress tested 09* is a dummy with value one if a bank was undergoing stress tests from 2009 on, while dummy *stress tested 14* takes on value one for banks that were stress tested by 2014, but not before. Coefficients on interaction terms ($\delta_5 - \delta_8$) indicate whether stress tested banks stress reduced their lending in

[25] Formally, lending between bank b and county c reflects bank supply ($s_{b,t}$, for example changes in management or regulation) and county demand ($d_{c,t}$, for example changes in consumer confidence or local house prices) factors, such that $loan_{b,c,t} = s_{b,t} + d_{c,t} + \epsilon_{b,c,t}$. Following Khwaja and Mian (2008); Jiménez, Ongena, Peydró and Saurina (2014); Amiti and Weinstein (2018), including county*time fixed effects absorbs unobservable changes in borrower-county characteristics and isolates supply effects. Regressing county*time fixed effects $\tau_{c,t}$ on log county employment $ln(emp)_{c,t}$ yields $R^2 = 0.72$ in the cross section, and $R^2 = 0.88$ with county and year fixed effects, indicating that time-varying fixed effects capture local business cycles. However, even with granular fixed effects, there remain two identifying assumptions I cannot test explicitly in the data: first, firms within two counties behave similarly towards the same bank, which is violated if for example a bank has a longer history of lending to one county; and second, within counties, loan demand does not differ between firms that borrow from stress tested and non-stress tested banks.

2009-2013 and/or 2014-2016. For banks stress tested by 2009, I expect a reduction in lending during both periods ($\delta_5 < 0$ and $\delta_6 < 0$), for banks stress tested by 2014 only from 2014 on ($\delta_7 = 0$ and $\delta_8 < 0$). All regressions include baseline bank controls, θ_b and $\tau_{c,t}$ denote bank and county*year fixed effects, and standard errors are clustered on the bank level.

In line with expectations, in column (3) with bank and year fixed effects, banks that were stress tested by 2009 reduce lending to small businesses from 2009 to 2013, as well as from 2014 to 2016. Banks that were added to the stress tested sample by 2014 reduce lending only from 2014 on. They reduce lending also in the 2009-2013 period, but to a small extent. Column (4) adds granular county*year fixed effects and confirms the pattern. Similar to columns (1) and (2), coefficient increase in size and the pattern becomes more pronounced. Although several regulatory changes were introduced during the post-crisis period, the pattern observed in columns (3)-(4) suggests that, unless these reforms affect stress tested banks in 2009 and 2014 differentially, the decline it small business lending is due to stress tests.

Column (5) excludes years 2008 and 2009 of the Great Financial Crisis (GFC), and column (6) includes the interaction of dummy *large (10-50bn)* and dummy $\mathbb{1}(2009-16)$ for the stress testing period. *large (10-50bn)* takes on value one for banks with total assets between 10bn and 50bn (as of 2010). Excluding the crisis years and controlling for other large banks leaves the coefficient of interest almost identical in terms of sign, size, and significance to column (2). The coefficient on $large\times\ \mathbb{1}(2009-16)$ is insignificantly negative and around one-tenth in magnitude, relative to the main coefficient. Hence, non-stress tested large banks do not reduce small business lending by significantly more than non-stress tested small banks, alleviating concerns that size alone explains findings.

Columns (1)-(6) establish that stress tested banks reduce their supply of small business credit. Figure 3 shows that the change in small business loans by stress tested banks is heterogeneous across loan types. Panel (a) shows that, while stress tested banks see a decline in total small business lending (grey short-dashed line), unsecured small business lending (red dashed line) recovered somewhat, while business loans secured by real estate (blue solid line) decreased by over 40 % relative to their pre-crisis peak. Secured and unsecured lending follow the same trend prior to the recession. Panel (b) shows that the contraction in secured small business lending leads to a strong fall in its share out of total small business lending for stress tested banks (blue solid line). For non-stress tested banks (grey dashed line), the share remains stable and similar to pre-crisis levels.[26] Loans secured by real estate collateral are important for entrepreneurs and young firms. CRA data does not provide info on secured vs. unsecured lending. I use FDIC SDI data to analyze how stress tested banks reduce collateralized small business loans. Using bank-year level data requires stronger identification assumptions with respect to changes in loan demand. However, columns (1)-(2) in Table 5 show that imperfectly controlling for local county characteristics leads to a lower-bound estimate of coefficients.

To estimate how stress tested banks adjust their secured lending relative to other banks during

[26]he Online Appendix shows that there is no differential trend for small business loans by non-stress tested banks. The aggregate decline in secured small business lending is thus due to the contraction in lending by stress tested banks.

the recovery, I estimate

$$y_{b,t} = \gamma \ stress \ tested_{b,t} + controls_{b,t-1} + \theta_b + \tau_t + \epsilon_{b,t}. \tag{5}$$

$y_{b,t}$ is the log volume of secured small business loans by bank b in year t. Alternatively, y is the log volume of unsecured small business loans, or the share of secured over total small business loans. After including baseline bank controls, as well as bank (θ_b) and time (τ_t) fixed effects, coefficient γ indicates whether stress tested banks reduce lending by more than non-stress tested banks, relative to their respective pre-crisis trends. Column (7) shows that the decline in small business lending secured by collateral is significantly stronger for stress tested banks than non-stress tested banks. Conditional on bank controls, as well as bank and year fixed effects, stress tested banks reduce secured small business lending by 40.3 % more than non-stress tested banks since the introduction of stress tests in 2009. Column (8) uses log unsecured business lending as dependent variable and shows that it also declines by more, although the coefficient is insignificant.[27] The decline in secured lending leads to a change in banks' portfolios: in column (9), stress tested banks see a significant decline in the share of secured out of total small business loans by 6.8 %.

To ensure that there is no effect of stress testing during the pre-crisis period, Figure 3 plots yearly coefficients on the interaction terms of *stress tested* and yearly dummies. Panel (c) compares secured and unsecured small business lending by stress tested banks (the analogue of panel (a)) and shows that there no significant effect of stress testing on loan volume in the pre-crisis period. Starting in 2009, stress tested banks see a significant and persistent decline in secured small business lending, relative to unsecured small business lending. Panel (d) compares trends across banks, i.e. secured small business lending of stress tested to non-stress tested banks. Similar to panel (c) and in line with panel (b), stress tested banks significantly reduce secured lending during the post-crisis period, relative to non-stress tested banks. Hence, while from 2009 on stress tested banks reduce secured small business lending relative to their own unsecured small business lending and relative to secured small business lending of non-stress tested banks, there were no differential trends prior to the crisis.

Taken together, results in Figure 3 and Table 5 suggest that stress tested banks reduce their lending to small businesses, especially if it is secured by collateral. In robustness tests in Section 5 I show that the pattern holds across different specifications and after including bank-specific trends; that banks that fail stress tests cut secured small business lending by significantly more than stress tested banks that do not fail; and that stress tested banks cut secured small business lending significantly more than unsecured small business lending, even after controlling for unobservable time-varying bank-specific and loan type-specific shocks through fixed effects. The following section analyzes the real effects of the contraction in loan supply.

[27] The smaller coefficient size in column (1) relative to column (7) is to be expected: CRA loans comprise both secured and unsecured small business loans, so the coefficient in column (1) should lie between those in columns (7) and (8).

3.2 County Exposure, Entrepreneurs, and Innovation

Figure 1 shows that job creation by young firms disappointed since the recession. Panel (a) shows that six years after the crisis, young firm employment as a share of total employment remains depressed (blue solid line). Panel (b) shows that young (blue solid) firms saw a 30 % decline in gross job creation during the crisis, similar in magnitude to older firms (black dashed). Since then, old firms are almost back to their pre-crisis levels, but young firms have not recovered. This section links the reduction in loan supply to the decline in young firms by showing that county exposure to stress tested banks depresses entrepreneurship. Since young firms have an outsized effect on aggregate innovation and productivity, in a second step I analyze how exposure to stress tested banks affects county patent applications.

I estimate regressions on the county-year (C-Y) and county-industry-year (C-I-Y) level. On the county-year level, I estimate the following difference-in-difference specification:

$$y_{c,t} = \beta \ exposure_c \times post_t + controls_{c,t-1} + \theta_c + \tau_t + \epsilon_{c,t}, \tag{6}$$

where $y_{c,t}$ denotes log small business lending (provided by CRA), log patent applications by young or old firms, or log labor productivity for county c in year t. *exposure* denotes county exposure to stress tested banks, as defined in equation (1). *post* is a dummy with value one for years 2009-2016. Baseline county controls include log population, labor force participation rate, unemployment rate, house prices, as well as the share of black population and share of population older than 65 years, all lagged by one period. Standard errors are clustered on the county level. $\beta < 0$ indicates that counties with higher pre-crisis exposure to stress tested banks see a stronger decline in outcome variables than counties with low exposure during the stress testing period.

Based on bank-level results, the strong contraction in secured loans should hurt young firms that use real estate collateral particularly hard. I test the hypothesis by estimating the following difference-in-difference-in-difference specification on the county-industry-year level:

$$\begin{aligned} y_{c,i,t} =& \gamma_1 \ exposure_c + \gamma_2 \ post_t + \gamma_3 \ exposure_c \times post_t \\ &+ \gamma_4 \ home\ equity_i + \gamma_5 \ exposure_c \times home\ equity_i + \gamma_6 \ home\ equity_i \times post_t \\ &+ \gamma_7 \ exposure_c \times home\ equity_i \times post_t + \theta_{c,i} + \tau^1_{c,t} + \tau^2_{i,t} + \epsilon_{c,i,t}, \end{aligned} \tag{7}$$

where $y_{c,i,t}$ is either log employment or the share out of total employment of firms aged zero to one, or log wages, in county c and industry i in year t. *home equity*$_i$ denotes the share of young firms in industry i that uses home equity financing to expand operations, as defined in equation (2). The coefficient of interest (γ_7) indicates whether counties with higher exposure see a stronger decline in the importance of young firms or wages in industries that rely more on home equity financing. If so, then $\gamma_7 < 0$. I include county-industry fixed effects ($\theta_{c,i}$), which absorb coefficients γ_1, γ_4, and γ_5. To control for time varying unobservables I include time fixed effects at the yearly level (τ_t, absorbs γ_2) or at the county*time and industry*time level ($\tau^1_{c,t}, \tau^2_{i,t}$), which absorb γ_2 and γ_3.

Identification – fixed effects The underlying assumption in regression equations (6) and (7) is that counties with higher exposure see a relative decline in young firms and innovation because stress tested banks *supply* less credit to young firms. To ensure that *exposure* reflects loan supply effects, I need to control for confounding unobservable shocks that affect employment of young firms. Regressions on the bank-county-year level allow me to isolate the relative contribution of loan supply to small business lending by controlling for county-specific loan demand. However, unobservable county or industry characteristics could still lead to a bias in county-level regressions.

The key identification challenge is thus to control for characteristics that affect young firms beyond the change in credit supply by stress tested banks. I overcome this issue in regression equation (7) by including granular fixed effects. First, county*industry fixed effects ($\theta_{c,i}$) exploit variation within the same county-industry combination over time and control for unobservable and time-invariant county and industry heterogeneity (for example location or sensitivity to the business cycle), as well as for unobservable time-invariant characteristics at the county-industry level, such as the importance of an industry within a county. Second, county*time fixed effects ($\tau^1_{c,t}$) allow shocks to affect each county at each point in time heterogeneously. Thereby I control for unobservable time-varying county fundamentals (such as house prices, unemployment, and other local characteristics) to identify credit supply. Third, industry*time fixed effects ($\tau^2_{i,t}$) absorb common shocks to two-digit industries that vary over time, for example the secular decline in manufacturing. Essentially, I am comparing employment by young firms in the same county and same industry for different levels of exposure, exploiting only the within variation of each county-industry pair (Jiménez, Ongena, Peydró and Saurina, 2014). After absorbing changes in local and industry demand, the remaining variation reflects the consequences of changes in loan supply.[28]

When employing county*time and industry*time fixed effects, the underlying assumption is that young and old firms react similarly to common shocks. In general, young firms could depend more on local demand than old firms, which often serve multiple markets (Mian and Sufi, 2014). To account for differences in the sensitivity firm age cells to common shocks, in robustness checks I estimate regressions at the county-industry-age cell-year-level. *Age cell* denotes five separate firm age cells (0-1, 2-3 ,4-5, 5-10, 11+). Including county*firm age*time and industry*firm age*time fixed effects controls for shocks that affect firms in different age groups heterogeneously within each county and industry. For example, they control for a local rise in house prices that increases consumer demand and hence sales of young firms by more than sales of old firms.

Identification – gravity model and deregulation Identification of the effect of stress tests on entrepreneurship and innovation rests on geographical variation in exposure across counties. Exposure is constructed based on banks' deposits in a given county, but banks' deposit share in a county is

[28] County*time and industry*time fixed effects assume that borrowers in the same county or industry exhibit a similar behavior towards different lenders. For example, they change their loan demand in a similar way with respect to large and small banks. While this needs not to be the case, it is generally a reasonable approximation for changes in loan demand (Khwaja and Mian, 2008; Jiménez, Ongena, Peydró and Saurina, 2014).

potentially endogenous to unobservable county characteristics. In addition to employing granular fixed effects, I thus instrument local bank deposits through a gravity model of bank expansion (Goetz, Laeven and Levine, 2013, 2016), combined with an index of interstate banking deregulation developed in Rice and Strahan (2010).[29] Intuitively, gravity models predict that distance and market size determine the degree of activity in a market. In the present context, a New York-based bank is more likely to have deposits in a county in nearby Pennsylvania than in Texas (given similar market size), and (given same distance) in a more populous county. I estimate the following equation:

$$deposit\ share_{b,B,c,t} = \gamma_1\ ln(distance_{b,c}) + \gamma_2\ ln\left(\frac{population_{c,t}}{population_{B,t}}\right) + \epsilon_{b,B,c,t}, \tag{8}$$

where b denotes bank, B bank headquarter county, and c the destination (branch) county. The gravity model predicts that $\gamma_1 > 0, \gamma_2 > 0$. Following Goetz, Laeven and Levine (2016) I use a fractional logit model to estimate equation (8) for year 2007. I then predict the deposit share for each bank-county combination based on distance and market size. I set negative predicted values equal zero.

However, distance and market size do not take into account that some states impose restrictions on entry by out-of-state banks. Rice and Strahan (2010) show that even after de-jure deregulation following the Interstate Banking and Branching Efficiency Act (IBBEA) in 1994, most states use different combinations of policy tools to protect domestic banks from outside competition. The regulation of local banking markets took one or more of the following forms:

a) minimum age of the targeted bank (5 years, 3 years or less)
b) de-novo branching without an explicit agreement by state authorities
c) acquisition of individual branches without acquiring the entire bank
d) statewide deposit cap on the total amount of statewide deposits controlled by a single bank or bank holding company.

Over time 43 states relaxed protection of their local banking markets. Omitting the degree of local banking regulation will thus lead to a bias in predicted deposit shares. Given similar distance from headquarters, equation (8) assigns counties A and B the same deposit share, even if county A prohibits out-of-state banks from opening local branches.

For each state I first construct a yearly index that ranges from 0 to 4 to capture each dimension of state-level branching restrictions. States with a value of zero regulate their banking sector in all four dimensions, states with a value of four are fully deregulated. I then define the state-level variable $deregulation_s$ as the cumulative index for each state s from 1994 to 2007:

$$deregulation_s = \sum_{t=1994}^{2007} index_{s,t}. \tag{9}$$

[29] For a detailed discussion, see Goetz, Laeven and Levine (2016). A large literature establishes that, in banking, distance matters (Degryse and Ongena, 2005; Agarwal and Hauswald, 2010). Goetz, Laeven and Levine (2013) show that banks 'are more likely to expand into geographically closer markets than into more distant ones'. The underlying argument is informational advantages and lower costs.

For example, Alabama increased its index from 0 to 1 in 1997, so $deregulation_{AL} = \sum_{1997}^{2007} 1 = 11$. Illinois increased its index from 0 to 1 in 1997 and from 1 to 4 in 2003, so $deregulation_{IL} = \sum_{1997}^{2002} 1 + \sum_{2003}^{2007} 4 = 26$. I then re-scale $deregulation_s$ to the range of $[0, 1]$. Since I use the instrument to predict the presence of stress tested banks in a given county, cumulative addition reflects that 'foreign' banks had more time to enter states that deregulated earlier.[30] I then scale predicted deposit shares $\widehat{deposit\ share}_{b,B,c}$ by $deregulation_s$ and construct local instrumented deposits by bank b in county c as $deposits^{IV}_{c,b} = \widehat{deposit\ share}_{b,B,c} \times deregulation_s \times total\ bank\ deposits_b$. If s equals a banks' headquarter state, I set $deregulation_s = 1$, since banks face no restrictions on expanding in their own state. Finally, I compute predicted exposure $exposure^{IV}_c$ according to equation (1), but based on $deposits^{IV}_{c,b}$. $exposure^{IV}_c$ hence provides exogenous variation in county-level exposure to stress tested banks.

Panel (a) in Figure 6 splits bank-county combinations into deciles by distance from bank headquarters to branches (in log miles) and plots banks' average deposits as share of total bank deposits. Deposit shares decline with distance. Banks hold on average 15 % of their total deposits in branches in the bottom decile in terms of distance to their headquarter, but only 1 % in the top decile.[31] Panels (b) and (c) show a binscatter and scatter plot of predicted and actual deposit shares and exposure. For both, there is a strong and significant positive relationship, indicating that the 'gravity+deregulation' model predicts deposit shares, and hence exposure, reasonably well. Regressing actual on predicted exposure at the county level yields a t-value of 27.23 and and R^2 of 0.55. Finally, panel (d) show the geographic variation in predicted exposure across U.S. counties. The online appendix reports results for regression equation (8) and the first stage.

Results – employment and innovation Table 6 shows that higher county exposure is associated with lower overall small business lending and a decline in employment among young firms. Column (1) reports results for baseline county-year (C-Y) regression equation (6) with log CRA small business loans as dependent variable. Counties with higher exposure to stress tested banks see a significant decline in total lending to small businesses. Note that the decline in small business lending includes secured and unsecured lending and imperfectly controls for local county characteristics. Since bank-level regressions in Table 5 show that stress tested banks reduce secured small business lending by more than three times as much than unsecured small business loans,and that including county*time

[30] Rice and Strahan (2010) and Celerier and Matray (2016) provide several tests to show that deregulation occurred independently of economic or political considerations that could affect the real economy (for example GDP per capita, unemployment rate, or personal income of low income households). Both studies use deregulation with contemporaneous outcome variables. Since my paper uses deregulation before the crisis to study its effect on growth during the recovery, endogeneity issues arising due to the initial timing of deregulation are less of a concern. Figure 19, panel (a), shows the timing of deregulation, as well as the average deregulation index. For each year, it lists states that deregulated, as well as the scope of deregulation (1-4). The majority of states deregulated from 1995-97, but to different degrees; several states deregulated more than once. Panel (b) shows a strong increase in local deposits owned by banks headquartered in a different state from 1995 (red dashed line) to 2005 (black solid line), i.e. an increase in cross-state banking since 1995. Dick (2006) finds that deregulation has translated into a dramatic decrease in the number of regional banks and a strong appreciation of bank density.

[31] The Online Appendix shows the distribution of deposits by the four largest U.S. banks across counties. There is strong geographic clustering, suggesting that 'distance matters'.

fixed effects increases coefficient size, column (1) understates the contraction in loans to young firms that use real estate collateral. The negative coefficient on $exposure \times \mathbb{1}(2009-16)$ indicates that non-stress tested banks do not increase their lending enough to compensate for the fall in lending by stress tested banks. In other words, borrowers cannot easily substitute credit across lenders.

[Table 6 about here]

Columns (2)-(11) report results for regression equation (7) on the county-industry-year (C-I-Y) level. Dependent variable in columns (2)-(5) is log employment of young firms. Column (2) shows that counties with higher exposure see a decline in employment of young firms during the post-crisis period, relative to counties with lower exposure. In terms of magnitude, a county in the top tercile of exposure sees a decrease in employment of young firms by 1.8 %, relative to a county in the bottom tercile.[32] Columns (3)-(5) add interaction terms with the share of firms using home equity in each industry. Column (3) absorbs common shocks through year fixed effects, column (4) adds granular county*time fixed effects to account for local changes in unobservable demand and county characteristics. The negative coefficient on the triple interaction term (γ_7) suggests that the decline in employees of young firms is stronger in industries with a higher share of firms using home equity to start or expand operations. Controlling for local demand effects slightly reduces the magnitude of the coefficient of interest. Yet, it is still significant at the 1 % level. Finally, column (5) adds industry*time fixed effects to control for time-varying changes to individual industries. Coefficient γ_7 is similar in sign, size, and significance to column (4). In terms of magnitude, for counties in the top tercile of home equity, moving a county from the 25^{th} to the 75^{th} percentile in terms of exposure reduces young firm employment by 4.6 % in column (6). Hence, even after controlling for local and industry shocks, counties with higher exposure see a decline in employment among young firms, in particular within home equity intensive industries.

Falling employment among young firms could reflect a general decline in employment in counties with high exposure. To show that the decline in employment among young firms leads to a fall in the relative importance of young firms, columns (6) and (7) replicate columns (3) and (5), but use the share of employment among young firms as dependent variable. Results are qualitatively identical: young firms in counties with higher exposure and industries that rely more on home equity financing fare particularly poorly during the recovery. Effects are significant at the 1 % level. Moving a county from the 25^{th} to the 75^{th} percentile in terms of exposure reduces the share of young firm employment by 0.5 p.p in column (6) for counties in the to tercile of home equity. The latter represents (0.5/2.2 =) 23 % of the average decline in young firm employment shares from 2002-2007 to 2010-2016.

Finally, columns (8)-(11) instrument actual with predicted exposure.[33] IV estimates confirm OLS findings: higher exposure to stress tested banks reduces employment among young firms, and the

[32] See Table 20 in the online appendix for simplified regressions with top/bottom tercile dummies for home equity.
[33] F-statistics are > 1000, so there is no weak instrument problem.

more so in home equity-intensive industries. IV estimates are slightly larger than OLS estimates. In line with fixed effects specifications, this could suggest that high-exposure counties have stronger fundamentals. In column (11), moving a county from the 25^{th} to the 75^{th} percentile in terms of exposure reduces the share of young firm employment by 0.8 p.p. (0.8/2.2 = 37% of the average decline over the crisis period).[34]

Table 6 establishes that counties with higher exposure to stress tested banks see a decline in small business lending and a fall in employment among young firms. Table 7 shows that counties with higher exposure to stress tested banks also see a fall in patent applications of young firms, but not of old firms. Each column runs baseline county regression (6) with a different dependent variable. Column (1) shows that patent applications by young firms decline significantly for counties with higher exposure. Moving a county from the bottom to the top tercile in terms of exposure reduces patenting activity by young firms by 6.5 % during the recovery. There is no significant effect on patent applications by old firms in column (2). Column (3) shows that the difference is statistically significant at the 10% level. To account for incremental innovations, columns (4)-(6) show that the effect (and difference) is stronger when I weigh patents by citations. In terms of magnitude, counties in the top tercile of exposure see a decline in patent applications by 16.2 %, relative to counties in the bottom tercile (column (3)). The larger effect size suggests that especially the number of highly innovative patents by young firms decline. Again, there is no significant effect on patent applications by old firms. Column (6) shows that the difference in the change of weighted patent applications between young and old firms is significant at the 1 % level. In column (6), top-tercile vs bottom-tercile exposure counties see a decline relative to patents by old firms of 14.6 %.

[Table 7 about here]

Column (7) instruments observed with predicted exposure and reports a significant negative coefficients similar in size to column (6). Since more recent patent data is less reliable and not all applications and citations are filed and recorded yet, column (8) replicates results in column (6), but exclude years 2014-2016. Effects remain similar in sign, size, and significance to baseline specifications. Column (9) includes state*year fixed effects instead of year fixed effects. Results increase in magnitude. Finally, Figure 5, panel (b), plots yearly coefficients and 90 % confidence intervals on interaction terms of exposure with yearly dummies in regression equation (6) with the difference between young and old patents as dependent variable. Estimates for coefficients for years before 2010 are insignificantly

[34]Unreported regressions shows strong and significant effect of small business lending on young firms. A ten percent increase in small business lending increase young firm employment by 1.2 %. Instrumenting small business lending with $exposure \times \mathbb{1}(2009-16)$, a decline in small business lending due to exposure leads to a significant and strong fall in young firm employment. The first stage F-Statistic equals 92.98. The coefficient increases in magnitude, which is reasonable if *exposure* isolates the variation in small business lending that is due to the contraction in secured small business lending. Unreported regressions show that IV regressions deliver similar results when CRA lending is interacted with home equity and instrumented through $exposure \times homeequity \times \mathbb{1}(2009-16)$, conditional on county*time and industry*time fixed effects (results available upon request).

different from zero. Starting in 2010, exposure has an increasingly negative and significant effect on patenting. Taken together, Tables 5 to 7 show the following: stress tested banks cut lending to small businesses that use real estate collateral to secure loans, which hurts young firms and entrepreneurs that rely on home equity financing. Since entrepreneurs matter for aggregate growth and innovation, counties with a stronger reduction in loan supply see a decline in patenting activity, particularly for highly-cited patents. The next section provides evidence that the decline in young firms and innovation contributes to the productivity slowdown.

4 The Productivity Slowdown

Following the financial crisis, the U.S. witnessed a dramatic decline in productivity growth. Output per capita growth fell by more than half since the financial crisis, averaging a meagre 1.3 % (Fernald, 2016).[35] Young firms have an outsized importance for aggregate productivity (Decker, Haltiwanger, Jarmin and Miranda, 2014; Alon, Berger, Pugsley and Dent, 2018; Curtis and Decker, 2018) and contribute around one-third to aggregate TFP (Haltiwanger, 2015). This raises the question whether their weak performance during the recovery contributes to the post-crisis productivity slowdown. Figure 7, panel (a) plots log labor productivity for counties in the top (blue dashed) and bottom (black solid) tercile of exposure. While labor productivity follows a common trend in both sets of counties until the crisis, there is an increasing divergence since. Counties with higher exposure to stress tested banks fall further and further behind. Panel (b) plots yearly coefficients and 90 % confidence intervals on interaction terms of exposure with yearly dummies in regression equation (6) with log labor productivity as dependent variable. There is no differential pre-trend (2010 is the omitted category): Estimates for coefficients for years before 2010 are insignificantly different from zero. Starting in 2010, exposure has an increasingly negative and significant effect on labor productivity.

Regression results in Table 8 confirm that counties with high exposure see a decline in labor productivity, relative to counties with low exposure to stress tested banks. Columns (1)-(2) are on the county-year (C-Y) level and use log labor productivity as dependent variable. The effect of county exposure on labor productivity is negative and significant at the 1 % level. Moving a county from the 25^{th} to the 75^{th} percentile in terms of exposure is associated with a relative decrease in labor productivity during the recovery of $(0.3 \times -0.044 =)$ 1.32 %. On average, labor productivity across counties grew by 2.6 % from 2010 to 2016, so the effect equals around half of the post-crisis mean.

[Figure 7 and Table 8 about here]

Previous results show that the dearth of young firms is more pronounced in industries with higher use of home equity financing. Labor productivity is not available at the county-industry level, so I

[35] Although some studies date the beginning of the productivity slowdown to the mid-2000s, it accelerated since 2008/09 (see Figure 9).

cannot test directly whether the decline in productivity is stronger in home equity intensive industries. To provide indirect evidence, in column (2) *home equity exposure* denotes 2007 employment-weighted county exposure to industries' home equity usage. Higher values of *home equity exposure* indicate that counties have a high share of employment within industries where home equity financing is important. Interacting *home equity exposure* with *exposure* to stress tested banks and a dummy for the post-crisis period shows that the decline in labor productivity for exposed counties is stronger if a larger share of employees work in home equity intensive industries.

Columns (3)-(7) confirm that exposure depresses labor productivity more in home-equity intensive industries. The dependent variable is log wages at the more granular county-industry-year (C-I-Y) level (see regression equation (7)). Column (3) shows that wages, a common proxy for labor productivity, decline significantly more in counties with higher exposure. The effect is comparable, but slightly stronger than for labor productivity in column (1). Columns (4)-(6) add interaction terms with industry home equity financing. Wages decline stronger in exposed counties within industries that rely more on home equity financing. The coefficient of interest on the triple interaction term (γ_7) remains significant at the 1 % level and similar in sign and size across specifications. Controlling for local and industry demand through county*time and industry*time fixed effects in columns (5) and (6) does not affect the main coefficient. Finally, column (7) instruments exposure with predicted exposure. Similar to regressions for young firm employment, coefficients are similar in sign and significance, but larger in IV regressions.

An emerging literature in macro examines how the drop in young firms during the crisis has lasting effects on productivity (Bassetto, Cagetti and De Nardi, 2015; Siemer, 2016). My results suggest that there is more to it: not only did employment among young firms decline during the crisis, but regulation of the financial sector prevented its recovery. The persistent collapse in lending to start-ups contributed to the productivity slowdown above and beyond the immediate effects of the crisis. Taking coefficients in Table 8 at face value, a back-of-the-envelope calculation shows that exposure to stress tested banks explains around one-quarter of the overall decline in productivity growth since the crisis.[36] However, my reduced form regressions attribute the overall effect of exposure on productivity growth solely to the decline in young firms. Since stress tested banks also adjust lending to households and other firms, for example listed companies, they likely have an impact on productivity through additional channels besides start-up financing. Without matched bank-firm credit registry data it is not possible to disentangle these channels, so my estimates need to be viewed with caution.

[36] TFP growth declined from 1.2 % to 0.75 % over the crisis, so roughly 0.5 %. Young firms contribute around 1/3 to TFP growth in normal times (Haltiwanger, 2015; Alon, Berger, Pugsley and Dent, 2018), and since TFP growth averaged 1.2 % over the 2000s, this yields 0.36 %. Taken at face value, my results show that, for average exposure, employment of young firms declines by around 1/3, which leads to a $(0.36 * 1/3 =)$ 0.12 % decline in productivity growth. Scaled by the overall decline in TFP growth since the crisis, this represents $(0.12/0.5 =)$ 25 % of the productivity slowdown.

5 Robustness

Bank Robustness Table 9 provides robustness checks on the bank level. For comparison, column (1) replicates baseline results from Table 5, column (1). Column (2) adds bank-specific time trends and shows that the effect of stress testing on secured small business lending remains unaffected. Bank-county level regressions showed that controlling for unobservable county characteristics increases the size of the effect of stress testing on CRA small business lending. It is not possible to control for local unobservable characteristics in an equally granular way on the bank-year level to see how demand affects secured and unsecured small business lending. As an approximation, columns (3) and (4) include time-varying fixed effects at the state and MSA level of banks' headquarters. Under the assumption that banks extend a significant share of their loans in their home markets, including fixed effects improves identification. In line with bank-county results for CRA lending, coefficients increase in size, indicating that stress tested banks lend to counties with stronger loan demand for secured loans.

To further control for differential trends in secured vs. unsecured small business lending, columns (5)-(7) move to the bank-loan type-year level, where *loan type* is a dummy with value one for secured small business loans (SSB), and value zero for unsecured small business (USB) loans. Hence, columns (5)-(7) not only compare lending by stress tested to non-stress tested banks, but also within each bank type secured vs. unsecured small business lending. Dependent variables are growth rates to pick up contemporaneous changes in both types of lending and facilitate comparison. This specification allows for granular fixed effects at the bank*year and loan type*year level, controlling for unobservable bank and loan characteristics. The latter include differential demand for each loan type. Across specifications, stress tested banks reduce SSB significantly more than USB, as indicated by the negative coefficient on the interaction terms. The sequential addition of fixed effects does not change the coefficient of interest in any statistically meaningful way. Note that columns (1)-(4) show that stress tested banks reduce secured small business lending more than non-stress tested banks, while columns (5)-(7) show that stress tested banks reduce SBB more than USB lending. Taken together, columns (1)-(7) suggest that the reduction in secured small business lending by stress tested banks is not due to demand effects.

[Table 9 about here]

Columns (8)-(9) focus on the sub-sample of stress tested banks and define dummy *failed ST* that takes on value one for banks that failed the stress test in a given year (see Table 15 in the Appendix). Within the group of stress tested banks, banks that failed a stress test reduce SSB lending significantly more than non-failing banks (column (8)), but also more than their own USB (column (9)). The latter holds after controlling for unobservable bank and loan characteristics through bank*year and loan type*year fixed effects. Columns (10)-(11) use nearest neighbor matching in the cross section for the recovery period. I match on baseline pre-crisis bank controls. Dependent variable is the change in secured small business lending from 2010 to 2016. Stress tested banks see significantly lower growth of SSB lending than non-stress tested banks (-52.2 %) in column (10), which uses the full sample of 5,836 banks. Column (11) restricts the sample to banks with total assets as of 2010 between 10bn and 150bn. Again, there is a significant negative effect of stress testing on the growth of secured small business lending. Within the group of the largest banks, stress tested banks reduce SSB loans by an additional 36.2 %, relative to non-stress tested large banks. In line with results in Table 5, Table 9 confirms that neither demand effects, unobservable time-varying bank and loan characteristics, nor bank size explain the negative effect of stress testing on secured small business lending.

County Robustness: Local house prices and county characteristics The negative effect of exposure to stress tested banks on young firm employment is stronger in industries where more firms rely on home equity financing. The underlying mechanism is a contraction in secured small business lending by stress tested banks. However, literature established the importance of the collateral channel: rising real estate prices increase collateral values and relax financial constraints (Chaney, Sraer and Thesmar, 2012; Adelino, Schoar and Severino, 2015; Bahaj, Foulis and Pinter, 2018). While in baseline regressions county*year fixed effects control for common shocks to firms across industries, changes in local real estate prices could affect industries heterogeneously, depending on their home equity intensity. Table 10, columns (1)-(4), thus control for local housing characteristics interacted with industries' home equity intensity. Each regression controls for time-varying shocks at the county and industry level, and exploits only within county*industry variation. Dependent variable is the employment share of young firms.

[Table 10 about here]

Column (1) interacts the change in county house prices from 2002 to 2007 (*HPI boom*) with industries' home equity dependence and a post dummy; column (2) uses the change in house prices from 2007 to 2010 (*HPI bust*); column (3) interacts exposure with the share of home owners in 2000 and the post dummy;[37] in column (4) I control for contemporaneous changes in house prices. Across specifications, the coefficient of interest (exposure $\times$ home equity $\times$ $\mathbb{1}$(2009-16)) remains stable. Neither rapidly increasing house prices in the pre-crisis period, a stronger collapse in house prices during the crisis, nor differences in home ownership rates materially change the effect of exposure to stress tested banks on young firm employment when added to the baseline regression. The stability of the main effect suggests that exposure reflects a fall in loan supply by stress tested banks, irrespective of characteristics and performance of local housing markets.

[37] Pre-crisis home ownership could have an effect on young firm employment due to a decline in home equity values and a corresponding fall in local demand since the recession (Mian and Sufi, 2014). If the decline in demand varies systematically across industries, main coefficients will be biased. Data is only available for 2000 or 2010. Since 2010 is after the crisis and housing bust, 2000 likely gives a better picture of pre-crisis home ownership at the county level. However, the correlation between both years is 0.94 and results identical under both metrics.

Table 4 shows that county exposure is significantly correlated with total population and share of urban population. Columns (5)-(6) directly control for pre-crisis log population and urban share, interacted with home equity intensity and post dummy. Controlling for both county characteristics increases the magnitude of the baseline coefficient, suggesting that the effect of county exposure on young firm employment does not hinge on the stronger presence of stress tested banks in urban and more populous counties. This result is confirmed in the online appendix, where regressions in a restricted sample of counties with population above 100 thousand or one million yield coefficients with similar size. To further control for local county characteristics, column (7) includes the Herfindahl Index (HHI) of county deposit concentration (a common measure for competition in the banking sector) as interaction term.[38] Controlling for local competition has a negligible effect on exposure. Finally, columns (8)-(9) allow exposure to affect industries differentially, depending on their pre-crisis share or pro-cyclicality to aggregate employment. Column (8) interacts exposure with the pre-crisis average employment share of industry i in county c (*industry share*) and the post dummy, which allows exposure to impact industries according to their relative importance in a local economy. Column (9) repeats the exercise, but replace *industry share* with industry betas from Cortés, Demyanyk, Li, Loutskina and Strahan (2018). Industry betas, or *industry risk*, measure how sensitive industry employment is to aggregate employment. Higher values indicate riskier industries. Including industry risk addresses the potential concern that industries with more firms using collateral are also riskier. In both specifications, including interaction terms increases baseline coefficients in magnitude. In conclusion, across all specifications, exposure has a significant negative effect on the performance of young firms in industries that rely more on home equity financing.

The online appendix reports further tests to ensure that county exposure to stress tested banks is the key driver of my results. I estimate baseline regressions at the county-industry-age cell-year level and allow local and industry unobservables to vary by firm age group. Young firms mostly depend on local demand, so they could be more responsive to local shocks and less responsive to industry shocks than old firms (Mian and Sufi, 2014). Including county*firm age*time and industry*firm age*time fixed effects yields coefficients of similar sign, size, and significance. Additionally, I include alternative exposure metrics. Based on equation (1), I compute exposure based on local deposits by the four largest instead of all stress tested banks; log total bank assets; the log difference in banks' loans from 2007 to 2009; and a dummy for banks with asset size 10bn to 50bn. Including interaction terms with these alternative exposure measures does not change the coefficient of interest, which suggests that the effect of stress tests is not solely due to the four largest banks, nor due to bank size or performance during the crisis, and not present for non-stress tested large banks. For sub samples, I find that the contraction in loan supply reduces young firm employment by more in risky areas and industries (in line with findings by Cortés, Demyanyk, Li, Loutskina and Strahan (2018)). When I split the sample into tradable and non-tradable industries, exposure has a negative impact on employment in both types of sectors, but the effect is stronger in tradable industries, suggesting that unobserved local

[38] The correlation between exposure and HHI is -0.17.

demand is not explaining results. Finally, restricting the sample to counties in which the largest four banks have no presence does not materially affect results. Further robustness tables look at net job creation (Adelino, Ma and Robinson, 2017) and cross-sectional pre-/post-crisis regressions instead of panel regressions.

County Robustness: Patents Table 11 takes a closer look at patenting activity. Columns (1)-(4) use disaggregated data on the county-patent classification-year level, where patent classification refers to eight distinct categories defined in the International Patent Classification (IPC). Dependent variable is the difference between log patents by young and old firms, weighted by citations. Each column adds more granular fixed effects, to control for common shocks affecting firms within an industry (industry*time) or state (state*time) over time. Across specifications, R^2 increases, but the size of the coefficient remains stable. In line with findings for bank and firm employment regressions, exposure is insensitive to changes in local and industry characteristics.

[Table 11 about here]

To ensure that the effect of exposure on patenting of young and old firms is not due to unobservable county characteristics, columns (5)-(8) control for time-varying shocks on the county and firm age cell level. Specifically, it estimates regressions on the county-firm age-year level, where firm age refers to young and old firms (young firms are firms that patented at most five years ago). Similar to regressions on the county-industry-year level in regression equation (7), this allows me to include county*time fixed effects that control for time-varying local shocks. In addition, firm age*year fixed effects absorb any common trends that differentially affect patenting activity by young and old firms, for example the secular decline in the importance of young firms. Finally, county*age fixed effects exploit only the variation within each county-firm age cell. Column (5) shows that counties with higher exposure see a fall in patent applications during the post-crisis period. It employs county*age and year fixed effects, as well as county controls. Column (6) uses the same specification, but introduces interaction terms with dummy *young*. The decline in patent applications in exposed counties is due to a decline by young firms, as indicated by the negative significant coefficient on the triple interaction term. Columns (7)-(8) add county*time and age*time fixed effects. Controlling for local and age-specific shocks does not change the coefficient of interest. Young firms still patent significantly less during the recovery. Across specifications, there is a negative effect of exposure on patenting by young firms and controlling for confounding unobservable factors does not materially affect results.[39]

County Robustness: Non-bank lending As a final robustness check, I examine alternative sources of financing. The contraction in loan supply by stress tested banks has real effects only

[39] In unreported regressions, I show that excluding IPC sectors/industries one for one does not materially affect the main coefficient, and estimating column (3) for each individual industry yields a negative coefficient in every single industry.)

if borrowers cannot substitute into other forms of financing. Small businesses are in general bank dependent and could turn to non-stress tested smaller local banks. Columns (1) and (2) in Table 8 show that counties with higher exposure see an overall decline in small business loans. This is also true in aggregate. As of 2016 small business lending remains below its pre-crisis peak, and this is particularly true for secured small business lending. On aggregate, secured small business lending contracted by \$ 85 bn from 2009 to 2016, while unsecured small business lending increased by \$ 6 bn. Hence, even if some borrowers were able to switch from secured to unsecured lending, or from stress tested to non-stress tested banks, the small increase in unsecured small business lending prevents a full substitution.[40]

Young firms could also turn to non-bank financing. I use publicly available data on peer-to-peer (P2P) lending by *LendingClub*, which represents more than half of the U.S. market share of P2P-based personal loans. Although primarily extending personal loans, LendingClub granted over 15,000 business loans from 2007 (earliest data available) to 2016. Figure 8 shows that, unlike bank lending, peer-to-peer business lending grew over the crisis and recovery period (panel (a)). From 2010 to 2016 it increased from around \$ 6 million to \$ 75 million. Panel (b) shows that interest rates are high − the median borrower paid around 13.5 % interest during the recovery. For comparison, interest on loans by the Small Business Administration averaged 5.9 %.

[Figure 8 about here]

In general, non-bank financing is still in its infancy, especially for businesses. For LendingClub, small business loans make up on average 2.5 % of the total loan portfolio. Figures for the aggregate suggest that non-bank lenders capture around 5 % of the overall small business loan market. With respect to venture capital, in the 2007 SBO only 0.6 % (0.3 %) of firms report using venture capital to start (expand) their business. They are 25 (56) times more likely to use bank capital.[41] While no definite evidence, Figure 8 suggests that as of now, non-bank lending is more expensive than bank financing and not large enough in absolute volume to allow for full substitution.[42] Furthermore, the strong real effects of the contraction in bank lending on entrepreneurs, patenting, and productivity indicate that substitution across lenders is limited at best.[43]

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[40] Median (average) loan size for secured small business loans with origination amount $< \$1,000,000$ equals \$149,000 (172,000), so the total decline in secured small business lending by \$86 bn represents roughly half a million individual loans.

[41] See BI Intelligence: "The Small Business Alternative Lending Report". For the 2012 SBO, 0.08 % of firms report using venture capital to expand operations and they 40 times more likely to use bank loans. Literature establishes that while venture capital finances some high growth firms in selected industries, in general few (less than 1 %) start-ups and small firms make use of it (see Drover, Busenitz, Matusik, Townsend, Anglin and Dushnitsky (2017) and Parker (2018), p. 372). In the online appendix, I restrict the sample to counties outside of California, Massachusetts, and New York, where most of the venture capital industry is concentrated (Matray, 2015). Results remain similar.

[42] This is in line with research by Chen, Hanson and Stein (2017); Chernenko, Erel and Prilmeier (2018) and Tang (2018) who show that non-bank lending is more expensive than bank financing and complement rather than substitute.

[43] The Online Appendix takes a closer look at non-bank lending and venture capital. First, I find that counties with higher exposure see a strong, but insignificant increase in small business peer-to-peer lending. Second, I exclude states

6 Conclusion

In this paper, I provide new evidence that post-crisis financial regulation hurts entrepreneurship and growth. I show that stress tested banks strongly cut small business lending that is secured by collateral and that the contraction in loan supply has real effects.

Exploiting geographic variation in county exposure to stress tested banks, I show that counties with higher exposure see weaker growth of entrepreneurs during the recovery. In line with literature that highlights the sensitivity of young firms to changes in collateral values, I find that the contraction in secured lending hits entrepreneurs disproportionately harder in industries that rely more on home equity financing. Granular county-industry data ensures that my results are not confounded by unobservable shock to local demand or industries. Results are also robust to an instrumental variable approach that predicts county exposure with a gravity model of bank expansion. Since young firms have an outsized effect on aggregate innovation and growth, the decline in entrepreneurship due to the contraction in loan supply reduces patent applications by young firms. The decline is more pronounced when I adjust for the quality of innovation and weigh patents by citations. There is no effect of the lending cut on patenting by old firms. I also provide evidence that labor productivity and wages grow slower during the recovery in exposed counties.

Capital regulation in general, and stress tests in particular, have the objective to reduce risk-taking. My findings suggest that post-crisis financial regulation leads to a reallocation of credit away from risky borrowers: young firms and entrepreneurs see a fall in credit supply. The shift in bank credit across borrowers has negative side effects: it reduces dynamism, innovation, and productivity growth during the recovery from the Great Recession. Taken at face value, stress testing contributes around one-quarter to the post-crisis productivity slowdown. Yet, my results do not necessarily imply that stress testing is bad for welfare. Reducing volatility and the incidence of crises might require a reduction in risky lending to young firms. My work highlights the inherent trade-off between financial stability and growth and does not take a stance on the efficiency or long-run implications of the implemented policy.

New York, Massachusetts, and California from regressions of young firms and patents on exposure; the venture capital industries strongly clusters in these three states (Matray, 2015). Excluding counties in these states does not materially affect coefficients of interest.

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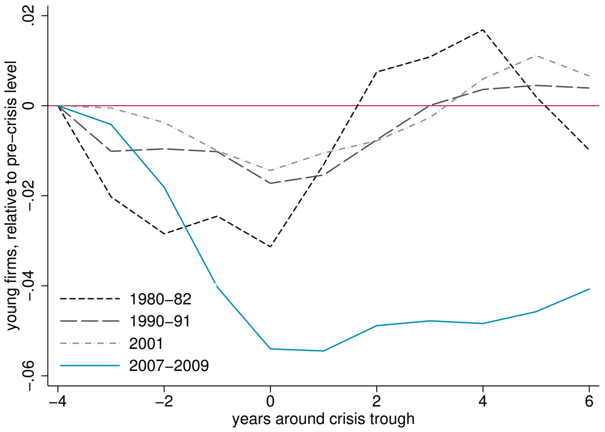
A Appendix

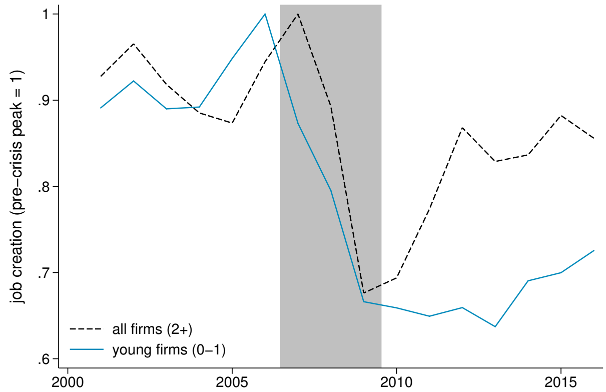
A.1 Descriptives and Figures

Figure 1: **Entrepreneurship since the recession**

(a) NBER recessions



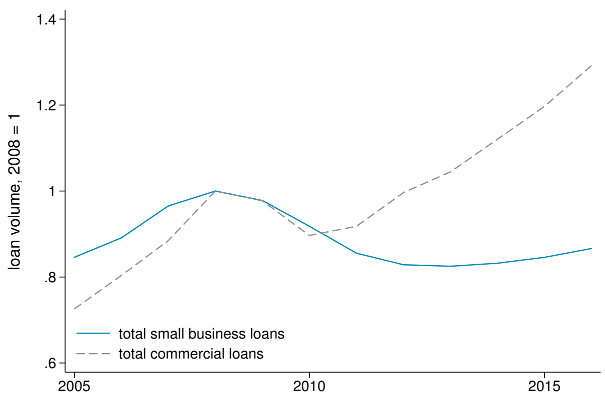
(b) Job creation



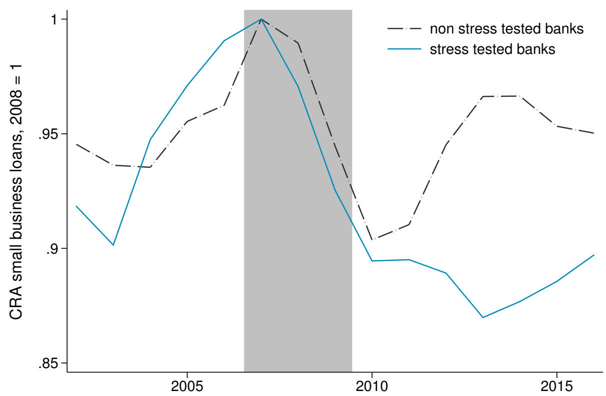
Note: Panel (a) plots employment of young firms (age 0-1), relative to its pre-crisis levels, normalized by pre-crisis peak total employment. Pre-crisis peak is defined as 4 years before trough of recession, where 0 on the x-axis indicates the trough. Recession dates are provided by NBER. Each line reflects how far away young firm employment is from its pre-crisis share out of total employment. When a line crosses zero on the y-axis (indicated by the red line), employment among young firms has reached its pre-crisis level. For the Great Recession, panel (b) plots gross job creation by young (age 0-1) and all other firms (age 2+) over the crisis (shaded area) and recovery period. Series are normalized to their pre-crisis peak. Data source: Census BDS Firm Characteristics Data Tables.

Figure 2: **Commercial lending since the recession**

(a) Commercial lending

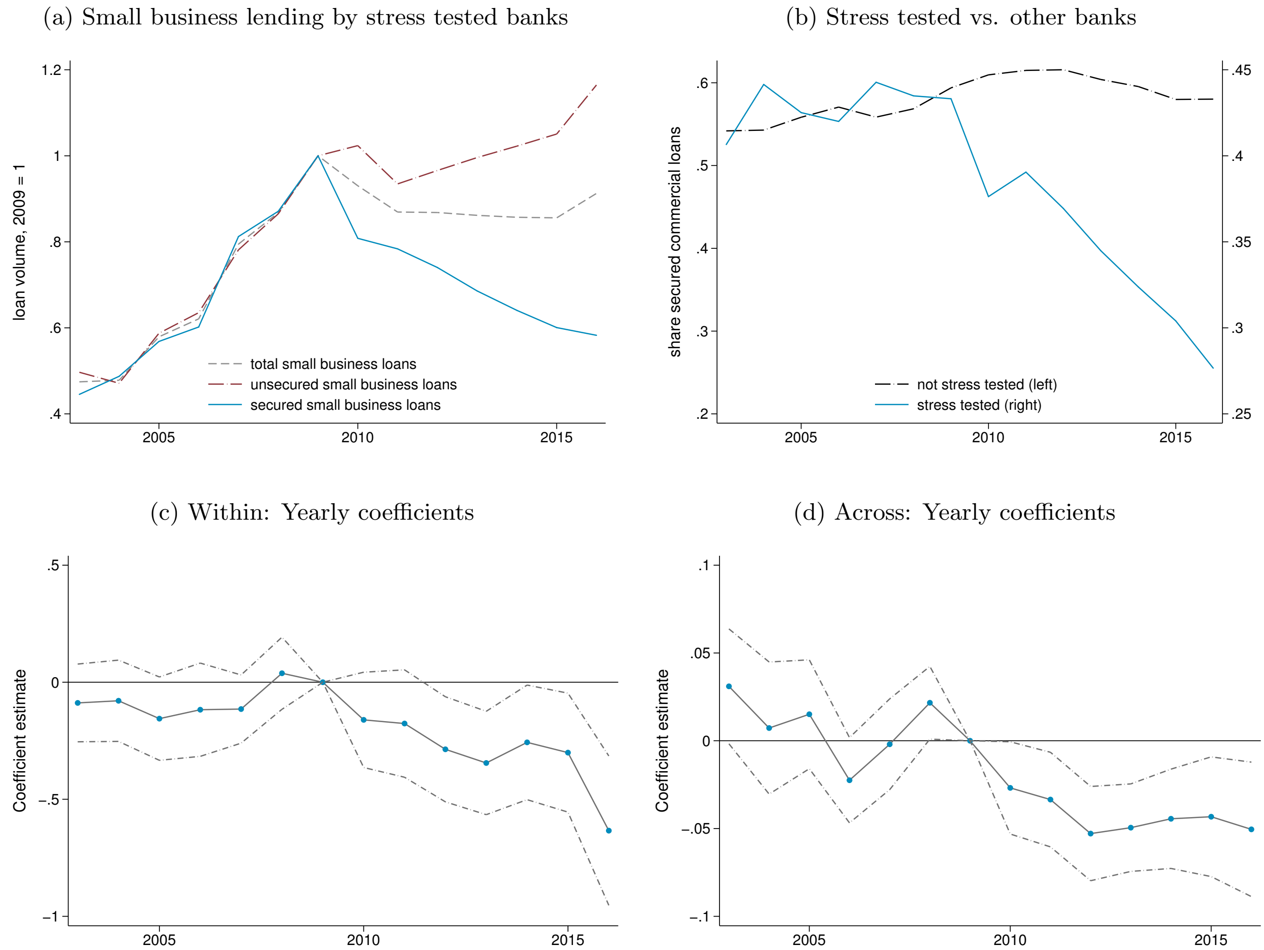


(b) Small business lending



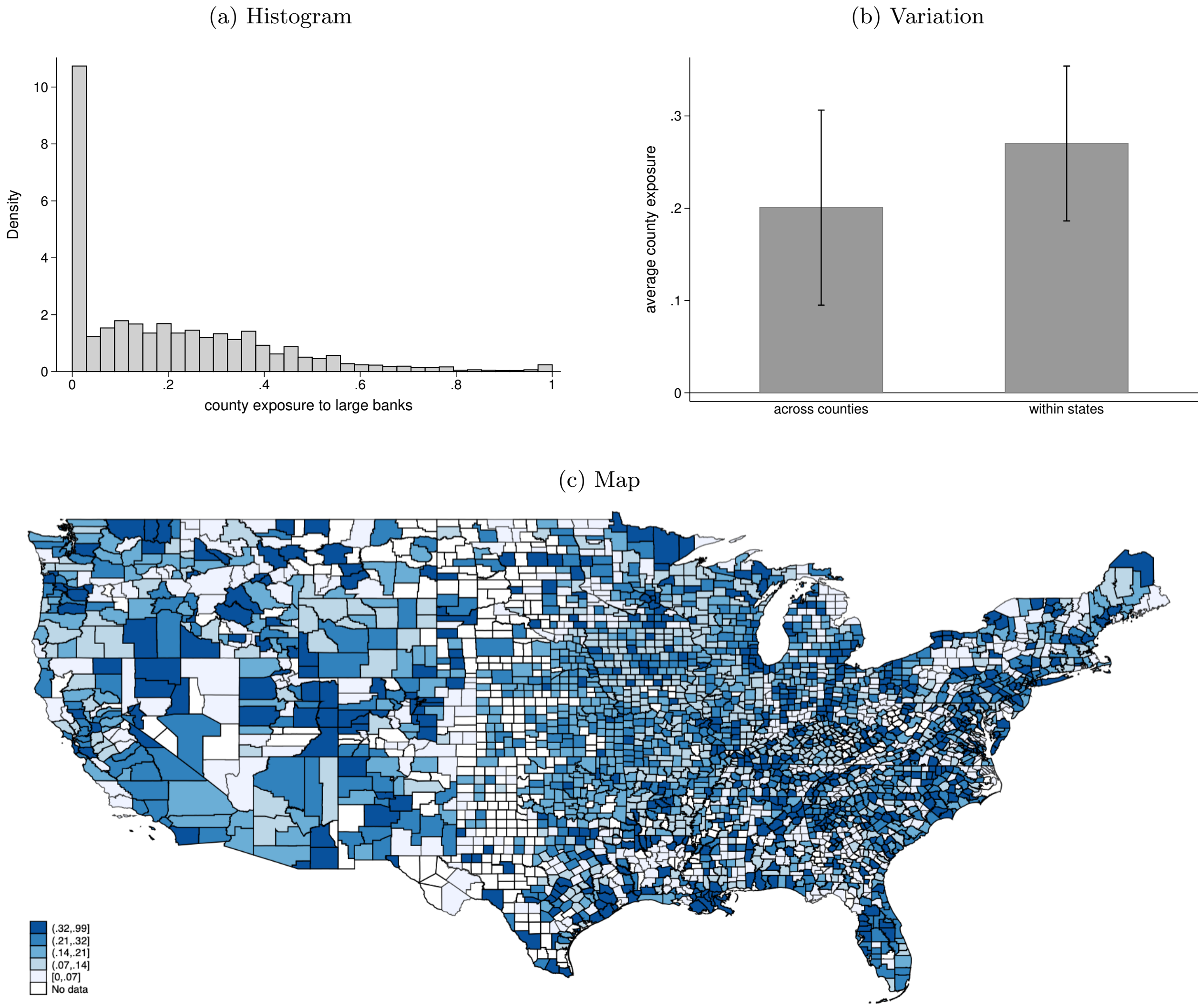
Note: Panel (a) shows commercial lending, defined as the sum of secured and unsecured loans. The grey dashed line is total lending (small and large loans), the blue solid line represents small business loans (loans with origination amounts less than $ 1,000,000). Data is provided by FDIC SDI. Since the crisis, small business lending is depressed, while total commercial lending recovered. Panel (b) shows CRA small business lending by bank type (stress tested in solid blue vs. non-stress tested in dashed grey), conditional on bank and county fixed effects. Both types of banks see a comparable decline in small business lending during the financial crisis (shaded area). During the recovery, stress tested banks see a persistent decline in small business lending, while non-stress tested banks increase lending already by 2010. All series are standardized to 1 in 2008.

Figure 3: **Secured small business lending**



Note: Panel (a) shows total (secured+unsecured), secured, and unsecured small business lending (loans with origination amounts less than \$ 1,000,000) by stress tested banks, normalized to 1 in 2009. Panel (b) shows the share of secured out of total small business lending for stress tested (blue solid line) and non-stress tested (black dashed line) banks. Stress tested banks strongly and persistently reduced their total secured small business lending, panel (a). This is mirrored in a decline in the relative share of secured small business loans for stress tested banks that is not present for non-stress tested banks, panel (b) (Source: FDIC SDI. Secured commercial loans are defined as "Nonresidential loans (excluding farm loans) primarily secured by real estate held in domestic offices", and excludes loans for construction purposes. Unsecured commercial loans are defined as "Commercial and industrial loans. Excludes all loans secured by real estate, loans to individuals, loans to depository institutions and foreign governments, loans to states and political subdivisions and lease financing receivables."). Panel (c) compares secured and unsecured small business lending among stress tested banks. It plots yearly coefficients on the interaction terms of the following equation on the bank-loan type-year level from 2003 to 2016, where 2009 is the omitted category: $log(loans)_{b,l,t} = \sum_{j\neq 2009} stress\ tested_b \times loantype_l \times \mathbb{1}_{t=j} + \theta^1_{b,l} + \theta^2_{b,t} + \theta^3_{l,t} + \epsilon_{b,l,t}$. Loan types refer to secured vs. unsecured small business lending. Panel (c) shows that stress tested banks reduced secured small business lending stronger during the post-crisis period, relative to unsecured small business lending. Panel (d) plots yearly coefficients on the interaction terms of the following equation on the bank-year level from 2003 to 2016, where 2009 is the omitted category: $log(secured)_{b,t} = \sum_{j\neq 2009} stress\ tested_b \times \mathbb{1}_{t=j} + controls_{b,t-1} + \theta_b + \tau_t + \epsilon_{b,t}$. Dashed lines denote 90 % confidence intervals, blue dots point estimates. After including bank controls and fixed effects, stress tested banks cut secured small business lending more than unsecured small business lending, and reduce secured small business lending more than non-stress tested banks.

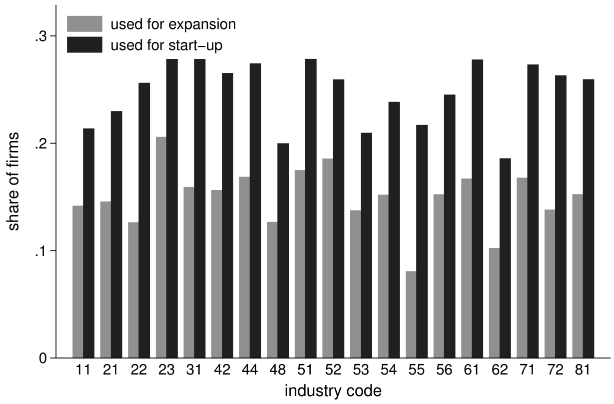
Figure 4: **County exposure**



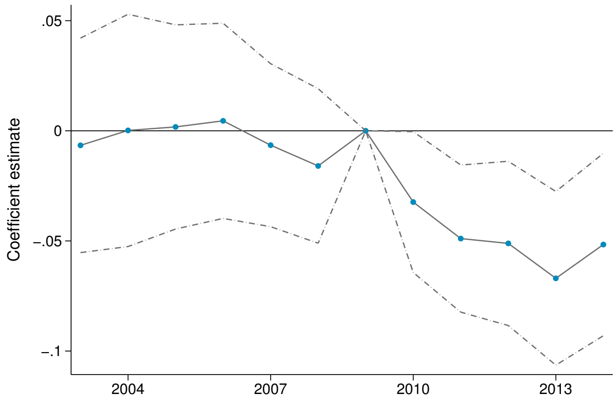
Note: Panel (a) shows the distribution of county *exposure* to stress tested banks. Panel (b) shows mean and standard deviation (black error bands) of county exposure across the full sample (left bar) and within states (weighted by state population for aggregation). There is significant variation in county exposure across the full sample, as well as within individual states. Panel (c) shows a map of U.S. counties, where darker areas indicate counties with higher exposure, where exposure is conditional on state fixed effects.

Figure 5: **Equity financing and patents**

(a) Equity financing by industry



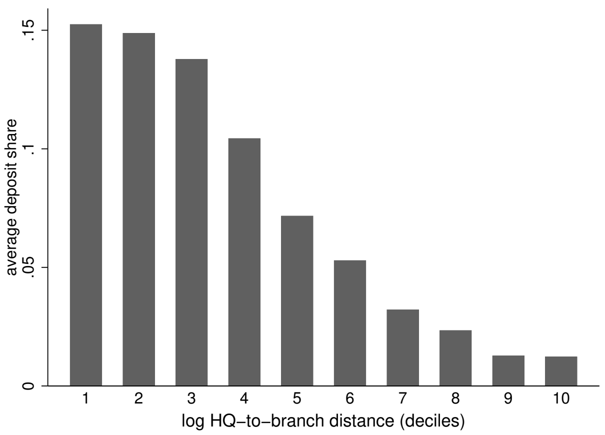
(b) Patents: pre-trends



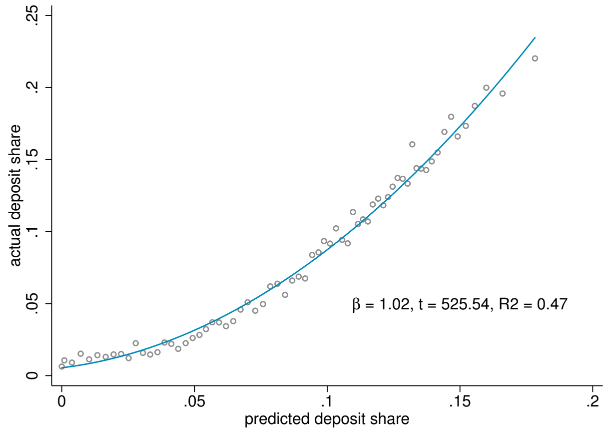
Note: Panel (a) shows the share of firms that report using home equity financing to start or expand operations. It plots the average share for firms age 1-7 for each industry. In general, younger firms rely more on home equity financing and there is significant variation across industries. The sample is restricted to firms that looked for financing and use bank financing. Panel (b) plots yearly coefficients on the interaction terms of the following equation on the county-year level from 2003 to 2014, where 2009 is the omitted category: $log(Y-O)_{c,t} = \sum_{j\neq 2009} exposure_c \times \mathbb{1}_{t=j} + controls_{c,t} + \theta_c + \tau_t + \epsilon_{c,t}$. $log(Y-O)_{c,t}$ denotes log of young - old patents. Dashed lines denote 90 % confidence intervals, blue dots point estimates.

Figure 6: **IV: gravity model of bank expansion**

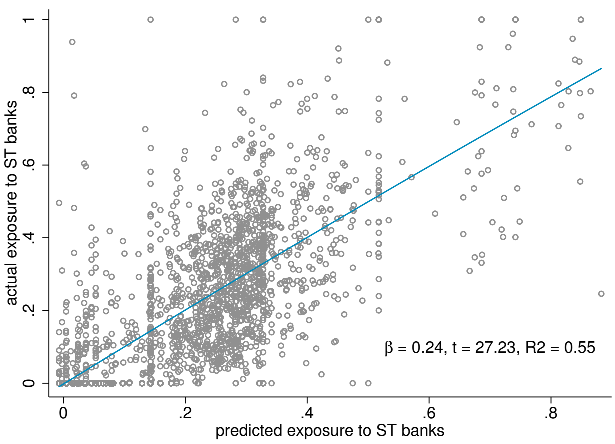
(a) Deposit share by HQ-branch distance



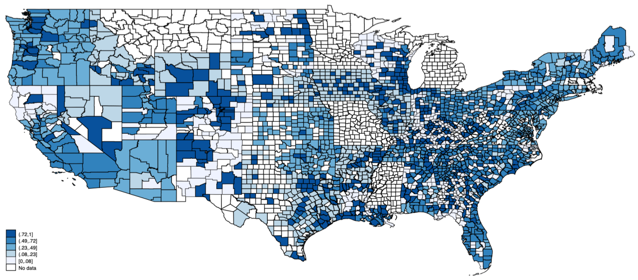
(b) Predicted and actual deposit share



(c) Predicted and actual exposure



(d) Predicted exposure: geographic variation

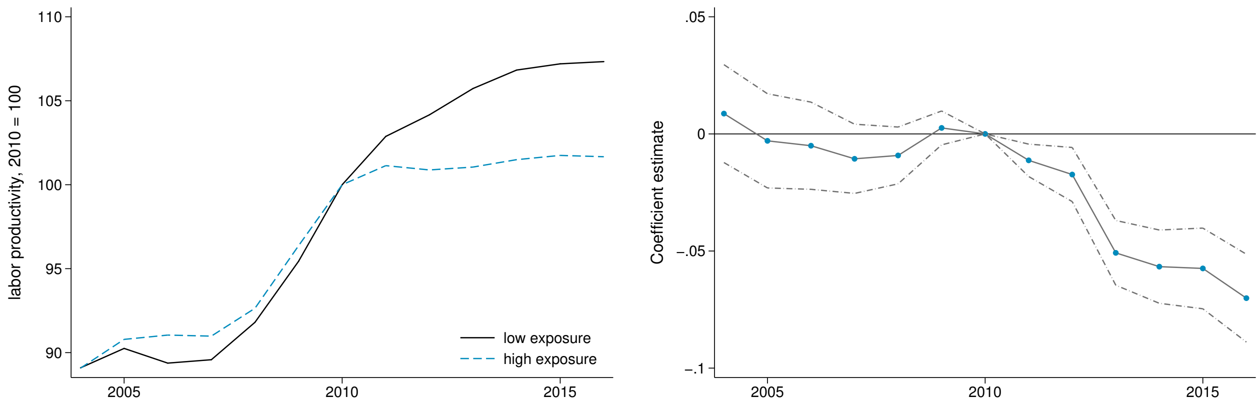


Note: Panel (a) plots the average share of deposits by bank b in county c over total deposits of bank b in year 2007 against deciles of log distance between the bank headquarter (HQ) county and bank branch county. With increasing distance, the share of deposits declines. Panel (b) plots actual and predicted deposit shares of bank b in county c, where deposit shares are predicted with log distance and log population ratio and adjusted for banking deregulation at the host-state level. Panel (c) plots actual and predicted exposure to stress tested banks at the county level. Exposure is constructed according to equation (1), once with actual and once with predicted deposits of bank b in county c. Panel (d) shows a map of U.S. counties, where darker areas indicate counties with higher predicted exposure. Predicted exposure is conditional on state fixed effects.

Figure 7: **County productivity**

(a) Labor productivity

(b) Pre-trends

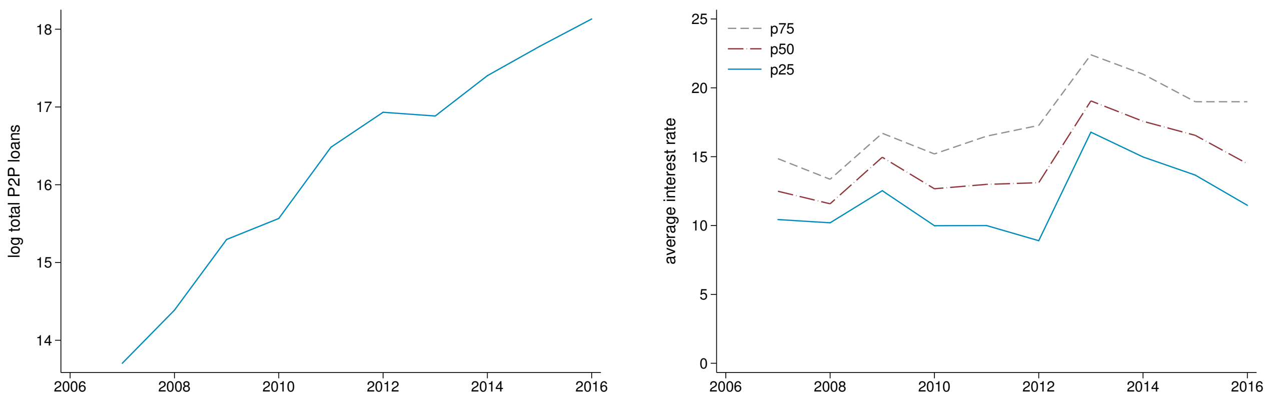


Note: Panel (a) plots labor productivity, defined as county GDP over county employment and standardized to 100 in 2010. *High/low exposure* denotes top (blue dashed line) and bottom (black solid line) tercile of county exposure to stress tested banks, as defined in equation (1). Counties with higher pre-crisis exposure to stress tested banks see slower productivity growth during the recovery. Panel (b) plots yearly coefficients on the interaction terms of the following equation on the county-year level from 2003 to 2016, where 2010 is the omitted category: $log(LP)_{c,t} = \sum_{j \neq 2010} exposure_c \times \mathbb{1}_{t=j} + controls_{c,t} + \theta_c + \tau_t + \epsilon_{c,t}$. Dashed lines denote 90 % confidence intervals, blue dots point estimates.

Figure 8: **Peer-to-peer lending**

(a) Loan volume

(b) Interest rate



Note: Panel (a) plots log total peer-to-peer loans to small businesses, panel (b) respective interest rates. Data are provided by LendingClub.

Table 1: **Bank descriptives**

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
stress tested	123545	.01	.09	0	1	0	0	0
log(secured SB loans)	123545	9.21	1.68	0	17.05	8.25	9.42	10.31
share secured SB loans	123545	.53	.24	0	1	.36	.54	.69
Δ secured SB loans	121165	.07	.36	-1.98	2.2	-.08	.04	.19
Δ share secured SB loans	122361	0	.1	-1	1	-.03	0	.04
log(unsecured SB loans)	123545	8.63	2.18	0	17.18	7.96	8.93	9.78
log(assets)	123545	11.95	1.33	7.68	21.44	11.07	11.8	12.63
return on assets	123545	.79	1.16	-6.92	5.49	.5	.9	1.31
capital ratio	123545	16.76	10.14	6	177.65	11.35	14.05	18.6
non-interest income	123545	.79	1.16	-.13	24.59	.34	.58	.91
overhead	123545	72.12	27	23.73	297.75	58.67	68.14	79.23
securities	123545	.22	.15	0	.77	.1	.19	.31
deposits to assets	123545	.83	.08	.05	.94	.79	.84	.88
log(loans per employee)	123545	7.72	.52	5.32	9.35	7.4	7.71	8.03
deposit interest	123545	.01	.01	0	.03	0	.01	.01

Note: This table shows descriptive statistics for main bank variables on the bank-year level.

Table 2: **Bank descriptives: multivariate**

VARIABLES	(1) stress tested	(2) stress tested	(3) stress tested	(4) 10-500bn stress tested	(5) 10-150bn stress tested	(6) failed
share secured SB loans	-0.01***	-0.01***	-0.01***	-0.04	-0.02	0.26**
Δ total loans	-0.00***	-0.00**	-0.00*	-0.07	-0.12	-0.12
Δ secured SB loans	0.00***	0.00**	0.00*	0.00	0.01	0.08
Δ unsecured SB loans	-0.00	-0.00	-0.00	0.09**	0.08**	0.15
log(assets)	0.02***	0.02***	0.03***	0.29***	0.35***	0.05
return on assets	-0.00**	-0.01**	-0.01**	-0.23	-0.16	0.17
capital ratio	0.01	0.01*	0.01	0.04	0.05	-0.02
non-interest income	0.00	0.00	0.00	0.01	-0.00	-0.06
overhead	0.00	0.00	0.00	-0.12	-0.04	0.25
securities	-0.01***	-0.00***	-0.01***	-0.09	-0.11	0.08
deposits to assets	-0.00	-0.00	-0.00	0.07*	0.07*	-0.10**
log(loans per employee)	0.00	0.00	0.00	-0.02	-0.02	0.28
deposit interest	-0.01***	-0.01***	-0.02***	-0.15**	-0.13	-0.09
Observations	7,719	7,719	5,556	80	75	55
R-squared	0.10	0.12	0.18	0.40	0.36	0.44
HQ State FE	-	✓	-	-	-	-
HQ MSA FE	-	-	✓	-	-	-

Note: This table shows multivariate descriptive statistics for main bank variables as of 2007, with stress tested dummy as dependent variable. Standard errors are clustered at the BHC level. For variable definitions see section B. All explanatory variables are standardized to mean zero, standard deviation one. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 3: **County descriptives**

Panel (a): County-year

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
exposure	36817	.2	.21	0	1	0	.14	.32
exposure (predicted)	36817	.2	.05	.1	.25	.19	.2	.24
log(CRA loans)	36635	.27	.14	.03	.88	.16	.25	.35
Δ CRA loans	34054	-.03	.26	-1.2	1.02	-.15	0	.11
log(labor productivity)	36817	-2.07	.44	-3.47	-.01	-2.37	-2.1	-1.8
Δ labor productivity	34187	.01	.07	-.5	.53	-.02	.01	.05
employment	36817	42396.75	145754.4	159	4007163	3442	8538	25311
unemployment rate	36817	6.66	2.71	1.1	28.9	4.7	6.1	8.1
log(population)	36817	10.57	1.28	7.5	16.13	9.68	10.4	11.3
% black population	36817	.09	.14	0	.85	.01	.03	.12
% elderly population	36817	.16	.04	.04	.56	.13	.16	.18
labor force participation rate	36817	.48	.06	.24	1	.44	.49	.52
Δ house price index	36577	1.89	5.91	-40.68	53.3	-1.43	1.63	4.77
income per capita	36817	34.19	10.07	14	200	28	32	38
debt-to-income ratio	36817	1.77	.88	0	3.46	1.15	1.62	2.34

Panel (b): County-industry-year

Variable	Obs	Mean	Std. Dev.	Min	Max	P25	P50	P75
log(young firms)	281225	3.84	1.52	1.1	8.78	2.71	3.66	4.82
Δ young firms	227829	-.02	.69	-2.53	2.42	-.39	0	.36
share young firms	281225	.07	.08	0	1	.02	.05	.09
Δ share young firms	227743	1.18	.89	0	7.17	.67	.97	1.39
wage	510483	716.09	374.74	125	2990	449	651	896
log(wage)	510483	6.44	.52	4.83	8	6.11	6.48	6.8
Δ wage	485112	.03	.12	-.6	.66	-.02	.03	.08

Note: This table shows descriptive statistics for main county variables on the county-year and county-industry-year level in panels (a) and (b).

Table 4: **County descriptives: multivariate**

VARIABLES	(1) exposure	(2) exposure	(3) >100k exposure	(4) >200k exposure	(5) no entry exposure
log population	0.05***	0.05***	0.04**	0.04	0.06***
share urban	0.05***	0.03***	0.04*	0.05	0.01*
share black population	0.00	0.01**	0.02*	0.02	0.01
share 65+ population	-0.03***	0.01	0.01	0.03	0.01
share 20-45 population	-0.05***	-0.01	0.00	0.04	0.01
share highschool	0.00	0.00	0.01	-0.00	-0.00
share college	0.01	0.01*	0.02*	0.02	0.01
unemployment rate	-0.01***	-0.00	0.01	0.02	0.01
share owner-occupied housing	-0.00	0.01	0.01	0.04*	0.01
Δ HPI 2000-07	0.05***	-0.00	-0.01	-0.01	-0.00
Δ debt-to-income 2000-07	-0.02***	-0.01**	-0.01	0.01	-0.00
Δ emp 2007-10	-0.01	0.00	0.02	0.04	0.01
log income per capita	-0.03***	0.00	-0.02	-0.04*	0.02*
emp. share 2007 in Naics 23	0.00	-0.01*	0.02	0.02	-0.01
emp. share 2007 in Naics 31	-0.01	-0.00	0.02	0.04	0.01
emp. share 2007 in Naics 42	0.00	0.00	0.01	0.00	0.00
emp. share 2007 in Naics 44	-0.00	0.00	-0.01	-0.02	0.00
emp. share 2007 in Naics 58	0.01*	0.01**	0.01	0.02	0.00
emp. share 2007 in Naics 52	-0.01***	-0.01***	0.00	0.03*	-0.00
emp. share 2007 in Naics 54	0.01	0.00	0.01	0.02	0.00
emp. share 2007 in Naics 55	-0.00	-0.00	-0.00	0.02	-0.01**
emp. share 2007 in Naics 56	0.01**	0.00	-0.01	-0.01	0.00
emp. share 2007 in Naics 62	0.01	0.00	0.01	0.03	0.01
emp. share 2007 in Naics 72	0.00	0.00	0.02	0.03	-0.00
emp. share 2007 in Naics 81	-0.01***	-0.00	0.00	-0.03	0.00
Observations	2,129	2,129	521	219	741
R-squared	0.29	0.51	0.55	0.57	0.62
State FE	-	✓	✓	✓	✓

Note: This table shows multivariate descriptive statistics for main county variables, with exposure as dependent variable. For variable definitions see section B. All explanatory variables are standardized to mean zero, standard deviation one. Key: *** p<0.01, ** p<0.05, * p<0.1.

A.2 Main Tables and Robustness

Table 5: **Stress tested banks reduce small businesses lending**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	B-C-Y	B-C-Y	B-C-Y	B-C-Y	B-C-Y	B-C-Y	B-Y	B-Y	B-Y
					No GFC				
VARIABLES	log(CRA)	log(CRA)	log(CRA)	log(CRA)	log(CRA)	log(CRA)	log(sec)	log(unsec)	share sec
stress tested	-0.241***	-0.345***			-0.350***	-0.351***	-0.403***	-0.088	-0.068***
	(0.048)	(0.048)			(0.055)	(0.048)	(0.132)	(0.186)	(0.010)
stress tested 09 × 𝟙(2009-2013)			-0.322***	-0.363***					
			(0.060)	(0.058)					
stress tested 09 × 𝟙(2014-2016)			-0.211**	-0.332***					
			(0.090)	(0.089)					
stress tested 14 × 𝟙(2009-2013)			0.090*	-0.087*					
			(0.048)	(0.045)					
stress tested 14 × 𝟙(2014-2016)			-0.110*	-0.373***					
			(0.062)	(0.077)					
large (10-50bn) × 𝟙(2009-16)						-0.034			
						(0.032)			
Observations	431,455	431,455	431,455	431,455	363,249	431,455	123,545	123,545	123,545
R-squared	0.888	0.922	0.888	0.922	0.924	0.922	0.922	0.906	0.778
Bank Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Bank*County FE	✓	✓	✓	✓	✓	✓	-	-	-
Bank FE	-	-	-	-	-	-	✓	✓	✓
Year FE	✓	-	✓	-	-	-	✓	✓	✓
County*Year FE	-	✓	-	✓	✓	✓	-	-	-
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Note: This table shows regression results for regression equations (3), (4), and (5) on the bank-county-year and bank-year level. The dependent variable in columns (1)-(6) is log CRA small business lending at the bank-county level; in column (7) it is banks' log small business lending secured by real estate collateral on the bank-year level. Columns (8) and (9) use log unsecured small business lending and the share of secured out of total small business lending as dependent variables. *stress tested* is a dummy with value if a bank was stress tested in a given year, $\mathbb{1}(2009-16)$ is a dummy with value 1 for years 2009 to 2016. Column (1) includes bank controls, as well as bank*county and year fixed effects. To absorb local unobservable county characteristics, column (2) includes county*time fixed effects. Columns (3) and (4) include separate interaction terms for banks stress tested by 2009 and 2014, interacted with separate *post* dummies for the 2009-2016 period. Banks stress tested by 2009 significantly reduce secured small business lending from 2009-2013 and 2014-2016, but banks stress tested by 2014 only do so from 2014 onward. Column (5) excludes crisis years 2008 and 2009 from the sample, column (6) adds a dummy *large (10-50bn)* with value one for banks with total asset size (as of 2010) between 10bn and 50bn that are not subject to stress tests. Non-stress tested large banks do not reduce their secured small business lending significantly. Columns (7)-(8) show that stress tested banks significantly reduce secured small business lending, but not unsecured small business lending, which leads to a decline in the relative share of secured business lending in column (9). All specifications cluster standard errors on the bank holding company (BHC) level to account for serial correlation of errors among banks belonging to the same holding company (the level at which stress tests are carried out). For variable definitions see section B. Values in parentheses denote standard errors. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: **Counties exposed to stress tested banks see a decline in young firm employment**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
								IV	IV	IV	IV
	C-Y	C-I-Y	C-I-Y	C-I-Y	C-I-Y	C-I-Y	C-I-Y	C-I-Y	C-I-Y	C-I-Y	C-I-Y
VARIABLES	log(CRA)	log(emp)	log(emp)	log(emp)	log(emp)	share	share	log(emp)	log(emp)	share	share
exposure × 𝟙(2009-16)	-0.048***	-0.034*	0.223***			0.022***		20.426**		2.022***	
	(0.006)	(0.018)	(0.054)			(0.005)		(8.026)		(0.766)	
home equity × 𝟙(2009-16)			-4.857***	-5.142***		-0.033		-4.463***		-0.018	
			(0.308)	(0.313)		(0.030)		(0.394)		(0.038)	
exposure × home equity × 𝟙(2009-16)			-5.071***	-3.952***	-4.294***	-0.300***	-0.386***	-6.928***	-6.848***	-0.389***	-0.632***
			(0.851)	(0.860)	(0.867)	(0.077)	(0.078)	(1.252)	(1.355)	(0.117)	(0.126)
Observations	36,401	293,722	293,722	293,722	293,722	293,722	293,722	293,722	293,722	293,722	293,722
R-squared	0.833	0.822	0.823	0.827	0.828	0.494	0.508	0.823	0.828	0.494	0.508
County FE	✓	-	-	-	-	-	-	-	-	-	-
County*Industry FE	-	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	-	-	✓	-	✓	-	✓	-
County*Year FE	-	-	-	✓	✓	-	✓	-	✓	-	✓
Industry*Year FE	-	-	-	-	✓	-	✓	-	✓	-	✓
Cluster	County	County	County	County	County	County	County	County	County	County	County

Note: This table shows regression results for equations (6) and (7) on the county-year and county-industry-year level. Dependent variable is log total small business loans on the county-year level (provided by CRA) in column (1); log number of young firms (age 0-1) in columns (2)-(5) and (8)-(9); and the share of young firms in column (6)-(7) and (10)-(11), all on the county-industry-year level. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). $\mathbb{1}(2009-16)$ is a dummy with value one for years 2009 to 2016, i.e. the years after the introduction of stress tests. *home equity* is the share of young firms within each two-digit industry that uses home equity financing to start or expand operations, provided by SBO. Column (1) shows that counties with higher exposure see a decline small business lending. Columns (2)-(11) show that counties with higher exposure see a decline in the number and share of young firms. Columns (2)-(3) present baseline regressions with county*industry and year fixed effects. Columns (4)-(5) add granular fixed effects to control for unobservable shocks that could affect local or industry demand over time. County*time fixed effects absorb local shocks at the county level in column (4), while industry*time fixed effects ensure that common shocks to industries over time are not driving results in column (5). Counties with higher exposure see a decline in the number of young firms during the post-crisis period, and the decline is concentrated within industries that rely more on home equity financing. Columns (6)-(7) replicate columns (4)-(5), but use the share of young firms as dependent variable. Finally, columns (8)-(11) instrument county exposure with predicted exposure based on the gravity model. F-statistics are > 1000, so there is no weak instrument problem. Standard errors are clustered on the county level. For variable definitions see section B. Values in parentheses denote standard errors. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 7: **Counties exposed to stress tested banks see a decline in patents by young firms**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
							IV	2013	S*Y
				cit. wt.	cit. wt.	cit. wt.	cit. wt.	cit. wt.	cit. wt.
VARIABLES	log(PT Young)	log(PT Old)	Δ PT Y-O	log(PT Young)	log(PT Old)	Δ PT Y-O	Δ PT Y-O	Δ PT Y-O	Δ PT Y-O
exposure $\times$ $\mathbb{1}$(2009-16)	-0.119**	-0.005	-0.114*	-0.310***	-0.025	-0.285***	-0.235**	-0.264***	-0.370***
	(0.049)	(0.045)	(0.066)	(0.067)	(0.072)	(0.096)	(0.114)	(0.101)	(0.126)
Observations	22,914	22,914	22,914	22,914	22,914	22,914	22,901	18,237	22,914
R-squared	0.891	0.945	0.527	0.816	0.878	0.413	0.414	0.426	0.438
County FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	S*Y
County Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cluster	County	County	County	County	County	County	County	County	County

Note: This table shows regression results for equation (6). Dependent variables are log patent applications (PT) by old and young firms, as well as the difference between young and old log series (Δ PT Y-O), from 2003-2016. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). $\mathbb{1}(2009-16)$ is a dummy with value one for years 2009 to 2016, i.e. the years after the introduction of stress tests. *cit. wt.* denotes citation weighted patents, *IV* instruments exposure with predicted exposure, *2013* excludes years 2014-2016, and *S*Y* includes state*year FE instead of year FE. For variable definitions see section B. Values in parentheses denote standard errors. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: **Stress testing and the productivity slowdown**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
							IV
	C-Y	C-Y	C-I-Y	C-I-Y	C-I-Y	C-I-Y	C-I-Y
VARIABLES	log(LP)	log(LP)	log(wage)	log(wage)	log(wage)	log(wage)	log(wage)
exposure × $\mathbb{1}$(2009-16)	-0.044***	0.246**	-0.042***	0.035***			
	(0.011)	(0.121)	(0.004)	(0.011)			
home equity exp. × $\mathbb{1}$(2009-16)		0.025***					
		(0.006)					
exposure × home equity exp. × $\mathbb{1}$(2009-16)		-0.045**					
		(0.019)					
home equity × $\mathbb{1}$(2009-16)				0.747***	0.696***		
				(0.061)	(0.061)		
exposure × home equity × $\mathbb{1}$(2009-16)				-1.323***	-1.412***	-1.363***	-2.001***
				(0.174)	(0.173)	(0.174)	(0.261)
Observations	30,802	30,802	510,353	510,353	510,353	510,353	510,263
R-squared	0.960	0.961	0.919	0.919	0.921	0.922	0.922
County Controls	✓	✓	✓	-	-	-	-
County FE	✓	✓	✓	-	-	-	-
Year FE	✓	✓	✓	✓	-	-	-
County*Industry FE	-	-	-	✓	✓	✓	✓
County*Year FE	-	-	-	-	✓	✓	✓
Industry*Year FE	-	-	-	-	-	✓	✓
Cluster	County	County	County	County	County	County	County

Note: This table shows regression results for equations (6) and (7) on the county-year and county-industry-year level. Dependent variables are log labor productivity on the county-year level in columns (1) to (2), and average wage in columns (3)-(7) on the county-industry-year level, provided by QCEW. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). $\mathbb{1}(2009-16)$ is a dummy with value one for years 2009 to 2016, i.e. the years after the introduction of stress tests. *home equity exp.* reflects the relative importance of home equity financing in each industry, aggregated to the county level, by weighting by the county employment share of young firms of each industry. *home equity* is the share of young firms within each two-digit industry that uses home equity financing to start or expand operations, provided by SBO. Columns (1) and (2) show that counties with higher exposure see a decline labor productivity, and that the effect is stronger for counties in which industries that use home equity financing are more important. Column (3)-(6) show that counties with higher exposure see a decline in wages. Columns (3)-(4) presents baseline regressions with county*industry and year fixed effects. Columns (5)-(6) use granular fixed effects to control for unobservable shocks that could affect local or industry demand over time. County*time fixed effects absorb local shocks at the county level in column (5), while industry*time fixed effects ensure that common shocks to industries over time are not driving results in column (6). Counties with higher exposure see a decline in average wage during the post-crisis period, and the decline is concentrated within industries that rely more on home equity financing. This finding is robust to instrumenting exposure in column (7). Standard errors are clustered on the county level. For variable definitions see section B. Values in parentheses denote standard errors. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 9: **Bank robustness**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
										full sample	$10-150$ bn
								failed banks	failed banks	NN=2	NN=2
VARIABLES	log(sec)	log(sec)	log(sec)	log(sec)	Δ loan	Δ loan	Δ loan	Δ sec	Δ loan	Δ sec 10-16	Δ sec 10-16
stress tested	-0.403***	-0.396***	-0.491***	-0.466***	0.084***						
	(0.132)	(0.131)	(0.140)	(0.155)	(0.030)						
loan type					0.033***	0.032***					
					(0.001)	(0.001)					
stress tested × loan type					-0.112***	-0.122***	-0.104***				
					(0.027)	(0.030)	(0.030)				
failed ST								-0.101*			
								(0.057)			
failed ST × loan type									-0.178*		
									(0.098)		
r1vs0.stresstested										-0.522***	-0.362**
										(0.129)	(0.146)
Observations	123,545	123,545	123,545	68,653	238,459	232,812	232,812	851	1,738	5,836	82
R-squared	0.922	0.922	0.923	0.925	0.091	0.593	0.595	0.230	0.621		
Bank Controls	✓	✓	✓	✓	✓	-	-	✓	-	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	-
Year FE	✓	B-Y	-	-	✓	-	-	✓	-	-	-
State*Year FE	-	-	✓	-	-	-	-	-	-	-	-
MSA*Year FE	-	-	-	✓	-	-	-	-	-	-	-
Bank*Year FE	-	-	-	-	-	✓	✓	-	✓	-	-
Loan type*Year FE	-	-	-	-	-	-	✓	-	✓	-	-
Cluster	BHC	BHC	BHC	BHC	BHC	BHC	BHC	BHC	BHC	-	-

Note: This table shows robustness checks for bank-level regressions. Columns (1)-(4) use log secured small business lending as dependent variable; columns (5)-(7) and (9) log difference of secured and unsecured loan volume; and column (8) the lof difference of secured small business lending. Finally, columns (10) and (11) use the log change in secured small business lending from 2010 to 2016. Regressions in columns (1)-(4) and (8) are on the bank-year level; in columns (5)-(6) and (9) on the bank-loan type-year level; in columns (10)-(11) on the bank level. *stress tested* is a dummy with value for each year a bank underwent stress tests; *loan type* is a dummy with value one (zero) for secured (unsecured) small business loans; *failed ST* denotes a dummy with value one if a bank failed a stress test in a given year. Columns (1)-(9) uses OLS regressions, columns (10)-(11) nearest neighbor matching. For variable definitions see section B. Values in parentheses denote standard errors. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 10: **County robustness: young firm employment**

VARIABLES	(1) share	(2) share	(3) share	(4) share	(5) share	(6) share	(7) share	(8) share	(9) share
exposure × home equity × $\mathbb{1}$(2009-16)	-0.335***	-0.397***	-0.372***	-0.363***	-0.450***	-0.428***	-0.367***	-0.433***	-0.518***
	(0.079)	(0.079)	(0.080)	(0.078)	(0.087)	(0.083)	(0.077)	(0.078)	(0.087)
HPI boom × home equity × $\mathbb{1}$(2009-16)	-0.129*								
	(0.078)								
HPI bust × home equity × $\mathbb{1}$(2009-16)		-0.082							
		(0.108)							
home ownership × home equity × $\mathbb{1}$(2009-16)			0.002						
			(0.002)						
Δ house price index (HPI) × home equity				0.003***					
				(0.000)					
log population × home equity × $\mathbb{1}$(2009-16)					0.000				
					(0.000)				
share urban × home equity × $\mathbb{1}$(2009-16)						0.001			
						(0.001)			
deposit HHI × home equity × $\mathbb{1}$(2009-16)							0.002		
							(0.002)		
exposure × industry share × $\mathbb{1}$(2009-16)								0.049***	
								(0.013)	
exposure × industry risk × $\mathbb{1}$(2009-16)									0.005***
									(0.001)
Observations	281,129	293,267	293,766	292,856	293,766	293,766	293,722	293,722	293,722
R-squared	0.499	0.508	0.508	0.508	0.508	0.508	0.508	0.508	0.508
County*Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
County*Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cluster	County	County	County	County	County	County	County	County	County

Note: This table shows regression results for regressions on the county-industry-year level (see regression equation (7)). Dependent variables is the employment share of young firms. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). *home equity* is the share of young firms within each two-digit industry that uses home equity financing to start or expand operations, provided by SBO. $\mathbb{1}(2009-16)$ is a dummy with value one for years 2009 to 2016, i.e. the years after the introduction of stress tests. *HPI boom* and *HPI bust* are changes in county house prices from 2000 to 2007 and 2007 to 2010; home ownership is the county share of home owners in 2000; $\Delta\ HPI$ is growth in yearly county house prices. log(population), share urban, and deposit HHI denote county log population, share of urban population, and Herfindahl index of bank deposit concentration. *industry share* is the average pre-crisis employment shares of each 2-digit Naics industry in each county, and *industry risk* denotes industry betas from Cortés et al. (2018). For variable definitions see section B. Values in parentheses denote standard errors. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 11: **County robustness: patents and innovation**

VARIABLES	(1) C-I-Y cit. wt. Δ PT Y-O	(2) C-I-Y cit. wt. Δ PT Y-O	(3) C-I-Y cit. wt. Δ PT Y-O	(4) C-I-Y cit. wt. Δ PT Y-O	(5) C-A-Y cit. wt. log(patents)	(6) C-A-Y cit. wt. log(patents)	(7) C-A-Y cit. wt. log(patents)	(8) C-A-Y cit. wt. log(patents)
exposure × $\mathbb{1}$(2009-16)	-0.221***	-0.231***	-0.234***	-0.257***				
	(0.055)	(0.056)	(0.059)	(0.070)				
exposure × $\mathbb{1}$(2009-16)					-0.168***	-0.026		
					(0.050)	(0.071)		
young× $\mathbb{1}$(2009-16)						-0.169***	-0.169***	
						(0.030)	(0.030)	
exposure × young × $\mathbb{1}$(2009-16)						-0.284***	-0.284***	-0.296***
						(0.093)	(0.093)	(0.093)
Observations	91,727	91,726	89,779	89,779	45,828	45,828	45,828	45,828
R-squared	0.201	0.250	0.404	0.414	0.861	0.862	0.932	0.933
County FE	✓	✓	-	-	-	-	-	-
County*Industry FE	-	-	✓	✓	-	-	-	-
Industry*Year FE	-	✓	✓	✓	-	-	-	-
State*Year FE	-	-	-	✓	-	-	-	-
County*Age FE	-	-	-	-	✓	✓	✓	✓
Year FE	✓	-	-	-	✓	✓	-	-
County*Year FE	-	-	-	-	-	-	✓	✓
Age*Year FE	-	-	-	-	-	-	-	✓
County Controls	✓	✓	✓	✓	✓	✓	-	-
Cluster	County	County	County	County	County	County	County	County

Note: This table shows regression results for county-industry-year (C-I-Y) and county-age-year (C-A-Y) regressions. Dependent variables are the difference between log patent applications by young and old firms (columns (1)-(4)), and log patent applications in columns (5)-(8). *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). $\mathbb{1}(2009-16)$ is a dummy with value one for years 2009 to 2016, i.e. the years after the introduction of stress tests. *young* is a dummy with value one for patents by young firms. *cit. wt.* denotes citation weighted patents. For variable definitions see section B. Values in parentheses denote standard errors. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

B Data Appendix

Table 12: **Steps of the mechanism**

Banks and Stress Tests	Entrepreneurs	Innovation & Productivity
1. Stress tests increase cost of (secured) small business lending	2. Entrepreneurs are small and use collateral to receive financing	3. Entrepreneurs are important for innovation and productivity
⇒ Stress tested banks reduce (secured) small business lending (Section 3.1, Table 5)	⇒ Decline in loan supply by stress tested banks hurts young firms (Section 3.2, Table 6)	⇒ Decline in young firms reduces innovation and productivity (Sec. 3.2+4, Tables 7+8)

Note: This table summarizes the steps of the empirical argument. Since stress tests make (secured) small business lending expensive for banks (in terms of capital requirements), I show that (a) stress tested banks reduce their credit supply to small firms, especially if firms use real estate collateral. Entrepreneurs are mostly small and opaque, so they rely on real estate collateral and home equity to start or expand their business. Consequently, (b) in counties where stress tested banks are more important, entrepreneurs are hit harder by the reduction in credit supply, and the more so in home equity intensive industries; and (c) entrepreneurs have an outsized importance for innovation and aggregate growth, so the decline in young firms due to the contraction in loan supply hurts innovation and productivity in counties with higher exposure to stress tested banks.

PatentsView Data on patent applications and patent citations is provided by *PatentsView*. It provides monthly data on granted patent applications, the inventor(s) and assignee(s) of each individual patent, as well as the location of inventors and assignees. Inventor refers to individuals, assignees can be individuals or corporations. For example, Sebastian Doerr could be inventor and assignee, but I could file the patent application in the name of my company Sebastian Inc. In the latter case, Sebastian Doerr is still the inventor, but Sebastian Inc. the assignee. I keep patent applications by U.S. and foreign companies or corporations, as well as individuals. I drop patent applications by universities and governments, and aggregate patent data at the inventor's county. If there are more than one inventor from the same county, the patent is counted once for the respective county. If there are more than one inventor in different counties, the patent is counted equally in each county (I split the patent on a pro-rata basis per inventor). Finally, I define patents by 'young firms' as patent application by assignees (i.e. corporations) that did not file a patent application more than five years ago. For example, suppose Sebastian Inc. files its first ever patent application in 2005. All patents filed until 2010 are then classified as patents by young firms, all patents from 2011 onward as old.

Patents are often used as a proxy for innovative activity. However, they have two important drawbacks. First, not all firms patent their ideas, and if and how they do so can vary across industries and areas. Yet, the correlation between R&D and the number of patents in the cross-section of firms is usually high (Griliches, 1990). Second, patents can contain a different amount of ideas. Aggregating to the county level mitigates this problem, because differences in the amount of ideas across patents 'average out' in the aggregate and level effects can be addressed via fixed effects (Peri, 2005; Matray, 2015).

County GDP Data on County GDP are not readily available. Instead, I assign state GDP (provided by the BEA's regional economic accounts) as follows. In a first step, I proxy county value added (VA_c) by county personal income (inc_c), so that

$$GDP_c = VA_c = \frac{VA_c}{VA_s}\, VA_s \approx \frac{inc_c}{inc_s}\, VA_s.$$

The underlying assumption is that income is a good proxy for value added, i.e. $inc_c \approx VA_c$. This need not be the case, since income data often understates corporate income, particularly in capital intensive industries. Suppose each county has firms in two industries, where industry L is labor intensive and hence income is a high share of value added (assume 90%), while industry C is capital intensive and income a low share of value added (10 %). If in county A, industry L is more important than H, and in county B vice versa, then we will overstate GDP in county A. Accordingly, since $inc_c \approx VA_c - cap_c$, where cap_c is capital compensation, we need to adjust income by $1/\theta_c$, where $\theta_c = \frac{inc_c}{VA_c}$, i.e. the share of labor compensation. I thereby re-scale county income by an adjustment factor that reflects how important income is as a share of GDP in each county. Since adjustment factor θ is not readily available at the county level, I impute it as follows: I use data on labor compensation from BEA's *Gross-Domestic-Product-(GDP)-by-Industry Data* at the two-digit NAICS level and compute $\theta_c = \sum_i \frac{emp_{c,i}}{emp_c}\theta_i$. Counties with a higher share of labor-intensive industries (industries that pay a lot of labor compensation as a share of value added) will get a higher weight. We now have

$$\widehat{VA}_c = \frac{inc_c/\theta_c}{\sum_c inc_c/\theta_c} VA_s = \frac{\bar{VA}_c}{\bar{VA}_s} VA_s.$$

Note that if θ_c is the same for all counties, this adjustment does not matter. However, in the data θ ranges from 0.21 to 0.77, with mean 0.60 and standard deviation 0.04.

Table 13: **Variable definitions: bank level**

Variable	Comment	Unit	Source
secured small business loans	lnrenres1+lnrenres2+lnrenres3	USD	FDIC SDI
unsecured SB loans	lnci1+lnci2+lnci3	USD	FDIC SDI
share secured SB loans	secured SB/(sec. SB+unsec. SB)	%	FDIC SDI
Δ secured SB loans	log difference from t-1 to t	%	FDIC SDI
Δ share secured SB loans	change from t-1 to t	%	FDIC SDI
log(assets)	ln(asset)	-	FDIC SDI
return on assets	roa	%	FDIC SDI
capital ratio (Tier 1 to RW assets)	rbc1rwaj	%	FDIC SDI
non-interest income (to avg. assets)	noniiay	%	FDIC SDI
overhead (efficiency ratio)	eeffr	-	FDIC SDI
securities to assets	sc/asset	%	FDIC SDI
deposits to assets	dep/asset	%	FDIC SDI
log(loans per employee)	ln(lnlsgr/emp)	-	FDIC SDI
deposit interest	edepdom/dep	%	FDIC SDI

Table 14: **Variable definitions: county level**

Variable	Comment	Unit	Source
exposure (to stress tested banks)	deposit share	[0-1]	FDIC SOD
CRA loans	SB loans covered in CRA	USD	CRA
labor productivity (LP)	ln(GDP/emp)	-	BEA/CBP
employment		unit	CBP
employment by firm age		unit	QWI
patent applications		unit	PatentsView
wages	average wage	USD	QCEW
unemployment rate		%	BLS LAUS
log(population)		-	Cen. Bureau
% black population	share of tot- pop.	%	Cen. Bureau
% elderly population	share of tot- pop.	%	Cen. Bureau
labor force part. rate	civilian labor force	%	BLS LAUS
Δ house prices	growth rate	%	FHFA HPI
income per capita		USD	BEA LAPI
debt-to-income ratio	Household debt	%	FED Fin. Accounts

Table 15: **Stress tested banks**

Bank Holding Company	2009	2011	2012	2013	2014	2015	2016
Ally Financial Inc.	†	✓	†	†	✓	✓	✓
American Express Company	✓	✓	†	✓	✓	✓	✓
Bank Of America Corporation	†	✓	✓	✓	✓	†	✓
The Bank Of New York Mellon Corporation	✓	✓	✓	✓	✓	✓	✓
BB&T Corporation	✓	✓	✓	†	✓	✓	✓
Capital One Financial Corporation	✓	✓	†	✓	✓	✓	✓
Citigroup Inc.	†	✓	✓	✓	†	✓	✓
Fifth Third Bancorp	†	✓	✓	✓	✓	✓	✓
The Goldman Sachs Group, Inc.	✓	✓	✓	†	✓	✓	✓
JPMorgan Chase & Co.	✓	✓	✓	†	✓	✓	✓
KeyCorp	†	✓	✓	✓	✓	✓	✓
Metlife, Inc.	✓	✓	†				
Morgan Stanley	†	✓	✓	✓	✓	✓	†
The PNC Financial Services Group, Inc.	†	✓	✓	✓	✓	✓	✓
Regions Financial Corporation	†	✓	✓	✓	✓	✓	✓
State Street Corporation	✓	✓	✓	✓	✓	✓	✓
SunTrust Banks, Inc.	†	✓	✓	✓	✓	✓	✓
U.S. Bancorp	✓	✓	✓	✓	✓	✓	✓
Wells Fargo & Company	†	✓	✓	✓	✓	✓	✓
Banco Bilbao Vizcaya Argentaria, S.A.					✓	✓	✓
Banco Santander, S.A.					†	†	†
BancWest, Inc.							✓
Bank Of Montreal					✓	✓	✓
Citizens Financial Group, Inc.					✓	✓	✓
Comerica Incorporated					✓	✓	✓
Deutsche Bank						†	†
Discover Financial Services					✓	✓	✓
HSBC Holdings PLC					†	✓	✓
Huntington Bancshares Incorporated					✓	✓	✓
M&T Bank Corporation					✓	✓	✓
Mitsubishi UFJ Financial Group, Inc.					✓	✓	✓
Northern Trust Corporation					✓	✓	✓
The Toronto-Dominion Bank							✓
Zions Bancorporation					†	✓	✓

Note: This table lists stress tested banks for each round of stress tests (SCAP in 2009, CCAR from 2011-2016). ✓ indicates that a bank was stress tested in the respective year, † indicates that a bank did not pass the test (results for the 2011 stress tests are not publicly available.

Online Appendix to

No Risk, No Growth:
The Effects of Stress Testing on Entrepreneurship and Innovation

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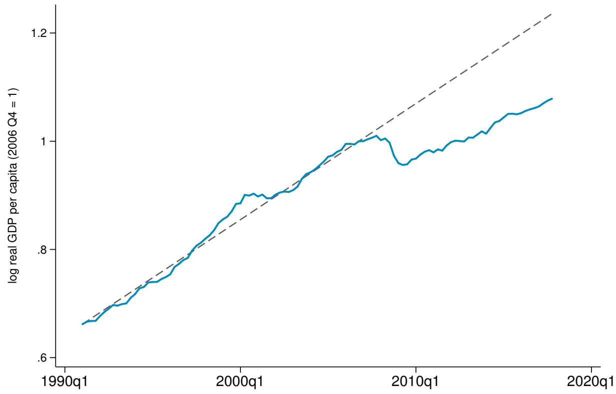
C Online Appendix

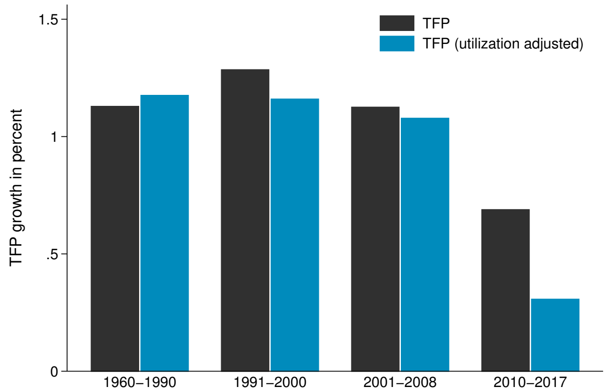
C.1 General: Figures and Tables

Figure 9: **Secular stagnation**

(a) GDP per capita



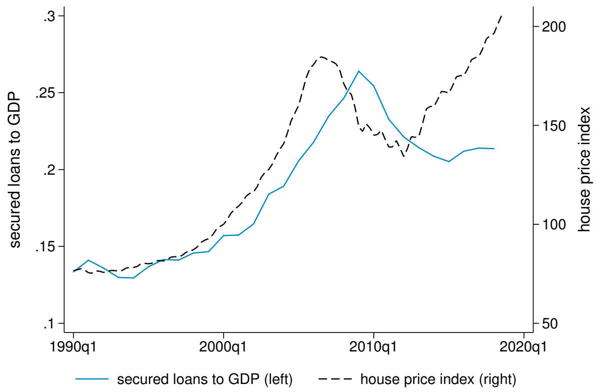
(b) Productivity (TFP) growth



Note: Panel (a) shows log real GDP per capita (blue line) and its 1990-2007 linear trend (black dashed line). Source FRED *Series A939RX0Q048SBEA*. Panel (b) shows average total factor productivity (TFP), provided by John Fernald's web page.

Figure 10: **Secured loans and house prices**

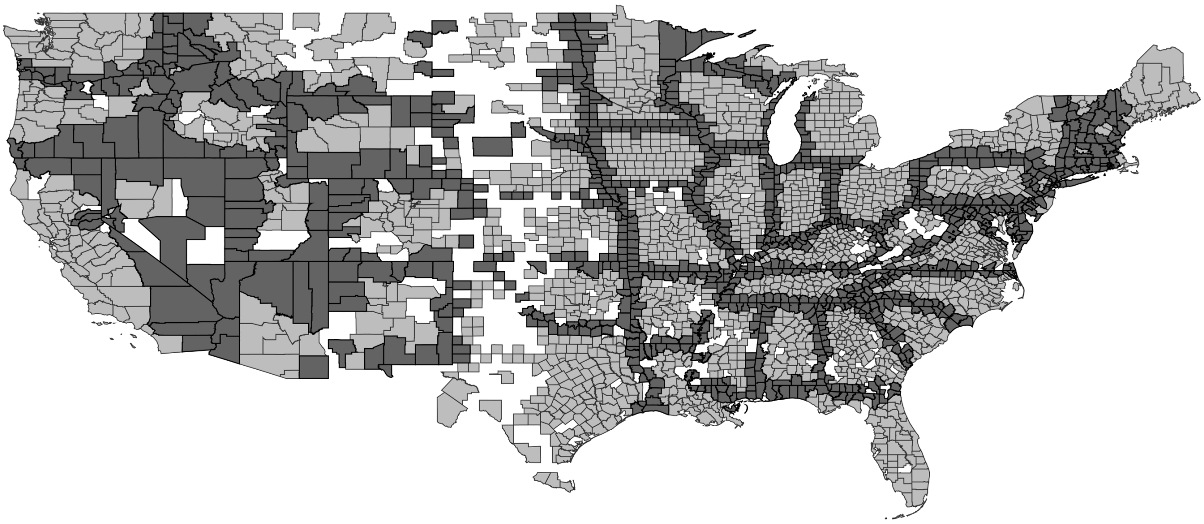
(a) Total secured business loans



(b) Secured small business loans

Note: Panels (a) and (b) plot commercial loans secured by real estate to nominal GDP and the S&P house price index. Panel (a) uses total secured loans, panel (b) secured small business loans with origination amount less than $1'000'000. While secured lending tracked house prices (in line with theories of a collateral channel), the relationship breaks down in the post-crisis period. Data sources: FRED and FDIC SDI.

Figure 11: **Adjacent border counties**

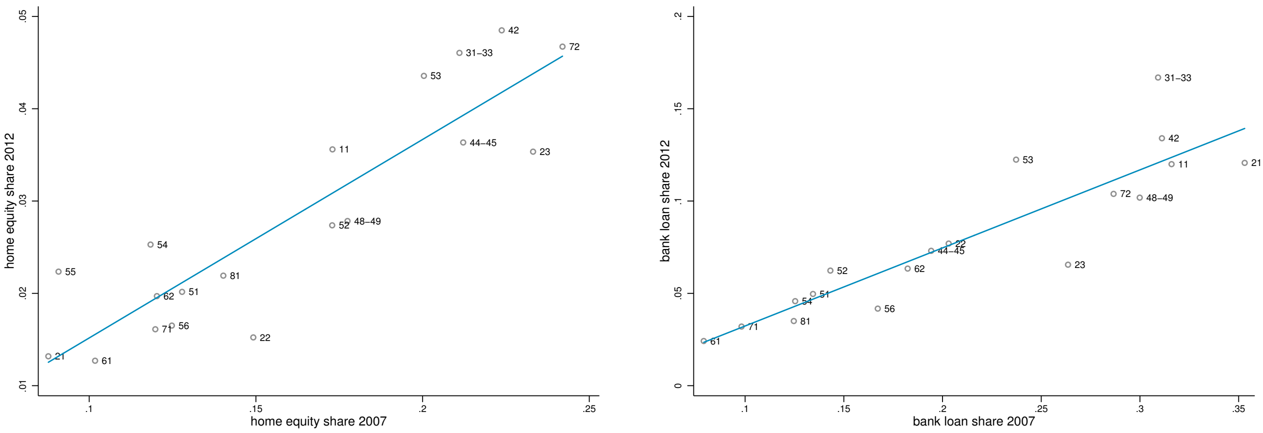


Note: Adjacent border counties across state lines (dark gray). White means no data available.

Figure 12: **Survey of Business Owners 2007 vs. 2012**

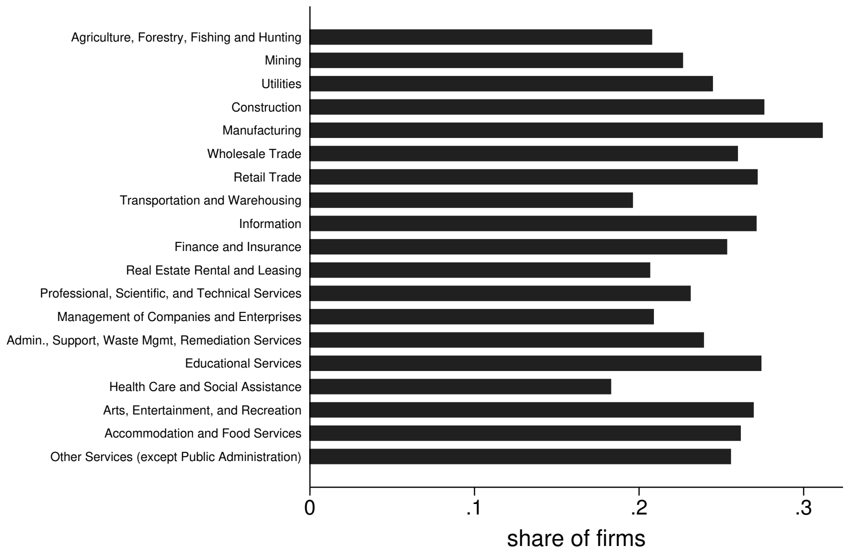
(a) Home equity

(b) Bank loans



Note: Panels (a) and (b) plot the share of firms using home equity financing (bank loans) to expand operations in 2007 on the x-axis, and 2012 on the y-axis. The correlation between values across years equals 0.89 and 0.94 and the relative ordering of industries across years is stable: every single industry in the top (bottom) tercile of home equity share or bank loan share is also in the top (bottom) tericle in 2012. Standardized regressions for 19 industries yield highly significant coefficients of 0.94 and 0.89 with R^2s of 0.79 and 0.88. Source: Survey of Business Owners 2007 and 2012.

Figure 13: **Start-up capital: home equity financing, share of firms by industry**



Note: For each two-digit Naics industry, this Figure shows the share of young firms using bank financing that report making use of home equity financing or personal assets to start their business (source: SBO 2007)

Table 16: **Change in aggregate small business lending**

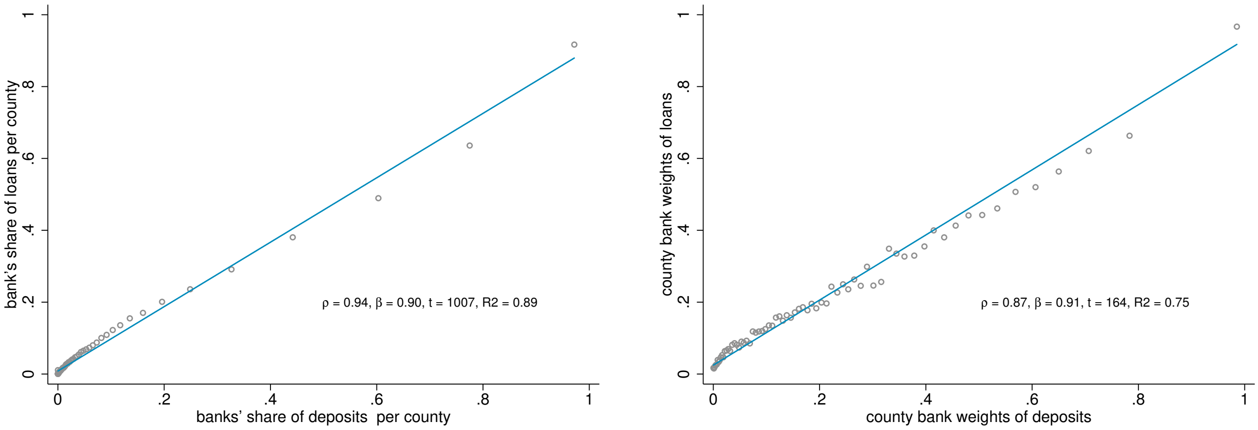
	year	stress tested	non-stress tested	total
unsecured	2009	144	176	320
	2016	168 (+16 %)	158 (-10 %)	326 (+2 %)
secured	2009	110	257	368
	2016	64 (-42 %)	219 (-15 %)	283 (-23 %)

Note: This table show the absolute volume of secured and unsecured small business lending for stress tested, non-stress tested, and all banks from 2009 to 2016 in billions. While stress tested and non-stress tested banks reduced secured lending, the decline is significantly larger for stress tested banks, both in absolute and relative terms. Stress tested banks also *increase* unsecured lending, while non-stress tested banks reduce unsecured and secured lending by similar amounts. Since the overall amount of unsecured lending increases by $ 6 bn, but unsecured lending falls by $ 85 bn, unsecured lending does not replace secured lending.

C.2 Bank Level: Figures and Tables

Figure 14: **Correlation between bank assets and liabilities**

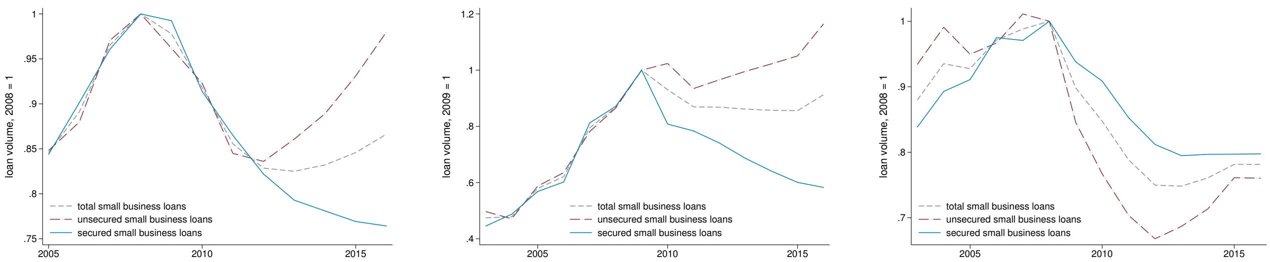
(a) Banks' loan and deposit shares across counties (b) Counties' exposure to banks, loans vs. deposits



Note: Panel (a) shows a binscatter plot and underlying correlations for the raw data of the share of bank b's loans in county c over total loans by bank b in each year (y-axis) vs. the share of bank b's deposits in county c over total deposits by bank b in each year (x-axis). Panel (b) shows a binscatter plot and underlying correlations for the raw data of the share of county c's loan share of bank b in county c over total loans in county c (y-axis) vs. county c's deposit share of bank b in county c over total deposit in county c (x-axis). These graphs show that approximating banks' or counties' loan exposure to each other with liability data on deposits provides a reasonable fit with correlations of around 90 %.

Figure 15: **Bank lending since the crisis**

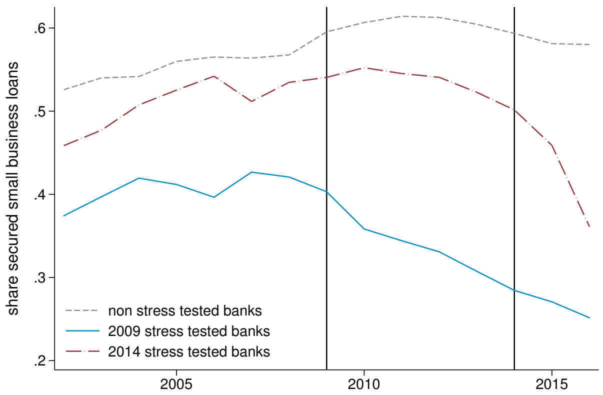
(a) All banks: small loans (b) ST banks: small loans (c) non-ST banks: small loans



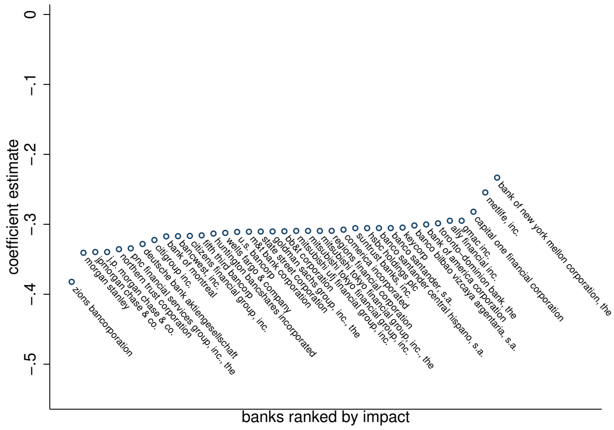
Note: Panel (a) shows total, secured, and unsecured business lending by all banks, panel (b) by stress tested (ST) banks, and panel (c) for non-stress tested banks. All series are normalized to 1 at their pre-crisis peak. Small loans (loans with origination amounts less than \$ 1,000,000). All series follow similar trajectories before the recession. Source: FDIC SDI.

Figure 16: **Bank lending: pre-trends and stability of coefficients**

(a) Small business lending by stress tested banks



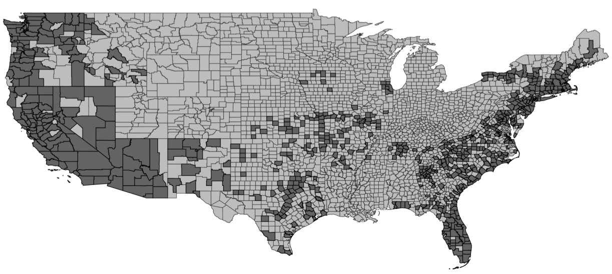
(b) Excluding stress tested banks one-by-one



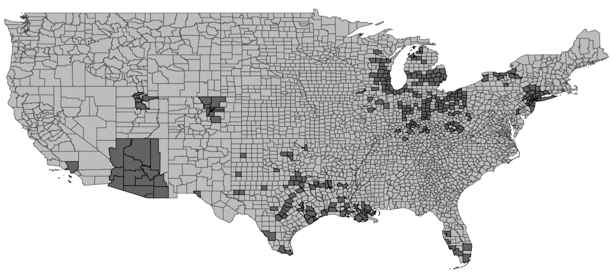
Note: Panel (a) shows the share of secured out of total small business lending for stress tested (blue solid line and red line) and non-stress tested (black dashed line) banks. Stress tested banks are split into banks stress tested from 2009 onward (blue line) and tested from 2014 onward (red). Panel (b) shows estimated coefficient γ in regression equation (5), where each scatter point represents the coefficient estimate when I drop the respective stress tested bank from the sample. Every coefficient is significant at the 1 % level.

Figure 17: **Geography: deposits by stress tested banks**

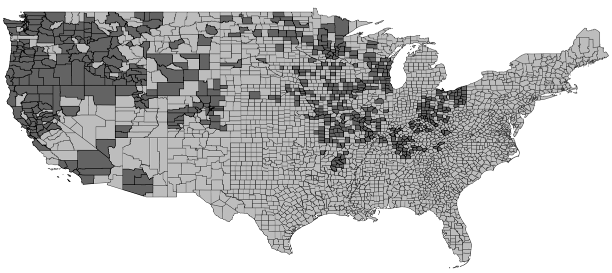
(a) Bank of America



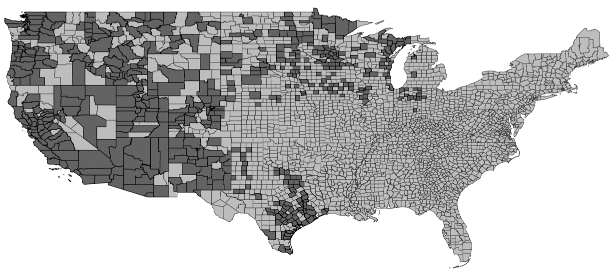
(b) JPMorgan Chase & Co.



(c) U.S. Bankcorp



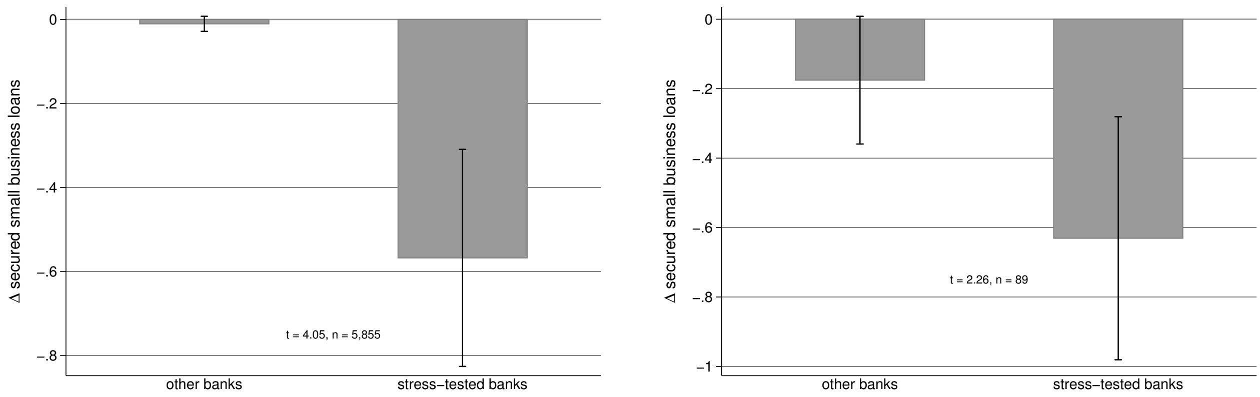
(d) Wells Fargo



Note: Deposits across U.S. counties by four largest stress tested banks (in terms of branches). Dark grey areas are counties in which the respective bank owns deposits, light grey areas where it does not. Data: FDIC SOD.

Figure 18: **Stress testing and secured lending**

(a) all banks (b) banks with assets 10bn-200bn



Note: This Figure shows the 2010-2016 change in small secured commercial loans by bank group. Panel (a) makes use of the full sample of banks, while panel (b) only compares stress tested banks with assets less than 200bn (as of 2011) to non stress tested banks with assets greater than 10bn. For the full sample of 5,885 banks, stress tested banks see a reduction in lending of around 60 % from 2010 to 2016, while the average non-stress tested sees a change insignificantly different from zero. The full sample of banks compares small and local banks with large, stress tested banks that operate across the country. Consequently, panel (b) restricts the sample to stress tested banks with total assets less that 200bn (so it excludes the largest stress tested banks) to non-stress tested banks with assets above 10bn (i.e. excluding the majority of smaller banks). While the difference narrows slightly, stressed banks with assets less than 200bn reduce secured small business lending by a similar amount (60 %), while the comparison group of large, but non stress tested banks, reduces secured lending by around 17 %. In both samples, the difference in means is statistically significant.

Table 17: **Bank lending during the recovery - CRA loans**

VARIABLES	(1) Δ CRA	(2) Δ CRA	(3) > 5bn Δ CRA	(4) Δ CRA	(5) extensive Δ CRA	(6) extensive Δ CRA
stress tested	-0.384***	-0.342***	-0.637***	-0.259***	-0.398***	-0.377***
	(0.034)	(0.035)	(0.045)	(0.040)	(0.029)	(0.030)
large (> 20bn)				0.208***		
				(0.057)		
Observations	30,268	30,224	24,539	30,224	34,281	34,243
R-squared	0.116	0.227	0.275	0.227	0.107	0.206
Bank Controls	✓	✓	✓	✓	✓	✓
County FE	-	✓	✓	✓	-	✓
Cluster	BHC*County	BHC*County	BHC*County	BHC*County	BHC*County	BHC*County

The change in stress tested banks' loan volume could reflect differential loan demand across counties. If counties with a high share of firms using collateral to secure financing see a decline in loan demand for reasons unrelated to the presence of large banks, then coefficients would reflect loan demand instead of change in banks' loan supply. This Tables uses bank-county data on the change from 2010 to 2015 in small business lending for all loans smaller $250,000 (CRA). Column (1) shows the baseline correlation with baseline bank controls. Column (2) adds county fixed effects to absorb changes in local demand. R^2 increases significantly, suggesting that unobservable demand factors explain part of the variation. The coefficient, however, does not change in any statistically meaningful way. Columns (3)-(4) control for the size of banks in the control group, columns (5)-(6) include the extensive margin, i.e. set loan growth to zero if banks no longer lend to a county in 2015. Note: Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 18: **Other lending by stress tested banks**

VARIABLES	(1) total	(2) mortgage	(3) CRE	(4) C&I	(5) CRE small	(6) C&I small	(7) consumer
stress tested	0.072***	-0.094	-0.044	0.162*	-0.403***	0.046	0.562***
	(0.021)	(0.133)	(0.066)	(0.090)	(0.132)	(0.165)	(0.103)
Observations	127,137	125,703	124,262	122,069	123,545	121,421	125,643
R-squared	0.993	0.966	0.948	0.928	0.922	0.904	0.913
Bank Controls	✓	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Cluster	BHC	BHC	BHC	BHC	BHC	BHC	BHC

Note: This table shows regression results for regression equation (5). *stress tested* is a dummy with value 1 for banks that underwent stress tests since 2009. All specifications cluster standard errors on the bank holding company (BHC) level to account for serial correlation of errors among banks belonging to the same holding company (the level at which stress tests are carried out). For variable definitions see section B. Values in parentheses denote standard errors. Key: *** p<0.01, ** p<0.05, * p<0.1.

Where do stress tested banks reduce lending? In table 19 I test the assumption underlying the definition of county exposure to stress tested banks (as defined in equation (1)), in which I assume that counties with higher exposure to stress tested banks are affected stronger by banks' contraction in loan supply. Stress tested banks reduce lending, but could do so in non-core markets. Then counties in which stress tested banks are important do not see an overall decline in lending. To this end, I define $core\ market_{b,c}$ as the average share of CRA loans by bank b in county c out of total CRA loans by bank b from 2000-2008. Higher values of *core market* imply that a bank lends relatively more to a county. I then add *core market* and its interaction with *stress tested* to equation (3):

$$\begin{aligned} log(CRA)_{b,c,t} =&\alpha_1\ core\ market_{b,c} \times post_t + \alpha_2\ stress\ tested_{b,t} \times core\ market_{b,c} \\ &+ \theta_{b,c} + \tau^1_{b,t} + \tau^2_{c,t} + \epsilon_{b,c,t}, \end{aligned}$$

A negative coefficient on the interaction term $stress\ tested_{b,t} \times core\ market_{b,c}$ indicates that stress tested banks reduce lending by more in their core markets, supporting the assumption that county exposure captures a local decline in loan supply. $\theta_{b,c}, \tau^1_{b,t}, \tau^2_{c,t}$ are bank*county, bank*time, and county*time fixed effects. By including bank*time in addition to county*time fixed effects, the coefficient isolates changes in bank lending that are unrelated to unobservable county and bank characteristics that vary over time. In other words, I compare lending by the same bank (once stress tested, and once not) to the same county. Note that I equate banks' exposure to counties in terms of lending (small business loans) with exposure to counties in terms of deposits. Figure 14, panel (a), shows that the correlation between both series is 0.94.

Table 19 shows that, across specifications, stress tested banks reduce small business lending by more in their core markets. I control for local unobservable county characteristics through county*time fixed effects in column (2), as well as unobservable changes at the bank level through bank*time fixed effects in column (3). Bank*time fixed effects remove any difference in characteristics between stress tested and non-stress tested banks, so column (3) in essence compares lending by the same bank (once stress tested, and once not) to the same county. The coefficient of interest on $stress\ tested \times core\ market \times \mathbb{1}(2009-16)$ increases in size from column (1) to (2) to (3), which indicates that controlling for unobservable county and bank characteristics increases the negative effect of stress testing on small business lending. The fact that the effect of stress testing on small business lending is stronger in core markets implies that counties with higher exposure to stress tested banks are hit harder by contractions in lending. This validates that exposure, defined in equation (1), reflects a local decline in bank lending.

Table 19: **Stress tested banks cut lending in their core markets**

VARIABLES	(1) log(CRA)	(2) log(CRA)	(3) log(CRA)
stress tested	-0.175***	-0.265***	
	(0.025)	(0.026)	
core market × $\mathbb{1}$(2009-16)	-0.039	-0.230***	-0.653***
	(0.035)	(0.042)	(0.034)
stress tested × core market × $\mathbb{1}$(2009-16)	-0.586	-1.360***	-1.828***
	(0.378)	(0.291)	(0.638)
Observations	430,978	430,978	430,978
R-squared	0.888	0.923	0.962
Bank Controls	✓	✓	-
Bank*County FE	✓	✓	✓
Year FE	✓	-	-
County*Year FE	-	✓	✓
Bank*Year FE	-	-	✓
Cluster	Bank	Bank	Bank

Note: This table shows regression results for regression equations (5) on the bank-county-year level. The dependent variable is log CRA small business lending at the bank-county level. *stress tested* is a dummy with value 1 for banks that underwent stress tests since 2009, $\mathbb{1}(2009-16)$ is a dummy with value 1 for years 2009 to 2016. *core market* measures the average share of small business loans out of total loans by bank b in county c over the sample period, i.e. higher values of *core market* indicate that a county is relatively more important in bank b's portfolio. The triple interaction effect indicates whether stress tested banks reduce lending in their core or non-core markets. Column (1) includes bank controls, as well as bank*county and year fixed effects. To absorb local unobservable county characteristics, column (2) includes county*time fixed effects. Column (3) adds bank*time fixed effects to control for unobservable bank characteristics that vary over time. Stress tested banks reduce small business lending significantly and the result is robust to controlling for unobservable county demand through county*time fixed effects. The effect is stronger in banks' core markets, even after controlling for unobservable changes on the bank level through bank*county fixed effects. All specifications cluster standard errors on the bank holding company (BHC) level to account for serial correlation of errors among banks belonging to the same holding company (the level at which stress tests are carried out). For variable definitions see section B. Values in parentheses denote standard errors. Key: *** p<0.01, ** p<0.05, * p<0.1.

C.3 County Level: Figures and Tables

Table 20: **County: effect size**

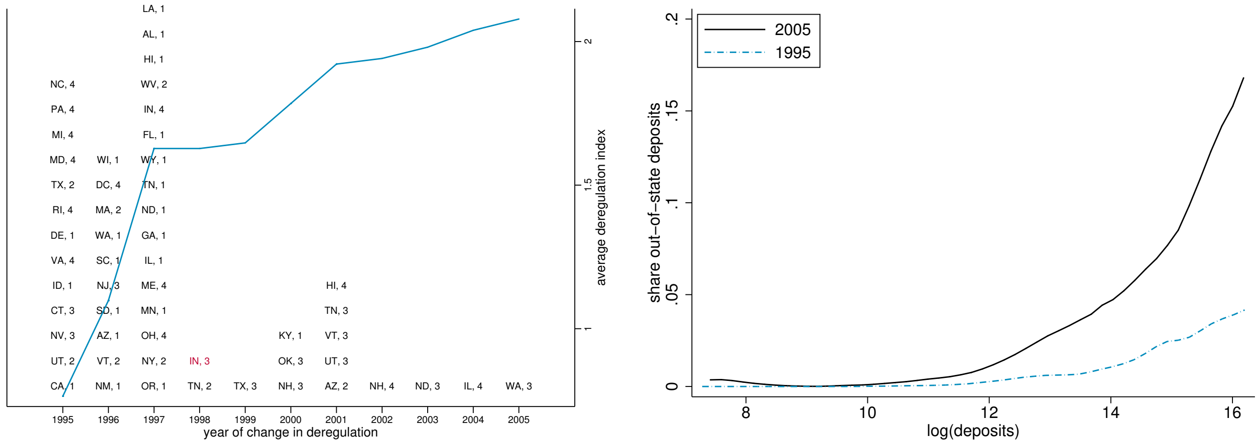
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		IV		IV		IV		IV		IV
VARIABLES	log(emp)	log(emp)	log(emp)	log(emp)	share	share	log(LP)	log(LP)	log(wage)	log(wage)
exposure × 𝟙(2009-16)	-0.037**	-0.158***					-0.047***	-0.087***		
	(0.017)	(0.026)					(0.011)	(0.015)		
exposure × home equity × 𝟙(2009-16)			-0.154***	-0.224***	-0.016***	-0.027***			-0.046***	-0.077***
			(0.033)	(0.052)	(0.003)	(0.005)			(0.007)	(0.011)
Observations	293,722	293,722	213,912	213,912	213,912	213,912	25,072	25,062	349,787	349,715
R-squared	0.823	0.823	0.830	0.830	0.506	0.505	0.962	0.962	0.926	0.926
mean y	3.73	3.73	3.73	3.73	0.07	0.07	-2.11	-2.11	6.39	6.39
sd y	1.63	1.63	1.63	1.63	0.08	0.08	0.43	0.43	0.55	0.55
sd exposure	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21
exposure 25-75	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30	0.30
F-stat	-	1858.25	-	1521.84	-	1521.84	-	1601.07	-	2795.80
County*Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	-	-	-	-	✓	✓	-	-
County*Year FE	-	-	✓	✓	✓	✓	-	-	✓	✓
Industry*Year FE	-	-	✓	✓	✓	✓	-	-	✓	✓
Cluster	County	County	County	County	County	County	County	County	County	County

Note: This table reports effect sizes for equation (7) on the county-industry-year level. Dependent variables are log number of young firms (age 0-1), and the share of young firms. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). *home equity* is a dummy for top and bottom tercile of home equity intensity by two-digit naics industry (with value one for top tercile industries). $\mathbb{1}(2009-16)$ is a dummy with value one for years 2009 to 2016, i.e. the years after the introduction of stress tests. Moving a county from the 25^{th} to the 75^{th} percentile in terms of exposure reduces young firm employment by: 1.1 % − 4.7 % in columns (1)-(2); and 4.6 % − 6.7 % in columns (3)-(4); and the share of young firm employment by 0.5 p.p and 0.8 p.p. in columns (5)-(6). The latter represent 12 % of the average share, or (0.8/2.2 =) 37 % of the average decline in young firm employment shares from 2002-2007 to 2010-2016. Columns (7)-(8) use log labor productivity on the county-year, and columns (9)-(1) log wages on the county-industry-year level as dependent variables. Standard errors are clustered on the county level. Moving a county from the 25^{th} to the 75^{th} percentile in terms of exposure reduces labor productivity and wages by: 1.4 % − 2.6 % in columns (7)-(10). For variable definitions see section B. Values in parentheses denote standard errors. Key: *** p<0.01, ** p<0.05, * p<0.1.

Figure 19: **State deregulation**

(a) State deregulation: timing

(b) Out-of-state deposit share

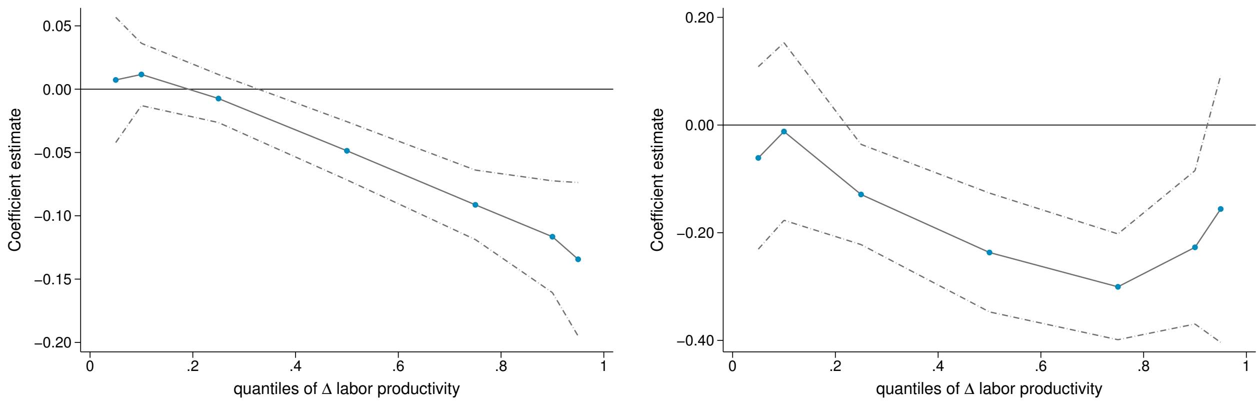


Note: In panel (a) each 'dot' represents a change in deregulation index. For each state, the number following the comma indicates the value of deregulation index after the change. Indiana (IN, red) is the only state that tightened regulation in any year. The blue line denotes the average deregulation index across all states for each year (right axis). Panel (b) shows the share of banks' deposits held in branches outside the headquarter state (y-axis) plotted against bank size in terms of log total deposits on the x-axis (source: FDIC SOD; local polynomial).

Figure 20: **County: quantile regressions**

(a) Labor productivity: OLS

(b) Labor productivity: IV



Note: This Figure 20 plots coefficients for quantile regressions of regression equation (10) with labor productivity growth as dependent variable. Panel (a) plots OLS results, panel (b) uses exposure instrumented with state deregulation. The effect of exposure is stronger for higher quantiles, i.e. within the group of counties with stronger labor productivity growth during the recovery. Hence it is not the case that stress tested banks exert a drag on counties with weak growth in general, but rather slow down growth in counties with a stronger recovery.

Instrumenting exposure with a gravity model Table 21 shows that distance and market size account for banks' geographic expansion. Column (1) uses a fractional logit model and shows a strong and significant negative effect of distance on banks' deposit share in a given county. Market size enters positively, suggesting that banks hold a higher share of deposits in larger markets. Columns (2)-(6) run OLS regressions and add fixed effects to check whether effects are sensitive to unobservable home (bank headquarter county) or host (bank branch county) market characteristics. Column (2) shows that, for distance, results are similar in OLS to logit regressions. Column (3) adds host county fixed effects, column (4) uses home county fixed effects. Accounting for unobservable characteristics in either location does not materially affect the coefficient of interest. Neither does including both types of fixed effects in column (5). Column (6) goes one step further and includes home and host county fixed effects, as well as home state*host county fixed effects. It thus compares deposit shares by banks located in the same state lending to the same county. For example, it exploits variation only in the distance across banks headquartered in California that lend to Kings County, NY. Again, the coefficient on log distance remains significantly negative and increases in magnitude. The stability of coefficients suggests that the effect of distance on local deposits is orthogonal to local unobservable county characteristics, i.e. not due to economic factors in home or host markets.

Finally, columns (7)-(9) report 'first stage' regressions of actual on predicted exposure, with and without state fixed effects and county controls. Across specifications, there is a strong positive effect of predicted on actual exposure. A higher level of predicted exposure to stress tested banks is positively associated with observed exposure to stress tested banks at the 1% level. Including fixed effects at the state level increases R^2 by a factor of three, but the coefficient remains similar in size. Further adding pre-crisis county characteristics does not materially affect results. First-stage results show that the gravity model, i.e. the instrument, explains the geographic distribution of local bank deposits across counties to a similar extent across and within states and does so largely independent of county characteristics.

Table 21: **IV: gravity equation and first stage**

VARIABLES	(1) logit deposit share	(2) OLS deposit share	(3) OLS deposit share	(4) OLS deposit share	(5) OLS deposit share	(6) OLS deposit share	(7) First Stage exposure	(8) First Stage exposure	(9) First Stage exposure
log(1+distance)	-0.960***	-0.136***	-0.138***	-0.132***	-0.138***	-0.159***			
	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)			
log(population ratio)	0.267***	0.003	-0.008**	0.024***					
	(0.009)	(0.003)	(0.003)	(0.003)					
exposure (predicted)							0.230***	0.241***	0.191***
							(0.031)	(0.017)	(0.016)
Observations	27,601	27,601	27,470	27,297	27,105	22,619	2,236	2,236	2,236
R-squared		0.729	0.785	0.796	0.830	0.850	0.186	0.549	0.579
Host County FE	-	-	✓	-	✓	✓	-	-	-
Home County FE	-	-	-	✓	✓	✓	-	-	-
Home State*Host County FE	-	-	-	-	-	✓	-	-	-
State FE	-	-	-	-	-	-	-	✓	✓
County Controls	-	-	-	-	-	-	-	-	✓
Cluster	Home County	Home County	Home County	Home County	Home County	Home County	State	State	State

Note: In columns (1)-(6), regressions are on the bank-county level for 2007. Dependent variable is the deposit share of bank b in county c (out of total bank deposits). *log(1+distance)* denotes log of one plus distance between the bank headquarter county and bank branch county. *log(population ratio)* is the log ratio of home (bank HQ) to host (bank branch) county population. Column (1) runs a fractional logit model. Columns (2)-(6) add fixed effects to account for unobservable county characteristics in banks' HQ and branch counties. Adding fixed effects does not materially change the coefficient of interest on distance. Column (6) exploits variation between banks located in the same state lending to the same county, i.e. differences in distance only reflect differences in banks' HQ locations within a given state. Columns (7)-(9) run 'first stage' regressions on the county level (as of 2007) of actual county exposure on county exposure based on predicted deposits. Column (7) is unconditional, column (8) adds state fixed effects, and column (9) state fixed effects plus pre-crisis county controls listed in Table 4. For variable definitions see section B. Values in parentheses denote standard errors. Key: *** p<0.01, ** p<0.05, * p<0.1.

Further county robustness checks Table 22, columns (1)-(2), estimate baseline regressions at the county-industry-age cell-year level and allow local and industry unobservables to vary by firm age group. Young firms mostly depend on local demand, so they could be more responsive to local shocks and less responsive to industry shocks than old firms (Mian and Sufi, 2014). If this differential sensitivity to shocks varies systematically with exposure or industries' home equity intensity, coefficients are biased. To this end, I include county*firm age*time and industry*firm age*time fixed effects. Dummy *young* takes on value one for young firms age 0-1. Other age groups are 2-3, 4-5, 5-10, and 11+. Baseline coefficients keep sign and significance and are of similar size across specifications. Columns (3)-(6) restrict the sample to counties with population above 100,000 (100k) and 1,000,000 (1mn); to counties with no change in exposure to stress tested banks from 2002 to 2007 (*no change*); and to counties outside of California, Massachusetts, and New York (*no VC*), where most of the venture capital industry is concentrated (Matray, 2015). Across regions, exposure has a significant negative effect on young firm employment in home equity intensive industries.

Table 23, columns (1)-(4), include alternative exposure metrics. Based on equation (1), column (1) re-computes exposure based on local deposits by the four largest instead of all stress tested banks; column (2) based on log total bank assets; column (3) based on the log difference in banks' loans from 2007 to 2009; and column (4) based on a dummy for banks with asset size 10bn to 50bn. Including interaction terms with these alternative exposure measures does not change the coefficient of interest, which suggests that the effect of stress tests is not solely due to the four largest banks, nor due to bank size or performance during the crisis, and not present for non-stress tested large banks. Columns (5)-(11) look at sub samples. Columns (5)-(6) and (7)-(8) split the sample into low- and high-risk counties and industries, based on industry betas. In line with findings by Cortés, Demyanyk, Li, Loutskina and Strahan (2018), the contraction in loan supply reduces young firm employment by more in risky areas and industries. Columns (9)-(10) split the sample into tradable and non-tradable industries.[44] Exposure has a negative impact on employment in both types of sectors. The effect is stronger in tradable industries, suggesting that unobserved local demand is not explaining results. Finally, column (11) restricts the sample to counties in which the largest four banks have no presence. The coefficient of interest increases in size. Further robustness checks look at net job creation (Adelino, Ma and Robinson, 2017) and cross-sectional pre-/post-crisis regressions instead of panel regressions (see Tables 24 and 25).

[44] Non-tradable industries cover 2-digit Naics Sectors 23, 54, 55, 71, and 72, and hence include construction.

Table 22: **County: age-specific local shocks and sub-samples**

	(1)	(2)	(3)	(4)	(5)	(6)
			$> 100k$	$> 1mn$	no change	no VC
VARIABLES	share	share	share	share	share	share
young$\times$ $\mathbb{1}$(2009-16)	-0.024***					
	(0.002)					
exposure $\times$ home equity $\times$ $\mathbb{1}$(2009-16)	0.050		-0.206**	-0.418*	-0.478***	-0.448***
	(0.033)		(0.080)	(0.230)	(0.164)	(0.084)
exposure $\times$ young $\times$ $\mathbb{1}$(2009-16)	0.030***					
	(0.006)					
home equity $\times$ young $\times$ $\mathbb{1}$(2009-16)	-0.072*					
	(0.037)					
exposure $\times$ home equity $\times$ young $\times$ $\mathbb{1}$(2009-16)	-0.333***	-0.267***				
	(0.096)	(0.102)				
Observations	1,286,529	1,285,577	108,101	7,264	99,709	270,892
R-squared	0.954	0.959	0.546	0.584	0.595	0.507
County*Industry*Age FE	✓	✓	-	-	-	-
County*Industry FE	-	-	✓	✓	✓	✓
County*Year FE	✓	-	✓	✓	✓	✓
Industry*Year FE	✓	-	✓	✓	✓	✓
County*Age*Year FE	-	✓	-	-	-	-
Industry*Age*Year FE	-	✓	-	-	-	-
County*Industry*Year FE	-	✓	-	-	-	-
Cluster	County	County	County	County	County	County

Note: This table shows regression results for regressions on the county-industry-firm age-year level. Dependent variables are log employment, share of young firms, and the change in the share of young firms. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). *home equity* is the share of young firms within each two-digit industry that uses home equity financing to start or expand operations, provided by SBO. *young* is a dummy with value one for start-up firms age zero to one. $\mathbb{1}(2009-16)$ is a dummy with value one for years 2009 to 2016, i.e. the years after the introduction of stress tests. For variable definitions see section B. Values in parentheses denote standard errors. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 23: **Young firms: alternative exposure and risk**

VARIABLES	(1) share	(2) share	(3) share	(4) share	(5) low risk county share	(6) high risk county share	(7) low risk ind share	(8) high risk ind share	(9) tradable share	(10) non-tradable share	(11) no top-4 cty share
exposure × home equity × 𝟙(2009-16)	-0.390***	-0.399***	-0.358***	-0.383***	-0.120	-0.466***	-0.147	-0.633***	-0.383***	-0.293**	-0.502***
	(0.092)	(0.107)	(0.078)	(0.077)	(0.083)	(0.128)	(0.131)	(0.136)	(0.104)	(0.114)	(0.141)
top 4 × home equity × 𝟙(2009-16)	0.002										
	(0.002)										
log(assets) × home equity × 𝟙(2009-16)		0.001									
		(0.002)									
Δ loans 2007-09 × home equity × 𝟙(2009-16)			0.005								
			(0.004)								
large (10bn-50bn) × home equity × 𝟙(2009-16)				0.073***							
				(0.025)							
Observations	274,593	274,593	274,593	274,593	134,440	134,841	105,880	163,716	191,882	78,071	136,423
R-squared	0.572	0.572	0.572	0.572	0.584	0.578	0.642	0.594	0.592	0.650	0.577
County*Industry FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
County*Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cluster	County	County	County	County	County	County	County	County	County	County	County

Note: This table shows regression results for regressions on the county-industry-year level (see regression equation (7)). Dependent variables is employment share of young firms. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). *home equity* is the share of young firms within each two-digit industry that uses home equity financing to start or expand operations, provided by SBO. $\mathbb{1}(2009-16)$ is a dummy with value one for years 2009 to 2016, i.e. the years after the introduction of stress tests. For variable definitions see section B. Values in parentheses denote standard errors. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 24: **Net job creation by firm age groups and small firms**

VARIABLES	(1) NJC entry	(2) NJC young	(3) NJC old	(4) log(emp small <20)	(5) share est small <20
exposure $\times$ home equity $\times$ $\mathbb{1}$(2009-16)	-0.032***	-0.031**	-0.011	-0.000	0.000
	(0.010)	(0.015)	(0.016)	(0.002)	(0.000)
Observations	240,223	129,531	145,165	239,750	239,835
R-squared	0.587	0.416	0.382	0.993	0.942
County*Industry FE	✓	✓	✓	✓	✓
County*Year FE	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓
Cluster	County	County	County	County	County

Note: This table shows regression results for equation (7) on the county-industry-year level. Dependent variables are net job creation rates by new firms (*entry*, age 0-1), *young* firms (aging from 0-3 in $t-2$ to 2-5 in t), and *old* firms (aging from 4-10 in $t-2$ to 6+ in t). All dependent variables are scaled by county-industry total employment as of 2003 and then standardized to mean zero, standard deviation 1 for comparison. See Adelino, Ma and Robinson (2017) for detailed variable construction. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). $\mathbb{1}(2009-16)$ is a dummy with value one for years 2009 to 2016, i.e. the years after the introduction of stress tests. *home equity* is the share of young firms within each two-digit industry that uses home equity financing to start or expand operations, provided by SBO. For each dependent variable, I estimate regressions with county*industry and year fixed effects, as well as with county*industry and granular fixed effects to control for unobservable shocks that could affect local or industry demand over time. County*time fixed effects absorb local shocks at the county level, while industry*time fixed effects ensure that common shocks to industries over time are not driving results. Standard errors are clustered on the county level. Table 24 shows net job creation by firms in different age groups. Controlling for local and industry demand, net job creation by new firms (*entry*) falls significantly in counties with higher exposure and in industries with higher home equity financing, columns (1)-(2) The same holds for net job creation by young firms with age 0-3 over a horizon of two years in column (3). There is an insignificant effect for net job creation by old firms (older 4 years) over a two year horizon in column (6). County business patterns (CBP) provide detailed yearly data on employment and establishments by firm size on the county-industry level.[45] Columns (5)-(6) show that there is no significant effect on small firm employment or establishments. For variable definitions see section B. Values in parentheses denote standard errors. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

Table 25: **Young firms in the cross-section**

VARIABLES	(1) C-I Δ emp pre/post	(2) C-I Δ emp pre/post	(3) C-I Δ emp pre/post	(4) C-I Δ share pre/post	(5) C-I Δ share pre/post	(6) C-I Δ share pre/post	(7) C-I-Y Δ emp	(8) C-I-Y Δ share	(9) C-I Δ share 07-09	(10) C-I Δ share 07-09	(11) C-I Δ share 07-09
exposure	0.103	0.158		0.011	0.013*				-0.004*	-0.001	
	(0.099)	(0.102)		(0.007)	(0.008)				(0.002)	(0.004)	
home equity	0.178***			0.007**						0.002	
	(0.046)			(0.003)						(0.002)	
exposure × home equity	-0.177	-0.259**	-0.238*	-0.016*	-0.020**	-0.020**				-0.005	-0.006
	(0.124)	(0.126)	(0.130)	(0.009)	(0.009)	(0.010)				(0.005)	(0.005)
exposure × home equity × post crisis							-0.288**	-0.019**			
							(0.133)	(0.010)			
Observations	9,983	9,983	9,863	10,111	10,111	9,997	19,656	19,954	17,980	17,980	17,980
R-squared	0.003	0.017	0.164	0.001	0.013	0.162	0.587	0.578	0.000	0.000	0.160
County FE	-	-	✓	-	-	✓	-	-	-	-	✓
Industry	-	✓	✓	-	✓	✓	-	-	-	-	✓
County*Industry FE	-	-	-	-	-	-	✓	✓	-	-	-
County*Year FE	-	-	-	-	-	-	✓	✓	-	-	-
Industry*Year FE	-	-	-	-	-	-	✓	✓	-	-	-
Cluster	County	County	County	County	County	County	County	County	County	County	County

Note: This table compares employment growth of firms age 0 to 1 in the pre- and post-crisis period. Columns (1)-(6) use the difference in employment growth or the change in the employment share of young firms from 2010 to 2015 to 2003 to 2007 as dependent variable for each county-industry pair, i.e. $\Delta emp_{c,i}^{10-15} - \Delta emp_{c,i}^{03-07}$. Columns (7)-(8) run similar regressions, but use employment growth in the pre- and post-crisis period as separate observations. Columns (9)-(11) use the change in the share of young firms during the Great Recession (2007-2009) as dependent variable. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). *home equity* is a dummy with vale one for home equity financing intensive industries (above/below median). *postcrisis* is a dummy with value one for years 2010 to 2015, i.e. the years after the Great Recession. Standard errors are clustered on the county level. Each regression thus compares whether young firms performed better or worse in counties with higher exposure and industries with higher home equity intensity. A negative coefficient on interaction terms indicate weaker employment growth of young firms during the post-crisis period, relative to the pre-crisis period. For columns (9)-(11), there is no differential decline in the share of young firms across counties with high exposure during the recession, and neither is there by industry equity intensity. For variable definitions see section B. Values in parentheses denote standard errors. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

Venture capital (VC), non-bank lending, and home equity Robb and Robinson (2014) show that newly founded firms rely heavily on formal debt financing through banks. They find that the amount of bank financing is on average seven times greater than insider-financed debt, three times as many firms rely on outside debt as they do inside debt. Even among firms that rely on inside debt, the average amount of outside debt is nearly twice that of inside debt. Even a firm that access outside equity sources (VC or angel financing) l has around 25% of its capital structure in the form of outside debt. They also find that having a capital structure that is more heavily tilted toward formal credit channels results in a greater likelihood of success.

Da Rin, Hellmann and Puri (2011) survey venture capital and conclude that we still know relatively little about the creation of ventures that demand VC finance. They report that only a small share of new companies uses VC, ranging from 0.11% to 2%, depending on the cited study and are concentrated in a few sectors. With regard to venture capital and productivity, they conclude that company-level data provides strong support for the importance of VC for productivity, while industry-level data does not. An increase in VC also increases firm entry. They conclude that while the literature seems to identify social value creation, there remains an open question on the social costs of VC, since private returns to VC are often disappointing, implying that VC investments have significant opportunity cost.

For the U.K., Cosh, Cumming and Hughes (2009) find support for the pecking order theory and show that bank financing is the most important source of financing for young firms. Chava, Oettl, Subramanian and Subramanian (2013) show that 70 % of firms in the SSBF use bank credit and that "while the venture capital market has grown considerably since the late 1990s, it has largely focused on the high-tech and biotech sectors. Innovative firms, especially young, private ones, in other industries continue to depend on banks as primary sources of credit." They also provide evidence that banking deregulation affects innovation and patenting by young firms, highlighting the importance of bank financing for young firms. Tang (2018) argues for consumer lending that peer-to-peer lenders are complements to bank lending, but not substitutes. Chernenko, Erel and Prilmeier (2018) look at publicly traded middle-market firms and find that non-bank lending is substantial, but that non-bank lenders have weaker fundamentals and pay significantly higher interest rates.

Table 26: **Non-bank lending**

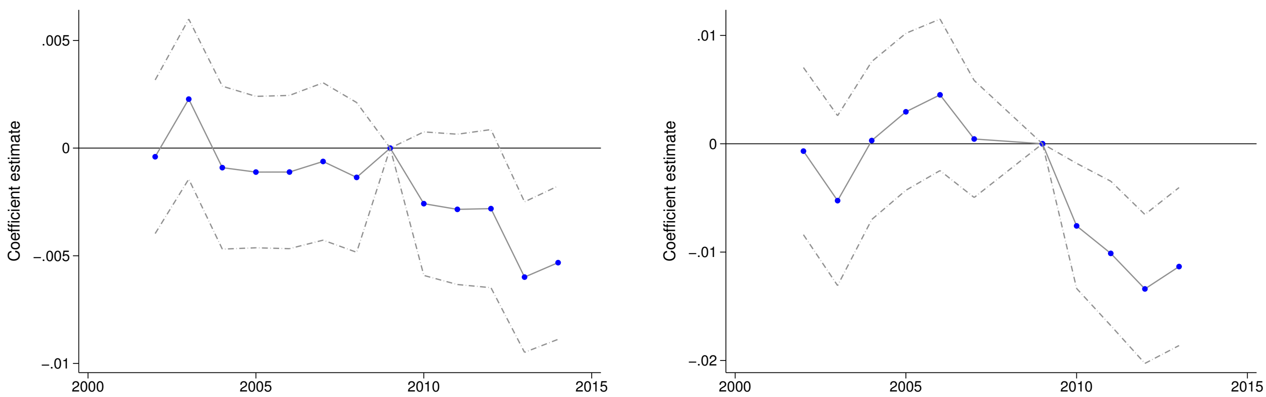
VARIABLES	(1) SB log(amt.)	(2) SB log(nr.)	(3) SB i-rate	(4) SB+CC log(amt.)	(5) SB+CC log(nr.)	(6) SB+CC i-rate
exposure $\times$ $\mathbb{1}$(2009-16)	0.435	0.890***	0.074	-0.044	0.099	0.889
	(0.442)	(0.312)	(0.982)	(0.345)	(0.263)	(0.756)
Observations	2,840	2,840	2,840	2,651	2,651	2,651
R-squared	0.668	0.768	0.488	0.971	0.975	0.535
County Controls	✓	✓	✓	✓	✓	✓
County FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Cluster	County	County	County	County	County	County

This Table shows results for regression equation (6). Dependent variable is log amount (amt.) or number (nr.) of small business (SB in columns (1)-(2)) or small business and credit card (SB+CC in columns (4)-(5)) loans by peer-to-peer lender *Lending Club*. Columns (3) and (6) use the respective interest rate. Data on peer-to-peer loans is available for 540 counties and from 2007 to 2016. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). $\mathbb{1}(2009-16)$ is a dummy with value one for years 2009 to 2016, i.e. the years after the introduction of stress tests. Counties with higher exposure see an increase in non-bank lending, but the effect is only significant for the number of loans in column (2). Standard errors are clustered on the county level. Note: Key: *** p<0.01, ** p<0.05, * p<0.1.

MSA level: Young firms, number vs. employment QWI provide data on young firms' employment and findings show that counties with higher exposure see a decline in employment among young firms. While employment is an important dimension, the nature of small businesses could have changed. Maybe start-ups require fewer workers today than a decade ago, so the *number* of young firms is more informative than their *employment*. Since data on the number of firms is not available for the county level, I use data on the MSA-year level, provided by the Census Bureaus' Business Dynamic Statistics (BDS) from 2003 to 2014. Analogous to county-year regressions in equation (6), Table 27 shows that the number and share of young firms declines more during the post-crisis period for MSAs with higher exposure. The decline in growth is confined to young firms, since older firms grow faster. Figure 21 provides the yearly coefficients and pre-trends for young firms and the pooled sample of young and old firms. Hence, not only did employment among young firms decline by more in exposed counties, but the absolute number of young firms, too. Columns (8)-(10) are placebo regressions for previous recessions and show that higher exposure did not lead to a decline in young firms in previous recessions.

Figure 21: **MSA: share of young firms**

(a) young firms (b) pooled sample



Note: Coefficient plots of regression $share_{MSA,t} = \theta_{MSA} + \tau_t + \sum_{t=2003}^{T=2014} \gamma_{q=t} exposure_{MSA} + controls_{MSA,t} + \epsilon_{MSA,t}$. Panel (a) shows regression for firms aged zero to one, panel (b) shows differential effect across young and old firms.

Table 27: **MSA: share of young firms**

VARIABLES	(1) share	(2) share	(3) share	(4) share	(5) share	(6) log(firms)	(7) log(firms)	(8) placebo 1980-82 share	(9) placebo 1990-91 share	(10) placebo 2000-01 share
exposure	0.025***									
	(0.005)									
𝟙(2009-14)	-0.036***									
	(0.002)									
exposure × 𝟙(2009-14)	-0.018***	-0.013***	0.013***			0.118***				
	(0.007)	(0.004)	(0.004)			(0.033)				
start-up × 𝟙(2009-14)			-0.060***	-0.060***		-0.294***				
			(0.004)	(0.004)		(0.020)				
exposure × 𝟙(2009-14) × start-up			-0.038***	-0.038***	-0.038***	-0.116**	-0.116**			
			(0.013)	(0.013)	(0.013)	(0.055)	(0.055)			
exposure × post								-0.009	-0.003	0.010
								(0.015)	(0.010)	(0.007)
Observations	4,264	4,264	12,792	12,792	12,792	8,528	8,528	1,369	1,894	3,603
R-squared	0.456	0.810	0.971	0.971	0.983	0.991	0.996	0.952	0.738	0.784
MSA Controls	✓	✓	✓	-	-	✓	-	✓	✓	✓
MSA FE	-	✓	-	-	-	-	-	✓	✓	✓
Year FE	-	✓	✓	-	-	✓	-	✓	✓	✓
MSA*Age FE	-	-	✓	✓	✓	✓	✓	-	-	-
MSA*Year FE	-	-	-	✓	✓	-	✓	-	-	-
Age*Year FE	-	-	-	-	✓	-	✓	-	-	-
Cluster	MSA	MSA	MSA	MSA	MSA	MSA	MSA	MSA	MSA	MSA

Note: Regressions are on the MSA-year level and use the number (share) of young firms as dependent variable. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). $\mathbb{1}(2009-16)$ is a dummy with value 1 for the respective time period. *start-up* denotes a dummy with values one for firms aged 0-1. Columns (1)-(2) are on the MSA-year level, columns (3)-(7) in the MSA-firm age-year level. Columns (8)-(10) are placebo regressions for previous recessions. For variable definitions see section B. Values in parentheses denote standard errors. Key: *** p<0.01, ** p<0.05, * p<0.1.

C.4 Further Extensions

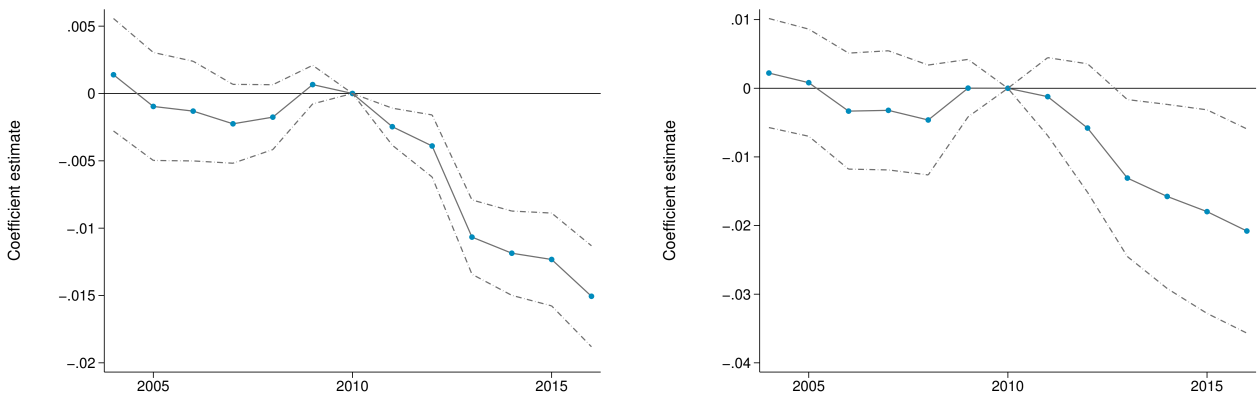
Table 28: **Aggregation: county vs. state, young firms**

VARIABLES	(1) county log(emp)	(2) county share	(3) state log(emp)	(4) state share
exposure × home equity × $\mathbb{1}$(2009-16)	-0.021*** (0.004)	-0.021*** (0.006)	-0.034*** (0.011)	-0.041** (0.019)
Observations	293,961	293,961	11,460	11,460
R-squared	0.828	0.508	0.964	0.818
County*Industry FE	✓	✓	-	-
State*Industry FE	-	-	✓	✓
County*Year FE	✓	✓	-	-
State*Year FE	-	-	✓	✓
Industry*Year FE	✓	✓	✓	✓
Cluster	County	County	State	State

Note: This table shows regression results for county-industry-year regressions on in columns (1) and (2), and state-industry-year regressions on in columns (3) and (4). Dependent variables are log employment and employment shares of young firms. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). *home equity* is a dummy with value one for two-digit industries with an above-median share of young firms that uses home equity financing to start or expand operations, provided by SBO. $\mathbb{1}(2009-16)$ is a dummy with value one for years 2009 to 2016, i.e. the years after the introduction of stress tests. For variable definitions see section B. Values in parentheses denote standard errors. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

Figure 22: **Aggregation: county vs. state, productivity**

(a) County (b) State



Note: Panels (a) and (b) plot yearly coefficients and 90 % confidence intervals of $log(LP)_{i,t} = \sum_{j\neq 2010} exposure_i \times \mathbb{1}_{t=j} + controls_{i,t} + \theta_i + \tau_t + \epsilon_{i,t}$. For panel (a), i denotes county, in panel (b) it denotes state. Exposure is standardized to mean zero and standard deviation of one. The corresponding point estimates (t-values) in a DiD regression of form (6) are -0.007 (-3.56) and -0.011 (-2.02) for the county and state level.

Is there a mechanical effect of employment growth on labor productivity growth?

Since $LP = \frac{AK^{\alpha}L^{1-\alpha}}{L}$, in logs we get

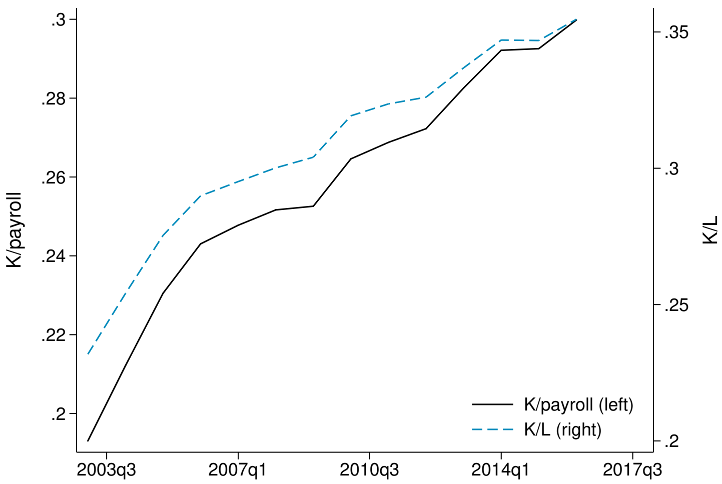
$$lp = a + \alpha k - \alpha l \quad \text{or} \quad \Delta lp = \Delta a + \alpha \Delta k - \alpha \Delta l.$$

Hence, an increase in employment growth could mechanically decrease labor productivity growth. Rearranging, we get that

$$\Delta lp = \Delta a + \underbrace{\alpha(\Delta k - \Delta l)}_{bias}.$$

A change in labor productivity reflects a change in productivity, as well as an error term that comprises changes in employment and capital for each county. If capital k recovers slower than labor during the recovery, part of the estimated coefficient of labor productivity growth on exposure will reflect faster employment growth and hence will be downward biased (overstate the true decline in productivity. However, if capital recovers at a similar or faster rate than labor, the true effect will be understated. Since estimated coefficients on exposure are similar for Δemp and ΔLP, for $\Delta k = 0$, the change in labor productivity will be overstated by $-\alpha \Delta LP$. For any $\Delta k > 0$, the bias will be lower. Since $\alpha \approx 0.55$ since the crisis, even under the most conservative scenario, half of the decline in labor productivity will be due to falling productivity. However, since the capital-to-labor ratio increased since the recent recession, the term $(\Delta k - \Delta l)$ is likely to be greater than zero (see Figure 23). So for a given decline in TFP $(-\Delta a)$, my coefficient on exposure will be biased towards zero and understate the true decline in productivity.

Figure 23: **Aggregate capital-to-labor ratio**



Note: This figure shows capital to payroll (left axis) and capital to labor (right axis) for the US. Capital is measured as *Current-Cost Net Stock of Fixed Assets: Private (FRED series K1PTOTL1ES000)*, payroll as *All Employees: Total Nonfarm Payrolls (FRED series PAYEMS)*, and employment as *Total Nonfarm Private Payroll Employment (FRED series NPPTTL)*.

Labor productivity in the cross section: OLS, IV, and border counties Difference-in-difference specifications rest on the parallel trends assumption, i.e. that confounders that vary across counties are time invariant, and that time-varying confounders do not vary across groups. Difference-in-difference-in-difference specifications and granular fixed effects bolster identification by allowing for time-varying confounders to vary across sub-groups. However, *exposure* is likely not randomly assigned across counties, which requires an instrumental variable (IV). To analyze whether exposure to stress tested banks reduces county productivity in instrumental variable regressions,

I run cross-sectional regressions for the recovery period of the following form:

$$\Delta LP_c = \beta\ exposure_c + controls_c + \epsilon_c, \tag{10}$$

where ΔLP_c denotes the log change in labor productivity for county c from 2010 to 2016, and exposure denotes county exposure to stress tested banks as defined in equation (1). Baseline county controls include the log change in employment and house prices from 2000 to 2007, as well as 2007 values of log population, share of black population, share of population older than 65 years, log income, unemployment rate, as well as employment shares in major 2-digit NAICS industries. I hence control for the pre-crisis boom in local house prices, underlying population characteristics and aging, as well as differential county exposure to industry trends. Standard errors are robust. A negative coefficient $\beta < 0$ indicates that counties with higher pre-crisis exposure to stress tested banks have weaker labor productivity growth than counties with low exposure.

Regression equation (6) will be biased if omitted variables affect county growth and bank exposure contemporaneously. For example, historically strong local consumer demand in Los Angeles County (CA) could attract banks based in Washington D.C., which decide to open branches in Los Angles. If local consumers spend more during the recovery, omitting consumer demand in equation (6) will lead to biased coefficients. I thus use interstate banking deregulation as instrument for exposure that isolates the supply component of county exposure to stress tested banks, i.e. the part of exposure that is due to banks' decision to enter a county (say management), but not due to local county characteristics (for example, a strong housing market).

Table 29 shows that county labor productivity growth during the recovery is significantly lower in counties with higher exposure. Columns (1) and (2) report results for regression equation (10) without and with county controls. In both columns, exposure has a significant negative effect on labor productivity growth. In column (2), increasing exposure by one standard deviation reduces productivity growth by ($0.21 \times -0.056 =$) 1.2 % (46 % of the mean). Column (3) instruments exposure with *deregulation*, as defined in equation (9). Instrumented exposure leads to a strong and significant fall in county labor productivity growth during the recovery, confirming OLS results. Increasing *predicted* exposure by one standard deviation reduces productivity growth by ($0.048 \times -0.162 =$) 0.8 % (31 % of the mean).

Columns (4)-(6) restrict the sample to counties that lie on state borders. Using adjacent county pairs allows me to include border-pair fixed effects, i.e. a separate dummy for each group of adjacent counties across state lines. Border fixed effects absorb any unobservable shock to local demand that affects counties within one border pair and thereby better isolates supply effects. For the sample of 878 counties that border state lines, there is a significant and negative effect of exposure on productivity growth in column (4). The effect is slightly larger in magnitude compared to the full sample in column (2). Columns (5) and (6) use the full set of 2,622 county-pairs along state lines and contrast specifications with and without border-pair fixed effects. The average county has 3 neighbors across state lines. From column (5) to (6), the coefficient does not change in any statistically meaningful sense, while R^2 increases from 0.097 to 0.499 when adding fixed effects. Hence, even after controlling for demand effects that explain a large part of the overall variation, the coefficient of interest remains close to the baseline scenario in column (5). The large increase in R^2 suggests that county exposure is orthogonal to a host of unobservables (Altonji, Elder and Taber, 2005; Oster, 2017).

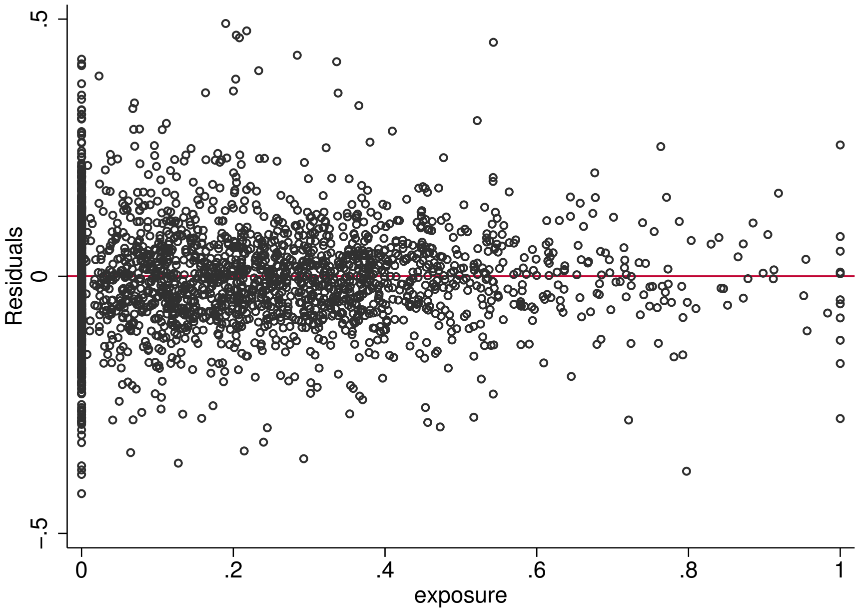
Columns (7)-(8) use wage growth as dependent variable and confirm findings in columns (1)-(8) for labor productivity. Finally, columns (9)-(10) run weighted least squares regressions with log population or log employment as weights. Point estimates and standard deviations are almost identical to baseline OLS in column (2), indicating that regression equation (10) is a "good enough approximation to enable nearly unbiased and consistent estimation of the causal effects of interest" (Solon, Haider and Wooldridge, 2013). Results in Table 29 suggest that exposure to stress tested banks hurts productivity growth and that the effect is not due to unobserved demand factors.

Table 29: **Identification: state deregulation and border counties**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
				adj. counties	pairs	pairs				
			IV					IV	WLS pop	WLS emp
VARIABLES	Δ LP	Δ LP	Δ LP	Δ LP	Δ LP	Δ LP	Δ wage	Δ wage	Δ LP	Δ LP
exposure	-0.067***	-0.056***	-0.162***	-0.074***	-0.080***	-0.082***	-0.023***	-0.088**	-0.053***	-0.050***
	(0.011)	(0.012)	(0.059)	(0.020)	(0.010)	(0.014)	(0.009)	(0.038)	(0.010)	(0.010)
Observations	2,308	2,308	2,308	878	2,622	2,622	2,288	2,288	2,308	2,308
R-squared	0.016	0.061	0.029	0.092	0.097	0.499	0.049	0.020	0.064	0.066
County Controls	-	✓	✓	✓	✓	✓	✓	✓	✓	✓
Border FE	-	-	-	-	-	✓	-	-	-	-

Note: This table shows regression results for equation (10). Dependent variables are log differences from 2010 to 2016 of labor productivity (LP) and average *wage*. *exposure* denotes pre-crisis county exposure to stress tested banks as defined in equation (1). IV refers to instrumental variable regressions in which exposure is instrumented with the log of (1+) cumulative inter-state banking deregulation, as defined in equation (9). Columns (1)-(3) and (7)-(10) use the baseline county sample. Columns (4)-(6) restrict the sample to counties that located along state borders. Column (4) uses the sub-sample of 878 counties that lie on state borders, columns (5)-(6) use the full set of adjacent county-pairs across state lines. Border fixed effects in columns (6) refer to fixed effects on the county-pair level, where each pair refers to a combination of adjacent counties sharing a common state border. Columns (9) and (10) use weighted least squares regressions (WLS) with log population and log employment as weights. Counties with larger pre-crisis exposure to stress tested banks see significantly slower labor productivity growth during the recovery. Counties with larger pre-crisis exposure to stress tested banks see significantly slower labor productivity and wage growth. For variable definitions see section B. Values in parentheses denote standard errors. Growth rates are log-differences. Key: *** p<0.01, ** p<0.05, * p<0.1.

Figure 24: **County residuals: heteroskedasticity (WLS)**



Note: This Figure plots residuals in regression equation (10) against exposure. There is no evidence for heteroskedasticity, which also visible from similar coefficients in WLS and OLS specifications in Table 29

Quotes

Personal residential property is in fact an important source of collateral for small business lending. For many households, the most valuable asset is a home, and the equity may be used by small business owners to secure a business loan. There is evidence, both in the survey and elsewhere, that for banks and small businesses alike, the acceptance (by banks) and use (by small businesses) of 1- to 4-family residential properties for collateral is common. Section 5 of this report shows that a majority of banks, particularly small ones, commonly accept 1- to 4-family residential properties as collateral for small business loans, and other studies estimate that over one-third of small businesses use personal assets to secure loans. [2018 FDIC Small Business Lending Survey, page 16]

The decomposition of five-year industry-level productivity growth (for the products analyzed in Foster et al. 2008) shows that, whether using TFPR or TFPQ, approximately 60% of the industry-level productivity growth over a five-year horizon is within establishments. This finding is common in the literature for the manufacturing sector and, as discussed below, is important in this context of the role of entrepreneurship and the role more generally of reallocation and productivity. But by construction this also implies that approximately 40% of five-year productivity growth is accounted for by reallocation effects. The role of net entry is substantially larger using TFPQ as opposed to TFPR. The net entry component accounts for 35% of productivity growth with TFPQ and 24% of productivity growth with TFPR.
[Haltiwanger AR 2015: "Job Creation, Job Destruction, and Productivity Growth: The Role of Young Businesses", page 353]

Bill Nelson, chief economist and head of research at The Clearing House Association, said that the new capital and liquidity rules – and especially the Fed's stress testing program – have made it especially hard for the largest banks to make loans that run a risk of default under economic stress.
"The stress tests achieve their stress by assuming a very severe macroeconomic downturn," Nelson said. "By [definition] that is going to lead banks to substitute away from loans that are exposed to such downturns."
That has a particularly negative effect on the formation of small businesses, said Francisco Covas, senior vice president and deputy head of research at The Clearing House. While the dollar amounts to get small businesses off the ground are relatively small, they account for a disproportionate segment of job creation and economic growth, he said. "That really impacts the long-term dynamics of economic growth," Covas said. "These are regulatory changes that, even though the numbers on lending are not huge, they are potentially very important because they are important for economic growth."

Covas said small businesses are often started with home equity lines of credit or other non-commercial vehicles – areas of lending that the H.8 data shows have been contracting for years. Commercial lending rates may seem stable and healthy, he said, but that may only reflect the market for loans to well-qualified borrowers who don't need credit as badly.
"This is consistent with the narrative that, if you're a very safe borrower or a large corporation, it is very easy for you to get a loan – in fact there is a lot of competition because these borrowers have access to lots of nonbank sources," Covas said. "However, if you are perceived to be a riskier borrower ... it's very hard for you to get credit."
[American Banker: "Is regulation really keeping banks from lending?"]

Lyons at Debevoise & Plimpton said the criticism of banks' dividend payments and stock repurchases makes superficial sense, but banks are funded through shareholder investment. If one prefers to reduce a bank's volatility through higher capital, that is a rational choice to make, he said, but it comes at the expense of the economic activity that banks can facilitate.
"In my mind, it's a philosophical view. Do you want to let the banks do more lending to promote the economy, understanding that it could result in the banks being potentially more volatile, or do you want to ... have them have such high capital ratios that they can't promote the economy to the same degree, but they are arguably more stable?" Lyons said.
[American Banker: "Is regulation really keeping banks from lending?"]

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