

Under Regulatory Pressure: Bank Stress Tests and Housing Prices¹

Abstract

We show bank stress tests raise housing prices through *selective credit rationing*. Exploiting county-level stress-test-exposure variation across U.S. counties, we find regulatory pressure increases housing price growth by 1.3% (\$2,600 on median homes). The effect is 23% larger for lower-priced homes. Stress-tested banks disproportionately curtail lending to high-risk borrowers, leading to greater concentration of housing transactions by financially stronger borrowers and driving prices higher. Using loan-level data, we document high-risk borrowers face substantially reduced approval rates and loan amounts. Affected counties experience net outmigration of lower-income households, revealing an unintended consequence: while stress tests enhance financial stability, they may restrict homeownership access and exacerbate wealth inequality.

JEL: G18, G21, G28

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1. Introduction

Housing costs represent the largest expense for American households, consuming approximately 30% of household income (Adelino, Schoar, and Severino, 2018). This burden is even more pronounced for low-income families, whose housing costs surged by over 50% between 1996 and 2014, disproportionately straining their financial resources compared to higher-income households (Pew Research, 2018). Given that most U.S. families rely on mortgage loans to purchase homes, understanding the role of banks' credit supply in shaping local housing markets is critical. Yet a fundamental tension exists in macroprudential regulation: while stress tests aim to enhance financial stability by constraining bank risk-taking, their effects on credit allocation and real outcomes, particularly in local housing markets, remain imperfectly understood.

In this paper, we provide the first comprehensive evidence on how bank stress tests affect local housing prices through credit reallocation across borrower types. Specifically, we explore this dynamic by leveraging an exogenous shock to banks' lending practices: the annual stress tests imposed on large bank holding companies after the 2007-2008 global financial crisis. These stress tests, as recent research demonstrates, reveal valuable insights, subject banks to regulatory scrutiny, and influence their risk management strategies (Flannery, Hirtle, and Kovner, 2017; Acharya, Berger, and Roman, 2018; Calem, Correa, and Lee, 2020; Cortes et al., 2020). We investigate how a county's exposure to this regulatory pressure translates into shifts in local housing prices, uncovering a striking and counterintuitive result: regulatory pressure that constrains credit supply actually drives housing prices higher. This seemingly paradoxical finding challenges conventional wisdom about the relationship between credit supply and asset prices, and reveals an important distributional channel through which bank regulation affects household welfare.

The Global Financial Crisis was driven, in part, by excessive risk-taking in the banking sector, resulting in widespread distress and bank failures. In response, policymakers introduced a series of regulations aimed at fortifying the financial system’s resilience. Among these, the Federal Reserve launched the Supervisory Capital Assessment Program (SCAP) in 2009, which later evolved into the Comprehensive Capital Analysis and Review (CCAR) program — an annual stress test designed to evaluate the assets, liquidity, and capital structures of systemically important banks under severe hypothetical scenarios. Recent evidence documents that these tests significantly alter bank behavior. Acharya, Berger, and Roman (2018) highlight that stress-tested banks adjust their risk management by curbing credit supply via charging higher loan spreads. Similarly, Calem, Correa, and Lee (2020) find that the introduction of the annual CCAR in 2011 significantly slowed jumbo mortgage lending by participating banks. Cortes et al. (2020) observe that stress-tested banks reallocate credit away from riskier markets toward safer ones, particularly in small business lending. Berrospide and Edge (2024) further demonstrate that these stress tests lead to reductions in bank lending and moderate increases in loan rates and spreads. Despite this growing evidence on credit supply responses, how these regulatory-induced credit reallocations translate into local housing market outcomes remains an open question.

Building on this prior research, we propose the following three competing hypotheses about how bank stress tests influence local housing prices, each based on a distinct lending mechanism. These hypotheses are also summarized in Table 1.

- (i) *The credit exclusion hypothesis:* if stress-tested banks behave in a similar way in the mortgage lending market as described in Acharya, Berger, and Roman (2018) and Cortes et al. (2020), they are likely to shift credit supply away from high-risk borrowers, while the credit supply for low-risk borrowers remains unaffected. Since high-risk borrowers also face

limitations in substituting across lenders (Gete and Reher, 2018), many buyers with tighter budgets will be forced to exit the housing market. As a result, home purchases will become increasingly concentrated among financially stronger borrowers. According to the literature on housing transactions, there exist significant frictions in the housing market such as searching costs and information barrier, hence house transactions occur after time-consuming sequential search and bargaining, and do not reflect a frictionless highest-bidder allocation (see, e.g., Wheaton, 1990; Williams, 1995; Genesove and Han, 2012; Diaz and Jerez, 2013; Anenberg, 2016). As a result, housing prices reflect an average valuation by all potential buyers in the market. When the distribution of potential buyers shifts towards financially stronger households in an area, transaction prices become higher.²

- (ii) *The uniform credit tightening hypothesis*: if stress-tested banks cut credit supply to all mortgage applications equally across the spectrum of borrower risk levels, then a lower across-the-board credit supply results in less housing demand. We would expect the credit tightening to put a *downward* pressure on local housing prices. Similar channels have been documented in the literature studying the role of credit supply in determining real allocations and prices (see, e.g., Mian and Sufi, 2009; Favara and Imbs, 2015; Lucca, Nadauld, and Shen, 2019; Adelino et al., 2025).
- (iii) *The bank irrelevance hypothesis*: credit supply changes by stress-tested banks in the mortgage market might not matter if smaller non-stress-tested banks and non-bank

² The idea can be described with a simple exercise as follows. Suppose that for a given type of house, the fraction of high-risk buyers among all potential buyers is q , and the fraction of financially strong buyers is $(1 - q)$, and their valuations of the house are V_L and V_H , respectively, with $V_L < V_H$. Due to sequential searching and bargaining, houses are not sold in a frictionless market such as auctions, where all bidders bid at the same time and the strongest bidder wins. Hence the average sale price of a given type of house can be calculated as the average valuation of all potential buyers: $P = qV_L + (1 - q)V_H$. When some high-risk buyers are forced to exit the housing market, we have lower q , resulting higher P .

institutions pick up their market shares.³ In that case, overall credit supply received by potential home buyers remains the same, so exposure to stress test shocks should not affect overall credit supply or the local housing prices. This hypothesis hence predicts *no relation* between a county's exposure to bank stress test outcomes and its housing prices.

Distinguishing between these hypotheses is crucial for understanding both the intended and unintended consequences of macroprudential regulation. If stress tests merely trigger substitution toward non-tested lenders (hypothesis iii), their real effects are minimal. If they uniformly tighten credit (hypothesis ii), they may cool overheated housing markets but at the cost of reduced homeownership. However, if they selectively exclude marginal borrowers (hypothesis i), they generate significant distributional consequences, concentrating homeownership among the wealthy while displacing lower-income households, an outcome with important implications for wealth inequality and social mobility.

To distinguish between these competing mechanisms, we exploit rich cross-sectional and time-series variation in regulatory pressure. In Table 2, we present the list of stress-tested banks in each stress test after the financial crisis until 2020 and the release quarter of the outcomes. To test the competing hypotheses, we build a dataset of county-quarter observations from 2008Q1 to 2016Q2, which includes the growth rate of local housing prices from Zillow and lagged county-level bank stress test outcome variables, as well as a broad set of bank characteristics and county economic and demographic factors. The sample period was deliberately chosen to end in 2016Q2 to avoid contamination from the phased implementation of Basel III, which introduced capital

³ Berrospide and Edge (2024) find that stress-tested banks reduce lending to firms, but firms find other credit sources. Cortes et al. (2020) show that stress-tested banks reduce credit supply in small business lending in riskier markets, but overall credit origination does not decline in these markets, as local small banks grow their market shares. Connolly (2018) finds that the 2009 SCAR test leads to a reduction in stress-tested banks' share in the syndicated loan market and the reduction is offset by non-tested institutions. Lux and Green (2015) document the strong growth of nonbank mortgage lending since the adoption of the Dodd-Frank Act in 2010.

conservation buffers and G-SIB surcharges that could distort our analysis. Moreover, key capital measures derived from stress tests, such as Tier 1 capital data, are unavailable since 2017, further justifying our period selection.⁴ Our control variables include bank characteristics aggregated at the county level, along with regional demographic, economic, and political factors, also measured at the county-quarter level. Following Cortes, Demyanyk, Li, Loutskina, and Strahan (2020), we construct several stress test outcome variables that reflect the difference between banks' stressed capital ratios and their regulatory thresholds. Banks closer to failing the stress tests face heightened regulatory pressure to adjust their equity and loan portfolios, often restricting capital distributions in subsequent quarters. These stress test outcomes represent exogenous shocks to banks' lending practices, forming the basis for our treatment variables.

To capture county-level effects, we compute weighted averages of these stress test variables, weighted by banks' market shares within each county (henceforth, county-bank stress test variables) measured in 2008Q1. This approach introduces three dimensions of variation in treatment effects: (1) over time, different sets of banks are subject to stress tests, while non-stress-tested banks remain unaffected by regulatory pressure, (2) within the same stress test year, banks face varying levels of regulatory pressure depending on their specific stress test outcomes, and (3) counties experience differing levels of exposure to stress tests based on the market shares of tested banks in their regions before stress tests. Thus, our county-quarter data exhibits both time-series and cross-sectional variation in treatment effects, and the treatment itself is a continuous variable.

This granular variation allows us to identify the causal effect of regulatory pressure on housing prices while controlling for unobserved county characteristics, regional economic trends, and time-varying shocks through county and year-quarter fixed effects. For example, Figure 1

⁴ See similar sample choice in Bräuning and Fillat (2025) for the same reasons.

shows the treatment intensity within each county across the U.S. when we use the main stress test outcome variable *Tier1 Lev Dist*, which measures a bank's distance from a threshold of 4% for leverage ratio and is standardized within the sample. Panel A presents a snapshot of a single stress test - SCAP 2009, while Panel B depicts the average treatment intensity throughout the sample period including SCAP 2009, CCAR 2012, DFAST 2013, DFAST 2014, DFAST 2015, and DFAST 2016.

We analyze the relationship between lagged county-level stress outcome variables and local housing prices. One potential concern is that the observed relationship between lagged stress test treatment effects and local housing prices may reflect endogeneity arising from reverse causality or omitted variables. Nevertheless, we believe reverse causality is unlikely for three reasons. First, utilizing the county-quarter data can mostly rule out reverse causality. Since the treatment effect is constructed as a county-level weighted average of banks' stress test outcomes, it is implausible for one county's local housing price trend to simultaneously drive multiple banks' stress test outcomes. Second, stress test outcomes measure a bank holding company's potential loss in forward-looking and hypothetical adverse scenarios rather than current economic situations, local housing price trends thus should not affect banks' stress test outcomes. Third, the stress test outcomes of these large bank holding companies are driven by their entire loan portfolios nationwide, and aggregate residential real estate loans constitute only 10% of their loan portfolios, hence are unlikely to be the result of local housing price trends.⁵

Regarding omitted variables, when constructing county-bank stress test variables, we measure banks' market shares using the number of branches they operated in each county in 2008Q1, prior to the implementation of any stress tests, to avoid capturing contemporaneous trends

⁵ See the "Quarterly Trends for Consolidated U.S. Banking Organizations" by Federal Reserve Bank of New York.

that may drive both stress test outcomes and housing price growth. In addition, Jayaratne and Strahan (1996) show that the spatial distribution of bank branches primarily reflects historical deregulation patterns, rather than current regional economic dynamics.⁶ We also control for county-level bank characteristics (hereinafter, county-bank characteristics) and county demographic, economic, and political factors to address heterogeneity across counties. To further mitigate concerns that unobserved county characteristics or time trends might simultaneously drive variation in lagged treatment status and housing prices, we include county fixed effects and year-quarter fixed effects in all specifications.

Our empirical findings provide strong support for the credit exclusion hypothesis and decisively reject the alternative explanations. In the baseline results, we find that a statistically and economically significant positive relation between a county's exposure to regulatory pressure brought by bank stress tests and subsequent housing price growth measured as the natural logarithm of the price index ratio, representing continuously-compounded growth rates. Economically, we find that one standard deviation increase (0.125) in the county-bank stress test variable *Tier1 Lev Dist*, corresponds to an additional quarterly housing price increase of 0.33%, which is equivalent to an annual housing price growth rate of 1.3%. To put this magnitude in perspective, for a median-priced home valued at \$200,000, this represents an additional \$2,600 annual price appreciation attributable solely to stress test exposure. The results remain consistent when we use alternative stress test measures, alternative weights to construct county-bank stress test variables, and alternative housing price index data. This finding supports the credit exclusion hypothesis and rejects the uniform credit tightening hypothesis and the bank irrelevance

⁶ In robustness checks, we use three alternative weights based on the lagged market share of bank branches, mortgage provision, and deposit, and the results remain the same.

hypothesis. When we investigate different sizes of homes, we find the effect is strong across all types of homes, and especially pronounced for smaller homes, as smaller homes would have attracted a larger share of budget-constrained potential buyers who must withdraw from the housing market due to credit unavailability. Specifically, the effect on bottom-tier homes (5th-35th percentile) is 23% larger than on top-tier homes (65th-95th percentile), consistent with marginal buyers being disproportionately excluded from the lower end of the market.

To further strengthen identification, we restrict the sample to the period from 2008Q1 to 2011Q4 and examine the impact of the 2009 SCAP on housing prices using a difference-in-differences (DiD) framework. This window provides a clean setting for the DiD analysis, as the 2009 SCAP was not anticipated and the results of the subsequent stress test (CCAR 2012) were not released until 2012Q1. It is challenging to conduct the DiD analysis with the whole sample, as stress tests after SCAP 2009 lack well-defined pre-treatment periods, hence we focus on this sub-period. Panel A of Figure 1 illustrates the cross-county variation in treatment intensity across the U.S., highlighting the control counties, where no locally operating banks were subject to the stress test, and the treated counties, where at least one bank participated in the test. A temporal dynamic test validates the parallel trend assumption before the treatment, and the post-treatment effect on housing price growth is positively related to the magnitude of the treatment intensity among the treated counties. We continue to find results that counties with higher stress test shocks experience higher housing price growth, consistent with the baseline finding. Importantly, we find no evidence of differential pre-trends, and the treatment effect manifests within one year of the SCAP announcement, consistent with banks rapidly adjusting their lending standards in response to regulatory pressure.

Having established the positive relation between housing price growth and lagged stress test shocks, we then explore the underlying mechanism by analyzing credit supply at the mortgage application level, providing additional evidence in support of the credit exclusion hypothesis. Using data from the Home Mortgage Disclosure Act of 1975 (HMDA), which requires both banks and non-banks to report mortgage origination activity, we focus on conventional home purchase loans for principal dwellings. Using linear probability models which control for bank characteristics, loan applicants' characteristics, and interacting county-year and bank-county fixed effects, we estimate loan outcomes including approval, origination, and loan amounts. Our analysis reveals that riskier borrowers (i.e., those with lower incomes or higher debt-to-income ratios) experience significantly greater credit reductions from stress-tested banks. Their likelihood of loan approval and origination is much lower compared to less risky borrowers. Furthermore, loan amounts are notably smaller, particularly for borrowers with high debt-to-income ratios. Quantitatively, low-income borrowers face a 3.2 percentage point reduction in approval probability at stress-tested banks relative to high-income borrowers, while high debt-to-income borrowers receive loan amounts that are 4.8% smaller on average. This evidence strongly corroborates the credit exclusion hypothesis while rejecting the uniform credit tightening hypothesis.

We next analyze aggregate credit supply in county-specific mortgage markets using county-year observations from our sample period. If the bank irrelevance hypothesis holds, that is, if smaller non-stress-tested banks and non-bank institutions compensate for the market gap left by stress-tested banks, there should be no observed reduction in total loan approvals or originations in counties with greater exposure to stress test shocks. However, after controlling for county-bank characteristics, demographic, economic, and political factors, as well as county and year fixed

effects, our results show a significantly larger decrease (or, smaller increase) not only in the total loan amounts approved or originated by banks, but also in the overall loan supply from both banks and non-bank institutions, in areas with larger bank stress test shocks. This suggests that in these counties, the increase in market share by other lenders is insufficient to fully offset the decline in lending by stress-tested banks. This evidence clearly contradicts the bank irrelevance hypothesis. These findings align with Gete and Reher (2018), who document frictions in borrowers' ability to substitute across lenders, but extend their analysis by showing that even aggregate credit supply remains constrained when stress-tested banks dominate local markets.

We also examine the plausible consequence of credit exclusion of risky borrowers by stress-tested banks: if mortgage lending of stress-tested banks is concentrated among low-risk and/or high-income borrowers, the subsequent default rate on these mortgage loans should be lower. Hence we should observe lower aggregate default risk on residential loan portfolios in counties with larger stress test shocks. Using county-year data from the Consumer Financial Protection Bureau (CFPB), we show that counties with higher lagged stress test shocks indeed exhibit significantly lower delinquency rates. For instance, a one standard deviation increase in the bank-county stress test shock (0.125) leads to a 0.25% reduction in loans delinquent for over 30 days. Additionally, data from the Federal Reserve Economic Data (FRED), which tracks subprime mortgage borrowers across 2,595 counties, reveals a negative relationship between lagged county-bank stress test shocks and the percentage of subprime loan borrowers. These findings provide robust support for the credit exclusion hypothesis, while contradicting both the uniform credit tightening and bank irrelevance hypotheses. The improvement in loan portfolio quality suggests that while stress tests enhance financial stability by reducing banks' exposure to risky mortgages, this comes at the cost of excluding marginal borrowers from homeownership.

Additionally, we examine the relationship between county-level bank stress test shocks and inter-county migration patterns. We find that counties more exposed to regulatory pressure experience greater net population outflows. Using IRS tax filing data, we show that the percentage of low-income residents decreases, while average taxable income (measured by Adjusted Gross Income) rises following more intense stress test shocks. This indicates that population outflows are concentrated among lower-income households, likely driven by higher housing costs and limited access to credit for homeownership. These migration patterns reveal the broader spatial and distributional consequences of bank regulation, demonstrating that credit market interventions can fundamentally reshape the socioeconomic composition of communities.

This paper contributes to two key strands of literature. First, it advances the growing body of research on the real effects of bank stress tests implemented in the aftermath of the global financial crisis. A closely related study by Gete and Reher (2018) finds that contractions in mortgage supply due to stress tests drive up local housing rents between 2010 and 2014, as households excluded from credit markets shift to renting. While their focus is on rental costs, our paper broadens this perspective by examining housing price dynamics and how regulatory pressure creates exogenous shocks to mortgage credit, coupled with lending frictions. Importantly, we document that the effects extend beyond rental markets to fundamentally alter homeownership patterns and housing prices, with first-order implications for wealth accumulation and intergenerational mobility.

By introducing housing price effects into the stress test literature, we offer new insights into how these regulatory tools reshape local real estate markets, not just rental markets. Other studies have explored similar credit contractions, such as Bordo, Cole, and Duca (2019), who document stress test-induced credit tightening for small firms, and Doerr (2021), who shows negative effects

on entrepreneurship and innovation as stress-tested banks reduce home equity-backed small business loans. Agarwal, An, Cordell, and Roman (2024) further demonstrate the feedback loop between credit supply, credit usage, and performance in consumer credit markets. Our contribution is to comprehensively map out the transmission channel from regulatory pressure to credit reallocation to housing market outcomes to demographic shifts, providing a unified framework for understanding the real effects of macroprudential regulation.

Second, our work contributes to the literature on financial access disparities across wealth levels. Previous research has shown that banks are less likely to operate in low-income areas and offer inferior services when they do (Goodstein and Rhine, 2017; Célerier and Matray, 2019; Begley and Purnanandam, 2021). Our findings complement this by highlighting that low-income households, even in higher-income neighborhoods, face heightened financial exclusion risks during periods of credit contraction, which can force relocations due to reduced access to homeownership. More broadly, our results speak to the unintended distributional consequences of well-intentioned regulations: while stress tests successfully enhance financial stability, they may inadvertently exacerbate wealth inequality by concentrating homeownership, the primary vehicle of wealth building for American families among the already affluent.

The rest of the paper is organized as follows. Section 2 describes the institutional background and history of the bank stress tests. Section 3 details the sample and variable construction. Section 4 presents empirical evidence of the relation between lagged county-bank stress test shocks and local housing price changes, the underlying mechanism, and the consequent inter-county migration. Section 5 concludes.

2. Institutional Background on Bank Stress Tests

Stress testing is a simulation exercise in which bankers and regulators test how the bank would perform under severely adverse conditions. In the United States, stress tests are only applied to large banks. The CCAR and DFAST programs, started in 2011 and discussed further below, were first applied to BHCs with consolidated assets exceeding \$50 billion and the intermediate holding companies (IHCs) of foreign banks. The 2018 Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA) modified this criterion for DFAST, providing relief for banks with assets less than \$100 billion in assets (Agarwal, et al., 2024). In part, for these institutions, capital requirements are determined by the results of these stress tests. For stress-tested banks, this additional capital buffer (a minimum of 2.5%), called the Stress Capital Buffer, replaces the capital conservation buffer we describe above.

After the Global Financial Crisis, bank stress tests have become a routine procedure in the U.S. banking system. The sweeping post-crisis regulatory change starts from 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act mandated stress testing. Since then, stress testing has evolved over time, beginning first with the Supervisory Capital Assessment Program (SCAP). Following this, in 2011, the stress testing process moved to a combination of the Comprehensive Capital Analysis and Review (CCAR) and the Dodd-Frank Act Stress Tests (DFAST). CCAR was originally a qualitative and quantitative assessment, of which the results were publicly reported. This assessment checked whether institutions had enough capital to withstand times of economic and financial stress. The qualitative portion examined whether banks had a forward-looking capital planning process that could account for the unique risks faced by each bank. In 2019, the qualitative assessment became a confidential, supervisory process, and in 2020, the quantitative process was replaced with the stress capital buffer mentioned above. Another change came in 2018, when the aforementioned Economic Growth, Regulatory Relief, and Consumer Protection Act was

signed into law. This act reduced both the frequency of stress testing and the number of stress scenarios required for smaller banks.

The DFAST component remains a stress test in which banks simulate the impact of worst-case scenarios on their business. Each year, the Federal Reserve presents at least two different stress scenarios for banks to consider. For example, in 2023, stress tests simulated a severe global recession with stress in commercial and residential real estate markets, as well as corporate debt markets. Moreover, within this scenario, the unemployment rate will rise by a simulated 6.5%, peaking at 10%. In addition to this hypothetical test, banks with large trading operations were tested against a global shock to financial markets that stresses their primary trading positions.

Overall, stress testing has become an important tool for regulators in achieving their goal of financial stability. Through simulated stress scenarios, banks and regulators can have a better understanding of how a bank would perform in a critically severe scenario, and plan accordingly. Of course, it is important to recognize that in addition to bank managers accurately simulating outcomes related to the stress events, it is imperative for regulators to pick plausible and realistic scenarios that are reflective of severe events that could potentially occur given the current economic climate. If executed properly, stress testing can reveal simulated weaknesses in the banking system before they become apparent during times of actual stress.⁷

3. Sample and Variable Construction

Our main sample is based on county-quarter observations from 2008Q1 to 2016Q2, and we compile data from several datasets to construct variables for housing price changes, bank stress

⁷ For more on bank regulations and how these regulations impact bank risk management, see Pagano and Sedunov (2025).

test outcomes, bank characteristics, county economic and demographic factors. Within a county, we calculate weighted averages of all bank-related variables including stress test outcomes and bank characteristics to measure the outcome of stress tests and characteristics of the banks on the county level. We also collect annual inter-county migration data from IRS. Details of variable and sample construction are as follows and summary statistics are provided in Table 3.

3.1 Housing price changes

We construct several measures capturing the change of housing prices in a county. We study the change (growth rate) of housing price, rather than the level of housing price, because the level of housing prices is not stationary, as shocks to housing price are likely to be persistent. We include both county and year-quarter fixed effects to account for heterogeneity across counties and time trends in the housing market. The main dependent variable is calculated using the county-level Zillow Home Value Index (ZHVI) provided by Zillow Group Inc., a real estate company that offers online house listing for sales and rentals and tracks housing transactions.⁸ This is a smoothed and seasonally-adjusted measure that reflects the typical home value including single family houses and condos for homes in the 35th to 65th percentile range within a county. We take the Zillow quarterly housing price index and calculate the housing price change in each county. Specifically, *Zillow Prc Chg 1Q* is equal to the natural logarithm of the housing index level in the current quarter divided by that in the last quarter. *Zillow Prc Chg 4Q* is the natural logarithm of the index level in the current quarter divided by that in the same quarter of last year. *Zillow Perc Prc Chg 1Q* is the percentage change of the housing index level from last quarter to the current quarter. All logarithmic transformations use natural logarithms (ln, base e), which measure continuously

⁸ The data and the details on the construction of the data are available at: <https://www.zillow.com/research/data/>.

compounded growth rates and are standard in empirical asset pricing and housing economics literature.⁹

We also use an alternative data source for housing prices: the Federal Housing Finance Agency House Price Index (FHFA HPI) at the county level with the annual frequency. FHFA HPI captures changes in single-family home values based on house price transaction data with a weighted, repeat-sale statistical technique (Bogin, Doerner, and Larson, 2019).¹⁰ We compute *FHFA Prc Chg Ann* as the natural logarithm of the index level in the current year divided by that in last year. In the baseline test and most of the analysis, we use *Zillow Prc Chg 1Q* as the main measure for housing price change with a county. We provide tabulated results using the other three measures as a robustness check. All regressions based on Zillow data use county-quarter observations and the regression based on FHFA data use county-year observations.

Panel A of Table 3 presents the summary statistics of house price changes. The average quarterly housing price change *Zillow Prc Chg 1Q* is 0.001 with a standard deviation of 0.016, while the average annual price change *Zillow Prc Chg 4Q* is 0.002 with a standard deviation of 0.054. The average *Zillow Perc Prc Chg 1Q* and *FHFA Prc Chg Ann* are 0 and -0.001, respectively. Note that there is a smaller number of observations for *FHFA Prc Chg Ann* because it is of annual frequency, while other three housing price change variables based on Zillow data are quarterly.

⁹ Throughout this paper, we use natural logarithms ($\ln$, base $e \approx 2.71828$) to measure growth rates, which is standard practice in finance and economics for calculating continuously compounded rates of return. For example, suppose in quarter $t-4$, $t-1$, and t , the index levels are 100, 105, and 110, respectively. Then our measures are calculated as follows: *Zillow Prc Chg 1Q* = $\ln(110/105) \approx 0.0465$; *Zillow Prc Chg 4Q* = $\ln(110/100) \approx 0.0953$; *Zillow Perc Prc Chg 1Q* = $(110-105)/105 = 0.0476$. The natural logarithm and simple percentage change are approximately equal for small changes ($0.0465 \approx 0.0476$), which is why both measures yield similar results. We use $\ln(\cdot)$ notation throughout to explicitly denote natural logarithms, though when we write "log" in the text or variable descriptions, this always refers to the natural logarithm, following standard economics and finance convention. The continuously compounded growth rates from natural logs have desirable properties for time-series analysis, including time-consistency and additivity across periods.

¹⁰ More information on the FHFA HPI data can be found at: <https://www.fhfa.gov/data/hpi>.

3.2 Banks' stress test exposures and bank characteristics

Stress test variables are constructed using the Federal Reserve confidential stress test data. Primarily, we follow Cortes, Demyanyk, Li, Loutskina, and Strahan (2020) and create measures of stress-test exposure that estimate the decline in bank capital in the Fed's "severely adverse stress-test scenario". We construct all variables so that higher values indicate greater perceived risk under stress scenarios, which allows for consistent interpretation.

For stress test outcome variables, we start with the ones based on *Tier 1 Equity* and *Tier 1 Capital*, and represent the difference/distance between the stressed capital ratios and their regulatory thresholds: 4% for the leverage ratio, 6% for the capital ratio.¹¹ *Tier1 Lev Dist* captures a bank's distance from the threshold of 4% for leverage ratio, and is equal to $4\% - \frac{\text{Tier 1 Equity}}{\text{Assets}}$.¹² As *Tier1 Lev Dist* increases, it signals that the average bank in a county has a larger distance from its current leverage ratio to the required threshold in projected stress scenarios. We use *Tier1 Lev Dist* as our main stress test outcome variable. Similarly, *Tier1 Cap Dist* reflects the distance of the bank's capital ratio from the threshold of 6%, which is calculated as $6\% - \frac{\text{Tier 1 Capital}}{\text{Risk-Weighted Assets}}$. One main difference between these two ratios is in their denominators, as the leverage ratio includes the bank's total assets, and the Tier 1 capital ratio includes risk-weighted assets. While both ratios are aimed at ensuring that banks have a sufficient amount of capital to provide a buffer against large and unexpected losses, the latter accounts for the relative risk of the various assets

¹¹ *Tier 1 Equity*, also called *Common Equity Tier 1* (CET1), is a bank's core equity capital that includes liquid assets like cash and stock, as well as ordinary shares and retained earnings. It's considered the bank's strongest form of capital and is used to fund business activities for clients. In the event of a crisis, equity is taken first from Tier 1. *Tier 1 Capital* refers to the core capital held in a bank's reserves and is used to fund business activities for the bank's clients. It includes common stock, as well as disclosed reserves and certain other assets.

¹² We emphasize leverage-based measures (*Tier1 Lev Dist*) alongside risk-weighted measures because Acharya, Engle, and Pierret (2014) demonstrate that leverage ratios better capture systemic risk and are more difficult for banks to manipulate through portfolio reweighting. For our purposes, this implies that leverage-based regulatory pressure should generate stronger credit reallocation effects."

on the bank's balance sheet, while the former ensures that banks cannot simply load up on low-risk assets in order to build up a large amount of leverage, thus reducing the bank's distance to default to exceptionally low levels.

Two other stress test variables that we consider are *Tier1 Lev Exp* and *Tier1 Cap Exp*. *Tier1 Lev Exp* (*Tier1 Cap Exp*) is the difference between the bank holding company's initial Tier 1 leverage ratio (Tier 1 capital ratio) and the lowest implied Tier 1 leverage ratio (Tier 1 capital ratio) expected under the severely adverse stress-test scenario. We also construct a dummy variable indicating whether a bank is stress tested. The county-level variable *Stress Tested* is then a weighted average of this dummy variable across all banks operating in a given county-quarter. For the sake of brevity, we use *Tier1 Lev Dist*, *Tier1 Lev Exp*, and *Stress Tested* in the baseline regression. As a measure of the regulatory pressure experienced by a county from bank stress tests, *Stress Tested* assumes that all stress-tested banks experience this pressure equally regardless of their balance sheet conditions. In contrast, *Tier1 Lev Dist* and *Tier1 Lev Exp* consider the actual outcomes of the stress tests and assign less regulatory pressure to better-capitalized banks.

In robustness checks, we use *Tier 1 Capital* and *Tier1 Cap Exp*, and five additional stress test measures: *Total Cap Dist*, *Min Stress Dist*, *Total Cap Exp*, *Tier1 Equity Exp*, and *Max Stress Exp*. *Total Cap Dist* measures the distance of the bank's total risk-based capital to its regulatory thresholds of 8%. *Min Stress Dist* combines all three capital ratios' distance from their respective threshold and chooses the most binding one, calculated as *Min (Tier1 Lev Dist, Tier1 Cap Dist, Total Cap Dist)*. *Total Cap Exp* (*Tier1 Equity Exp*) is the difference between the bank's initial total capital ratio (Tier 1 equity ratio) and the lowest implied capital ratio (Tier 1 equity ratio) expected under the severely adverse stress-test scenario. Similar to *Min Stress Dist*, *Max Stress Exp*

incorporate all stress test exposure variables and is the maximum of them, calculated as $Max(Tier1 Lev Exp, Tier1 Cap Exp, Total Cap Exp)$.

As sample observations are at the county-quarter level, we calculate county-bank stress test variables as the weighted average of stress test variables of all banks present in each county-quarter. We consider four different weights, each intended to capture the business share of a particular bank in the credit market within a county. In the baseline analysis, we calculate bank i 's business share as the number of bank i 's branches divided by the total number of all bank branches measured in 2008Q1. We choose this as the main weighting scheme, because its value is determined before any bank stress tests are conducted, and the distribution of bank branches crucially determines credit access and is largely exogenous (Jayaratne and Strahan, 1996). Alternatively, we construct three other measures of business shares: the first is still the bank branch share but lagged by one year relative to the year when the housing price growth is measured; the second is based on a bank's annual dollar value of owner-occupied conventional mortgage loans for home purchases divided by the annual county-wide total amount of such loans in HMDA data, lagged by one year; the third is based on a bank's annual dollar value of deposits divided by the annual county-wide total dollar amount of bank deposits, also lagged by one year. To avoid showing repetitive results, we only use these three weights in the robustness checks. In all following analysis except the section on mortgage loan applications, stress test variables always refer to county-bank stress test variables: the county-level weighted average of individual bank holding company's stress test variables in each county-quarter.

Since our samples contain county-quarter observations where no banks undergo stress tests, and the raw stress test outcome variables can take both positive and negative values, we cannot assign the value of zero to stress test outcomes (the treatment variables) for non-stress-tested

banks. To solve this problem, we normalize all the original values of bank-level stress test variables to be in the range of $[0, 1]$ and then assign the value of zero to non-tested banks. Since larger values of stress test variables imply higher perceived risk, a value of zero for a stress-tested bank implies no regulatory pressure. Similarly, non-tested banks with zero values for their stress test variables face no regulatory pressure either. Normalization of all stress test variables also facilitates the comparison of coefficient estimates across different variables. Panel B of Table 3 presents the distribution statistics of county-bank stress test variables. Note that the maximum value of these stress test variables is not equal to one, because normalization occurs at the bank level, and these are the weighted averages at the county-quarter level. Even though these are weighted averages of the original stress test variables, there is still a large variation in the sample. For example, *Tier1 Lev Dist* has a mean of 0.105 and standard deviation of 0.125. What also stands out is the large skewness of these variables, as the median values are close to zero. This is mostly because a significant fraction of county-quarter observations faces no regulatory pressure either because no banks undergo the stress tests or stress-tested banks account for a small business share in the county and their stress test outcomes present minimal stress risk.

We include a host of bank characteristics as control variables to account for bank conditions, other regulations, and other factors that could impact local housing markets beyond bank stress tests. *Bank Age* is the oldest age of all banks in the bank holding company (BHC). *No FRS District* is a regulatory dummy indicating the Federal Reserve district of the BHC, which accounts for regional economic conditions and possible differences across individual Reserve Banks in the administration of stress tests. *Cap Ratio* is calculated as the ratio of total bank capital to bank gross total assets. *Asset Quality* is the ratio of nonperforming loans to total bank loans. *Overhead Costs* is the ratio of overhead costs to bank gross total assets. *ROA* is the bank's return on assets. *Liquidity*

Ratio is the ratio of liquid assets to bank gross total assets. *Market Risk Sensitivity* is measured by the ratio of the absolute difference between short-term assets and short-term liabilities to the bank gross total assets. *Bank Size* is the natural logarithm of the bank's gross total assets. *Loan to Asset Ratio* is the bank's total loans divided by the bank's gross total assets. *Asset Diversity* is a measure of bank diversification across different asset groups and is calculated as $1 - |(\text{Net Loans} - \text{Other Operating Assets})/(\text{Total Earning Assets})|$ as per Laeven and Levine (2007). The bank-level control variables are then aggregated to county-level controls, in the same fashion as we calculate county-level stress test variables. Since bank characteristics are non-missing even when the banks are not stress tested, we do not normalize them at the bank level before calculating the weighted average.

Table 3 continues to show the distribution of the county-level weighted bank characteristics in Panel C. The average county-level bank age is 77 years. The median county's banks have a *Cap Ratio* of 8.4%, and a value at the 25th percentile of 7%, indicating that most banks are well-capitalized in general, regulatory ratios notwithstanding. Moreover, the median county's bank *Liquidity Ratio* is 21% with a standard deviation of 8.5%. This also indicates that the majority of banks are in a stable position. Consistent with *Cap Ratio* and *Liquidity Ratio*, the median county's *Loan to Asset Ratio* is 50%. This ratio measures the value of a bank's loan portfolio relative to its gross total assets, and our summary statistics indicate that the banks in our sample are generally focused on the traditional banking services related to liquidity creation (Berger and Bouwman, 2009).

3.3 County demographic, economic, and political factors

Since the main dependent variable of the study is the county-level housing price growth rate, and it is closely related to demographic and economic factors in the area, we include the following

controls at the county-year level: the natural logarithm of population density equal to the number of residents per square mile, *Population Dens*; the natural logarithm of per capita income, *Per Capita Income*; the Gini Index measuring income inequality, *Gini Index*; the percentage of females, *Female Perc*; the percentage of non-white minorities, *Minority Perc*; the percentage of population with the age of 65 or older, *Age65 Perc*; the percentage of the population with high school or lower levels of education experience, *Low Edu Perc*; the unemployment rate, *Unemployment*; the percentage of the population that voted for the Democratic party candidate in the most recent presidential election, *Dem Vote*; the one-quarter-lagged HHI index measuring the competition level among banks within the county, *Bank HHI*; and the one-year-lagged business share of non-bank financial institutions in the mortgage market, *Nonbank Share*. Note that all the county-level control variables are of annual frequency, and we transform them into quarterly data by assigning the same value to the four quarters in the same year.

We present summary statistics for these variables in Panel D of Table 3. The median natural logarithm of population density is equal to 4 with a standard deviation of 1.5, which translates to around 57 residents per square mile on average. The median natural logarithm of per capita income is 10, which implies a median annual income of \$22,026.¹³ The average county exhibits moderate income inequality as the Gini index is 0.43. Based on the median values, 50.6% of the population are female, 10.3% of the population are minorities, and 15.1% of the population are age 65 or older. In terms of education level, 51.7% of the population do not have a degree higher than a high school education. In the median county, the unemployment rate is 7.7%. Turning to political choices, the median share of voters voting for a Democrat in the most recent presidential elections

¹³ We focus on the median value of these two log variables since the mean of the log value is not the same as the log value of the mean.

is 40.4% and the 75 percentile is 49.7%. Though our sample would reference voting data from both the 2008 and 2012 elections when the Democratic candidate Barack Obama won both elections, the distribution of *Dem Vote* reflects the fact that most counties in the U.S. are in rural areas, whereas Democratic voters tend to be clustered more in urban areas.

3.4 Mortgage application evidence

We investigate the underlying mechanism of our main results by analyzing credit supply directly at the mortgage application level. Specifically, we analyze the effects of bank-level stress tests regulatory pressure on household lending activity, namely mortgage loan approvals, originations, and loan amounts. To conduct these tests, we use the public loan-level Home Mortgage Disclosure Act data, which represents approximately 90% of mortgage lending in the US. The Home Mortgage Disclosure Act (HMDA) of 1975 requires all institutions including both banks and nonbanks to disclose mortgage origination activity at the application level. The frequency of the public data is annual. We match bank stress test information and Call Report bank data with the HMDA mortgage application data using the lender file developed by Robert Avery. We follow the prior literature to filter the mortgage applications data by excluding: (1) loans insured by government agencies (i.e., FHA, VA, FAS, or RHS), (2) refinancing and home improvement loans, (3) loans neither approved nor rejected, (4) loans to finance non-owner-occupied units, and (5) loans sold by the lender upon origination to another party. After these filters, our final dataset contains information on 1,976,107 loan applications for households.

The data contains information on the requested loan size, loan purpose, property type, and application status, as well as loan applicant characteristics including self-reported income, gender, and race information. To investigate whether stress-tested banks indeed reallocate credit supply pulling away from risky borrowers, we focus on the outcome of the loan and the granted loan

amount. We create the dummy variables *Approved* and *Originated* to indicate whether the loan is approved or originated. The third dependent variable is *Loan Amount*, calculated as the natural logarithm of the loan amount in the application. For the key explanatory variable is the dummy variable *Low Income (High Debt to Income)*, which is equal to one if the loan applicant's income is below (the loan applicant's debt to income ratio is above) the median of the sample. Both variables are intended to capture the higher risk of the loan borrower compared to others.

We present summary statistics for these variables in Panel E of Table 3. The mean approval rate for mortgage application is 84.3% with a standard deviation of 0.364, while the mean origination rate is 83.6% with a standard deviation of 0.371. The median natural logarithm of loan amount of the average loan originated is 5.425, which implies a median dollar loan amount of \$227,000.

3.5 Migration across counties

A related question to the relation between housing price and stress test variables is whether the stress test variables can impact migration patterns among counties. Housing expenses normally account for the largest share of living costs. We hypothesize that the effect of stress tests on local housing markets can manifest in the county-level migration data. We collect county-level annual outflow and inflow migration data from the IRS.¹⁴ The Statistics of Income (SOI) calculate population inflows and outflows using address changes reported in tax filings every year. We construct three variables to capture the population migration pattern among counties. For each county, we consider the total number of people moving out of it, the total number of people moving in, and the net out that is the moving out number minus the moving in number, scaled by the total number of tax filings of the county or the total population of the county in the year. Specifically,

¹⁴ The data is available at <https://www.irs.gov/statistics/soi-tax-stats-migration-data>.

Net Out1 (Out1, In1) is equal to the natural logarithm of one plus the net number of out-movers (the total number of out-mover, the total number of in-movers) divided by the total number of tax filings of the county. Specifically, *Net Out2 (Out2, In2)* is equal to the natural logarithm of one plus the net number of out-movers (the total number of out-mover, the total number of in-movers) divided by the total number of populations of the county. Panel F of Table 3 provides summary statistics of migration variables. Both measures of migration scaled by the number of tax filings and the size of population show a similar pattern: the average outflow is slightly higher than the average inflow, which results in a marginally positive net flow. *Out1 (Out2)* has a mean of 0.192 (0.184) and *In1 (In2)* has a mean of 0.185 (0.177).

4. Empirical analysis

4.1 County-bank stress test shocks and local housing prices

4.1.1 The baseline regression

In our baseline test, we regress the quarterly growth in the Zillow Home Value Index *Zillow Prc Chg 1Q*¹⁵ on county-bank stress test variables, controlling for county-bank characteristics, county demographic, economic, and political factors, with county fixed effects and year-quarter fixed effects. The OLS regression equation is as follows,

$$\begin{aligned} Zillow\ Prc\ Chg\ 1Q_{c,t} = & \alpha_c + \alpha_t + \beta_1 \times County\ Bank\ Stress\ Test_{c,t-1} \\ & + \gamma_1 \times County\ Bank\ Characteristics_{c,t-1} + \gamma_2 \times County\ Controls_{c,t-1} + \varepsilon_{c,t}, \end{aligned} \quad (1)$$

where *County Bank Stress Test*_{c,t-1} represents lagged county-bank stress test variables including *Tier1 Lev Dist*, *Tier1 Lev Exp*, and *Stress Tested*. Higher values of these variables

¹⁵ Following standard practice in empirical housing economics (e.g., Favara and Imbs, 2015; Adelino et al., 2025), we measure housing price growth using natural logarithms of price index ratios.

indicate higher stress risk and more regulatory pressure from the stress tests experienced by a county in a given quarter. Banks are more likely to suffer from regulatory sanctions, including caps on growth, limits on dividends, or other consequences, and they have more incentive to adjust their loan portfolios and change their lending practice. *County Bank Characteristics* $_{c,t-1}$ is a vector of lagged county-bank characteristics, which are weighted average values of bank characteristics described in Section 3.2. *County Controls* $_{c,t-1}$ is a vector of county demographic, economic, and political factors described in Section 3.3. α_c and α_t are the county and year-quarter fixed effects, respectively. Alternatively, we also run the regression with county fixed effects and state-year interacted fixed effects.

Table 4 presents the regression results. The stress test variable is *Tier1 Lev Dist* in columns (1) and (2), *Tier1 Lev Exp* in columns (3) and (4), and *Stress Tested* in columns (5) and (6). Columns (1), (3), and (5) include county and quarter fixed effects while columns (2), (4), and (6) include county and state-year fixed effects. Regardless of what stress test variable or set of fixed effects we include, we find a positive and highly statistically significant relation between bank stress test risk and housing prices: *t*-stats range from 2.5 to 12. The economic magnitude is also large. Taking the coefficient on *Tier1 Lev Dist* in column (1) that is equal to 0.026, we estimate that a one standard deviation increase in stress test risk (0.125 for *Tier1 Lev Dist*) relates to an increase in the quarterly housing price growth of 0.325%, which translates to an annual housing price growth rate of 1.3%. Coefficient estimates across all specifications in the table are of similar magnitude, suggesting that the positive relation between lagged county-bank stress test variables and housing price growth is stable regardless the exact measure of the stress test shock. Note that the results continue to hold even when we use *Stress Tested*, suggesting that a stress test itself can cause regulatory pressure on a bank regardless of its actual test outcomes. The results in Table 4

also show reasonable coefficient estimates for the control variables. The housing price growth rate is higher when per capita income is lower, the Gini index is higher, the nonbank mortgage share is higher, and in more democratic area.

4.1.2 Robustness: alternative bank weights, stress test variables, and housing prices

Next, we run robustness analysis to show that the baseline findings do not hinge on a particular choice of measures for bank-stress test variables or housing prices. We start with alternative weights to construct the county-bank stress test variables. Instead of using the number of bank branches in 2008Q1 to calculate the market share of each bank in the baseline, we use the lagged branch share, bank deposit share or mortgage share. Panel A of Table 5 reports the results. Column (1) to (3) show the regression results when the lagged bank branch share is used as the weight; column (4) to (6) use the lagged bank deposit share, and column (7) to (9) use the lagged mortgage share of each bank as the weight. The coefficient estimates on all three main stress test variables remain economically and statistically significant with the alternative weights, and coefficient magnitudes are comparable to the baseline result.

Panel B of Table 5 reports results for an expanded set of county-bank stress test risk variables: *Tier1 Cap Dist*, *Tier1 Cap Exp*, *Total Cap Dist*, *Min Stress Dist*, *Total Cap Exp*, *Tier1 Equity Exp*, and *Max Stress Exp*, as described in Section 3.2. We continue to find a statistically and economically large positive impact of the alternative county-bank stress test variables on the local housing price growth rate. For example, considering the coefficient estimate on *Tier1 Cap Dist*, one standard deviation increase in it is associated with a quarterly housing price growth rate of 0.22% ($= 0.144 \times 0.015$), or an annual housing price growth rate of 0.9%.

In Section 3.1, we described four measures for housing price growth rate: *Zillow Prc Chg 1Q*, *Zillow Prc Chg 4Q*, *Zillow Perc Prc Chg 1Q*, and *FHFA Prc Chg Ann*. The first three measures

are based on data provided by Zillow Inc. and are of quarterly frequency, and the last measure is based on FHFA data and of annual frequency. The baseline regression uses *Zillow Prc Chg 1Q*, and we repeat the regression using the other three measures. County fixed effects and year-quarter (year) fixed effects are included in regression with measures based on Zillow (FHFA) data. The results are shown in Table 6. We continue to find the positive and significant effect of county-bank stress test variables on local housing price growth. Take the results from column (7) of Table 5, one standard deviation increase in *Tier1 Lev Dist* (0.125) is associated with the annual FHFA housing price index growth rate of 1.1% ($= 0.125 \times 0.087$), which is very close in magnitude to the baseline result in Table 4, where one standard deviation increase in *Tier1 Lev Dist* is related to an annual housing price growth rate of 1.3%.

4.1.3 Housing prices of different types of houses

As illustrated in the Introduction, the credit exclusion hypothesis predicts a positive relationship between county-level stress test shocks and local housing price growth, because budget-constrained high-risk buyers are forced out of the housing market due to reduced credit availability. Hence this relation should hold across all types of houses. However, the effect of stress tests should be particularly pronounced for lower-priced smaller homes, which would have attracted a larger share of budget-constrained and low-income potential buyers, while on the other hand, luxurious homes have a smaller share of high-risk buyers in the first place. In this section, we use Zillow Home Value Index (ZHVI) for different segments of the housing markets, in our sample period of 2008Q1-2016Q4, to calculate the quarterly housing price change *Zillow Prc Chg 1Q* and study the impact of stress tests on these segments separately.

First, we construct *Zillow Prc Chg 1Q* using the housing time series of ZHVI Bottom Tier and ZHVI Top Tier for each county. ZHVI Bottom Tier housing index measures the typical value

for homes within the 5th to 35th percentile range for a given region, while the Top Tier index measures the typical value for homes within the 65th to 95th percentile range. We repeat the baseline regression with these two samples, respectively. The results are shown in Column (1) and (2) of Table 7. We continue to find a significant and positive impact of county-level stress test shock on local housing prices, and the magnitude of the effect is very similar to the baseline estimate shown in Table 4. Furthermore, when we compare the coefficient estimate on *Tier1 Lev Dist* in the Bottom Tier sample to the Top Tier sample, there is a larger impact in the Bottom Tier than the Top Tier (0.032 vs. 0.026), which is statistically significant with a t -stat of 1.66.

Next, we use the time series of ZHVI one-bedroom, two-bedroom, three-bedroom, four-bedroom, and five-bedroom housing prices and run the baseline regression and present the results in Column (3) to (7) in Table 7.¹⁶ Again, we find that stress test shocks drive up housing prices across all these types of homes. And the coefficient estimate on *Tier1 Lev Dist* is monotonically declining as the homes become larger or more upscale (0.036 for one-bedroom homes and 0.026 for five-bedroom homes), and the difference in coefficient magnitude is significant at the 5% level.

4.1.4 DiD analysis for SCAP 2009

As discussed in the Introduction, the main findings reported in Table 4 are unlikely to be driven by reverse causality. With county and year–quarter fixed effects included, omitted variable bias is also an unlikely explanation. Nevertheless, in this section, we further strengthen identification by focusing on the first regulatory stress test, the 2009 SCAP. The ideal strategy for identifying treatment effects is to conduct a dynamic test around the treatment period to rule out confounding pre-treatment trends. However, given the near-annual frequency of subsequent stress tests, as

¹⁶ Due to the limitation of data availability from Zillow, the number of observations vary among the regression samples.

summarized in Table 2, it is difficult to implement such an analysis using the full sample because later stress tests lack a clearly defined pre-treatment window. Another advantage of using SCAP 2009 is that it is entirely unexpected by the banks, eliminating concern about any anticipatory effect. As the next stress test does not occur until 2012, we restrict our analysis to the subperiod from 2008Q1 to 2011Q4. The Fed released the SCAP results in 2009Q2, which we designate as the event quarter for this period.

We first run a temporal dynamic test, specified as the following,

$$\begin{aligned} Zillow\ Prc\ Chg\ 1Q_{c,t} = & \alpha_c + \alpha_t + \beta^{-5} \times Before_{c,t}^5 + \beta^{-4} \times Before_{c,t}^4 + \beta^{-3} \times \\ & Before_{c,t}^3 + \beta^{-2} \times Before_{c,t}^2 + \beta^{-1} \times Before_{c,t}^1 + \beta^1 \times After_{c,t}^1 + \beta^2 \times After_{c,t}^2 + \beta^3 \times \\ & After_{c,t}^3 + \beta^4 \times After_{c,t}^4 + \beta^{\geq 5} \times After_{c,t}^{\geq 5} + \gamma_1 \times County\ Bank\ Characteristics_{c,t-1} + \gamma_2 \times \\ & County\ Controls_{c,t-1} + \varepsilon_{c,t}, \end{aligned} \quad (2)$$

where $Before^k$ is a dummy variable that takes the value of one if the county has positive stress test shocks measured by *Tier1 Lev Dist* (treated counties) in SCAP 2009 and the quarter t is k quarters before the event quarter of 2009Q2, and $After^k$ is a dummy variable indicating a treated county and the quarter t is k quarters after 2009Q2. For example, $Before^5$ is equal to one for a treated county in the quarter of 2008Q1 but zero in all other quarters, as 2008Q1 is five quarters before 2009Q2. For counties without any banks undergoing SCAP 2009, these ten $Treated \times Event\ Quarter$ dummies will always take the value of zero, as these counties serve as controls. Figure 2 plots the coefficient estimates β of the ten dummies and their 95% confidence intervals. Panel A estimates the full sample comparing all treated counties with control counties. It shows clearly that none of the coefficients in the pre-treatment periods are significantly different from zero, indicating no pre-treatment differences among the control and treated counties in house

price trends. In contrast, all the post-treatment effects are statistically positive, and the largest treatment effect manifested within a year after SCAP 2009.

In Panel B, we divide the treated counties into three tercile groups sorted by the treatment intensity *Tier1 Lev Dist*: the low tercile, mid tercile, and high tercile group. Intuitively, treated counties in the high tercile (low tercile) group experience the highest (lowest) amount of regulatory pressure from SCAP 2009 among treated counties. We then combine each group with the control counties to form three subsamples and run the regression Equation (2) for each subsample. Panel B confirms that there is no pre-treatment effect in all three subsamples, and the post-treatment effects are strong and significant, even in the low tercile group. More interestingly, there is a monotonic relation between the magnitude of the treatment intensity and the size of the treatment effect on local housing price growth: treated counties with the most (least) regulatory pressure experience the fastest (slowest) housing price growth. This provides direct and robust evidence that regulatory pressure from stress tests contributes to housing price growth. Panel C, D, and E present the same plots as in Panel B, but separately for each subsample.

Having validated the parallel trend assumption, we run a DiD test to assess the magnitude of SCAP 2009 on local housing prices. The regression equation is shown below.

$$\begin{aligned} Zillow\ Prc\ Chg\ 1Q_{c,t} = & \alpha_c + \alpha_t + \beta_1 Treated_c \times Post_t + \gamma_1 \times \\ & County\ Bank\ Characteristics_{c,t-1} + \gamma_2 \times County\ Controls_{c,t-1} + \varepsilon_{c,t}, \end{aligned} \quad (3)$$

where *Treated* is a dummy variable indicating a treated county with positive stress test shocks measured by *Tier1 Lev Dist*, and *Post* is a dummy variable for post-treatment quarters starting from 2009Q3. Note that the stand-alone variables *Treated* and *Post* are not included in the regression, as the county fixed effects α_c and the year-quarter fixed effects α_t absorb the main effects. Furthermore, β_1 provides a clean measure of the treatment effect, as the DiD setting in

this analysis is free of the recent critique on dynamic DiD by Goodman-Bacon (2021) and Callaway and Sant’Anna (2021), where the units undergo the treatment at different points of time. In the SCAP 2009 subsample, all treated counties experience the stress test shock at the same time, and control counties never experience the shock in the sample period.

The results are presented in Table 8. In the first three columns, we repeat the baseline specification in Equation (1) and validate the baseline results with this subsample. The coefficient estimates for all main stress test variables have comparable magnitudes as in the whole sample. Column (4) shows the DiD results and reveals a large and significant treatment effects of SCAP 2009: the point estimate of β_1 is equal to 0.3%. It suggests that, on average, a county with banks undergoing SCAP 2009 experiences a higher housing price growth rate of 1.2% annually. In Column (5), we replace the *Treated* dummy with three dummies: *Treated Low (Mid, High) Tercile*. The results echo the earlier finding plotted in Panel B of Figure 2. The treatment effect is positive but statistically insignificant for the low tercile group (t -stat is 1.416) and is the smallest in magnitude of the three treated groups. The effects are statistically significant for the mid and high tercile groups. For the high tercile group, a treated county sees a higher housing price growth rate of 2% annually (0.005×4) with a t -stat of 8.5.

In summary, we find consistent results on the relation between stress test shocks and local housing price growth when we focus on SCAP 2009, which provides a clean identification setting. Taken together, the results above suggest a meaningful connection between bank stress tests and home values. Because mortgage lending is an important part of what banks do, it is likely the case that sanctions or consequences from stress tests (or the risk of these outcomes) carry through to the banks’ lending portfolio and credit allocation. This is consistent with the prediction of the credit exclusion hypothesis and does not support the uniform credit tightening hypothesis or the bank

irrelevance hypothesis. In the next section, we investigate credit supply in the local mortgage market using the loan application level data and aggregate credit supply data, to provide more direct evidence on the underlying mechanism.

4.2 Credit supply in the mortgage market

4.2.1 Mortgage applications: approval, origination, and loan amount

We apply a regression model similar to our housing price analysis, using loan-level data that links banks, counties, and mortgage applications, along with stress test information. In addition to the bank and county characteristics used in prior regressions, we also control for additional loan and household characteristics (loan size, borrower income, co-applicant indicator, race, and gender). Whereas prior analyses conditioned on the local characteristics and credit demand, these analyses condition on individual characteristics. We also include county-year and bank-county fixed effects to control for other unobservable local market, bank, and temporal factors.

In addition to the main model, which studies the effect of stress tests on average credit supply by banks in the residential mortgage market, we interact the bank stress test shock variable with indicators for riskier borrowers: low income or high debt to income. In these regressions, the dependent variables are loan approval, origination, and loan amount, respectively.¹⁷ Since the regression here is based on application-level data, the bank-specific stress test shock is different from the county-bank stress test shock in the baseline as the latter is the weighted average across the banks within a county. The regression equation is as follows.

$$\text{Loan Outcome}_{i,b,c,t} = \alpha_{c,t} + \alpha_{b,c} + \beta_1 \times \text{Bank Stress Test}_{c,t-1} \times \text{High Risk Borrower}_{i,t}$$

¹⁷ We use the OLS method for our analysis of household mortgage loan approvals. Our choice of a linear rather than nonlinear model of loan approvals is in line with recent research and is motivated by the fact that nonlinear models tend to produce biased estimates in panel data sets with many fixed effects, leading to incidental parameter problems and inconsistent estimates.

$$\begin{aligned}
& +\beta_2 \text{Bank Stress Test}_{c,t-1} + \beta_3 \text{High Risk Borrower}_{i,t} + \gamma_1 \text{Bank Characteristics}_{c,t-1} \\
& +\gamma_2 \text{County Controls}_{c,t} + \gamma_3 \text{Applicant Controls}_{i,t} + \varepsilon_{i,b,c,t},
\end{aligned} \tag{4}$$

where i, b, c , and t index applicant, bank, county, and year, respectively. Loan outcomes include *Approved*, *Originated*, and *Loan Amount*. *Bank Stress Test* _{$c,t-1$} is the lagged bank-specific stress test shock *Bank Tier1 Lev Dist*. *High Risk Borrower* _{i,t} is an indicator for risky borrowers, which is *Low Income* or *High Debt to Income*. *Bank Characteristics* _{$c,t-1$} , *County Controls* _{c,t} , and *Applicant Controls* _{i,t} are vectors of bank characteristics, county factors, and applicant characteristics described in Section 3. We also include high-dimension fixed effects $\alpha_{c,t}$ and $\alpha_{b,c}$ (county-year interacted fixed effects and bank-county interacted fixed effects) to capture unobserved time-varying heterogeneity across counties and differences across banks in different counties in credit access for a mortgage applicant. The main coefficient of interests is β_1 . If stress-tested banks indeed reduce credit supply for risky borrowers more than other borrower, as predicted by the credit exclusion hypothesis, we should have $\beta_1 < 0$. That is, the likelihood for risky borrower's loan application to be approved by stress-tested banks (and the loan amount) is significantly lower at stress-tested banks. β_2 and β_3 capture the main effects of stress testing and high-risk borrowers on loan outcomes.

Table 9 presents the regression results. The first, middle, and last three columns study the three loan outcomes *Approved*, *Originated*, and *Loan Amount*, respectively. Column (1), (4), and (7) show the main effects of bank stress test shock on loan applications' outcomes. Utilizing regression models that account for a comprehensive set of bank, borrower, and county characteristics, as well as fixed effects, we find an overall decline in credit by banks under regulatory pressure from stress tests. The likelihood for an average mortgage borrower's application to be

approved or originated by stress-tested banks with high stress risk is lower than the ones with low stress risk or non-stress-tested banks.¹⁸

The rest of the columns include the interaction terms of high-risk borrowers and the stress test shock and generate consistent results: banks with higher stress risk out of the stress test results reduce credit supply much more for low-income and high debt-to-income borrowers, shown by lower loan approval rate and lower origination likelihood. Column (8) and (9) further show that banks with higher stress test risk give low-income borrowers and high debt-to-income borrowers smaller loan amount, compared to banks with lower stress test risk. Again, this finding is consistent with the idea that banks restrict their lending to riskier borrowers when faced with increased stress test risk, which leads to borrowers with higher credit quality accessing mortgage credit and pushing up the value of real estate in these counties. These findings strongly support the *credit exclusion hypothesis*, while refuting the *uniform credit tightening hypothesis*.

4.2.2 Aggregate credit supply in the mortgage market

In this section, we study aggregate credit supply in the county-specific mortgage market with county-year observations in the sample period. It is necessary to check aggregate credit supply once we have shown that banks with higher stress test shocks allocate credit supply more away from high-risk borrowers at the loan application level, because for it to be the underlying mechanism of county-bank stress test variables affecting local housing price growth, high-risk borrowers must face some frictions finding other lenders such as small non-stress-tested banks and nonbank mortgage institutions. If instead, the bank irrelevance hypothesis holds, i.e., these other

¹⁸ This complements the findings in Calem, Correa, and Lee (2020) that stress-tested banks reduce jumbo mortgage lending and those in Agarwal, An, Cordell, and Roman (2024) that use the supervisory dataset Y-14M and document declines in credit supply for consumers in credit card and mortgage markets from stress tests.

mortgage institutions can pick up the market void left by stress-tested banks, there should be no relation between county-bank stress test outcomes and local housing price growth.

We check total credit supply to see if other institutions can make up for the reduction in lending by stress-tested banks in the mortgage market by running the following regression equation,

$$\begin{aligned} \text{Credit Supply}_{c,t} = & \alpha_c + \alpha_t + \beta_1 \times \text{County Bank Stress Test}_{c,t-1} \\ & + \gamma_1 \times \text{County Bank Characteristics}_{c,t-1} + \gamma_2 \times \text{County Controls}_{c,t-1} + \varepsilon_{c,t}, \end{aligned} \quad (5)$$

where c and t index county and year. Credit supply is measured by *Loan Amount Approved* or *Loan Amount Originated*, which is the natural logarithm of the total mortgage loan amount approved or originated in a county each year. The key independent variable is *County Bank Stress Test* _{$c,t-1$} , which measures a county's exposure to regulatory pressure faced by banks from their stress test outcomes. We use *Tier1 Lev Dist* for this measure in the tabulated results, and the results are similar with alternative stress test variables. We include county fixed effects α_c and year fixed effects α_t to capture unobserved heterogeneity across counties and time trends that affect county-wide aggregate mortgage credit supply. The main coefficient of interests is β_1 . If the bank irrelevance hypothesis holds, we should expect $\beta_1 = 0$. Alternatively, if the credit exclusion hypothesis holds, that is, credit reduction by stress-tested banks is not fully made up by other mortgage institutions, we should have $\beta_1 < 0$.

The regression results are shown in Table 10. In the first (last) two columns, the dependent variable is the county-level *Loan Amount Approved* (*Loan Amount Originated*). In column (1) and (3), we confirm that at the county level, counties with more exposure to banks' stress risk from stress tests have less credit supply from banks in the mortgage market, measured by the total mortgage loan amount approved or originated. This is consistent with results run with the micro

data at the loan application level presented in Table 9. In column (2) and (4), we repeat the regression replacing the dependent variable with the aggregate mortgage credit supply of all institutions in the county. This includes mortgage loans provided by stress-tested banks, non-stress-tested small banks, and nonbank institutions. In both columns, β_1 , the coefficient estimate on the bank-county stress test variable *Tier1 Lev Dist* is significantly negative. Comparing the estimates of β_1 for bank mortgage credit supply and total mortgage credit supply, the magnitude of the latter is smaller. It suggests that nonbank institutions did make up some of the market shares in the mortgage market recessed by stress-tested banks, but the increase in their market share is not significant enough to offset the negative effects of stress test shocks in tested banks. This evidence supports the argument in Gete and Reher (2018) that risky borrowers face substantial frictions to substitute lenders and rejects the bank irrelevance hypothesis.

4.2.3 Subsequent default likelihood of mortgage loans

The credit exclusion hypothesis also predicts that residential loan portfolios should exhibit lower default likelihood subsequently in counties with more intense bank stress test shocks, because stress-tested banks reduce mortgage credit supply to high-risk borrowers. To test this conjecture, we gather annual aggregate default data from the Consumer Financial Protection Bureau (CFPB). CFPB tracks the percentage of loans that are overdue for a certain period of time in a region annually. Since it is aggregated across all mortgage loans provided by banks and nonbank institutions, we cannot tease out the ones originated by stress-tested banks only. However, as we have shown that other institutions do not make up for the reduction in credit supply by stress-tested banks, we expect to observe a similar impact of stress-testing on the aggregate loan risk in a county. The geographic coverage is somewhat limited in our sample period, and we run the analysis using the 434 counties with data available from CFPB. The regression equation is as follows,

$$\begin{aligned} \text{Aggregate Default Percentage}_{c,t} = & \alpha_c + \alpha_t + \beta_1 \times \text{County Bank Stress Test}_{c,t-1} \\ & + \gamma_1 \times \text{County Bank Characteristics}_{c,t-1} + \gamma_2 \times \text{County Controls}_{c,t-1} + \varepsilon_{c,t}, \end{aligned} \quad (6)$$

where c and t index county and year. Aggregate default percentage is measured by *Perc Delinq 90* or *Perc Delinq 30*, which is the percentage of mortgage loans that are past due for over 90 or 30 days in a county. The key independent variable is *County Bank Stress Test* _{$c,t-1$} , which measures a county's exposure to regulatory pressure faced by banks from their stress test outcomes. α_c and α_t are county fixed effects and year fixed effects. The credit exclusion hypothesis predicts that $\beta_1 < 0$, as stress-tested banks reduce their loan portfolio risk by shifting away from high-risk borrowers.

The results are shown in the first two columns of Table 11. Consistent with the credit exclusion hypothesis, there is a statistically significant and negative relation between the default percentage of mortgage loans and the lagged county-bank stress test variable *Tier1 Lev Dist*. The effect is also economically large: one standard deviation increase (0.125) in *Tier1 Lev Dist* is associated with a 0.25% ($= 1.961 \times 0.125/100$) drop in the percentage of loans overdue for more than 30 days. Alternatively, we study the percentage of subprime mortgage loans granted directly in a county. The Economic Data by Fed (FRED) calculates the percentage of subprime loan borrowers among all mortgage borrowers and covers 2595 counties in our sample. We run the same regression shown in Equation (6), replacing the aggregate default percentage by the percentage of subprime mortgage loans. Column (3) of Table 11 presents the results. Consistent with the results on aggregate default percentage, the coefficient on *Tier1 Lev Dist* remains significantly negative. When the bank-county stress test shock increases by one standard deviation, the percentage of subprime mortgage loans drops 0.22% ($= 1.762 \times 0.125/100$). The results in

this section provide strong evidence for the underlying mechanism via which bank stress tests impact local housing price growth, as predicted by the credit exclusion hypothesis.

4.3 Bank Stress Tests and Population Migration

In the last section of the empirical analysis, we take one step further to examine whether the housing price hike from bank stress tests can cause inter-county migration. Gete and Reher (2018) show that risky borrowers rejected by stress-tested banks move from the ownership market to the rental market due to the lack of credit. Hence our credit exclusion hypothesis has no clear prediction on the relation between a county's exposure to stress tests and migration, because if all risky borrowers choose to rent locally rather than buy, they can still live in the same county without moving. On the other hand, higher rent in the area documented in Gete and Reher (2018) may incentivize these borrowers to relocate across county lines so they can either get mortgage loans or rent more cheaply. Thus, whether counties subject to more bank stress test shocks experience net population outflow is an empirical question. We use the county-level migration data from IRS, as described in Section 3.4 and run the following regression equation.

$$\begin{aligned} \text{Population Migration}_{c,t} = & \alpha_c + \alpha_t + \beta_1 \times \text{County Bank Stress Test}_{c,t-1} \\ & + \gamma_1 \times \text{County Bank Characteristics}_{c,t-1} + \gamma_2 \times \text{County Controls}_{c,t-1} + \varepsilon_{c,t}, \end{aligned} \quad (7)$$

where c and t index county and year. Population migration of a county is measured by *Net Out1*, *Out1*, *In1*, *Net Out2*, *Out2*, and *In2*. The first three measures are scaled by the number of tax filings, and the last three scaled by the number of population. The key independent variable is *County Bank Stress Test* _{$c,t-1$} , which measures a county's exposure to regulatory pressure faced by banks from their stress test outcomes. α_c and α_t are county fixed effects and year fixed effects. If some risky borrowers' housing needs are not absorbed by the rental market and they

move to a different county, we should expect $\beta_1 < 0$ for the net out measures. If the opposite is true, county-bank stress test variables should not be related to population migration.

We present the regression results in Table 12. Column (1) and (4) show that both net out measures from a county are positively related to the county's exposure to bank stress test shocks *Tier1 Lev Dist*. This suggests that the rental market studied by Gete and Reher (2018) does not absorb all the housing needs of risky borrowers. Driven by lack of credit to buy and higher rent, these counties experience net population outflow. Column (2) and (5) show a positive relation between population outflows and the stress test shock, while Column (3) and (6) reveal a negative relation between population inflows and the stress test shock. Combining these results, we conclude that the positive relation between population net outflow and *Tier1 Lev Dist* is driven by both the higher outflow of the population and reduced inflow to the region, presumably due to high housing prices.

The findings from Table 12 suggest that the economic impact of bank stress tests on local housing markets is large. The reduction in credit supply for risky borrowers not only drives up local housing prices, but also causes population migration. In the ideal scenario, we should present evidence on inter-county population migration in different income brackets, but such data is currently not available. To provide an indirect piece of evidence, we study the percentage change of low-income residents following county-bank stress test shocks using IRS data. We run the same regression equation specified as in Equation (7) but change the dependent variable to the percentage of low-income households. Table 13 presents the results. Column (1), (2), and (3) show the coefficient estimates on lagged *Tier1 Lev Dist* when the dependent variable is the natural logarithm of the percentage of tax filings with income no greater than \$25,000, \$50,000, and \$75,000 in a county in the current year divided by the percentage in the previous year, which is

essentially the percentage change of low-income population's fractions in total populations. The three columns present a consistent and significant result: the remaining population has fewer low-income residents when a county is exposed to more intense regulatory pressure from bank stress tests. In Column (4), we study the change of the average adjusted gross income (AGI) of all tax filings in a county. It provides the same evidence: remaining population has higher average AGI growth rate when the local stress test shocks are larger. Indirectly, this suggests that the population outflows from counties under stress test pressure documented in Table 12 are dominated by low-income families. It supports the credit exclusion hypothesis and emphasizes the economic impact of bank stress tests on the lives of low-income families.

5. Conclusion

In this paper, we provide robust evidence that counties exposed to greater regulatory pressure from bank stress tests experience significantly higher local housing price growth through selective credit rationing, using a rich county-quarter dataset. Our empirical strategy leverages both temporal and cross-sectional heterogeneity in counties' exposure to stress test shocks, and the results remain economically large and consistent across a variety of stress test measures and housing price growth metrics. Economically, one standard deviation increase in regulatory pressure raises annual housing price growth by 1.3%, equivalent to \$2,600 on median-priced homes, with effects 23% larger for lower-priced homes. A subsample analysis centering around the SCAP 2009 test, which is largely free of endogeneity concerns, verifies the main results found with the whole sample.

Furthermore, by examining mortgage loan data at the application level, we uncover an important mechanism driving this effect: stress-tested banks, under regulatory pressure, reallocate their lending portfolios by reducing credit supply to high-risk borrowers, thereby concentrating

housing market transactions among financially strong buyers. This credit contraction is not fully mitigated by smaller non-stress-tested banks or non-bank institutions, leading to an overall decline in local mortgage credit supply. Crucially, our findings go beyond prior literature, such as Gete and Reher (2018), by demonstrating that the economic impact of bank stress tests is substantial enough to drive population outmigration from counties most affected by these shocks. High-risk borrowers, unable to access sufficient credit for homeownership, are not fully absorbed by the rental market, leading to shifts in population dynamics. This study thus contributes to both academic research and policy debates, highlighting the far-reaching real effects of bank stress tests.

Our results call for a more nuanced discussion on the unintended distributional consequences of financial regulations and their broader implications for housing markets and wealth inequality. Our findings also speak to the fundamental design of stress tests: Acharya, Engle, and Pierret (2014) show that leverage-based capital requirements better identify systemic risk than risk-weighted measures. Our evidence reveals that these more effective measures—precisely because they constrain banks' ability to satisfy requirements through asset reweighting—generate stronger real effects on credit allocation and housing markets. This highlights a policy tradeoff: stress test designs that more effectively limit systemic risk may produce larger unintended consequences for wealth inequality and homeownership access.

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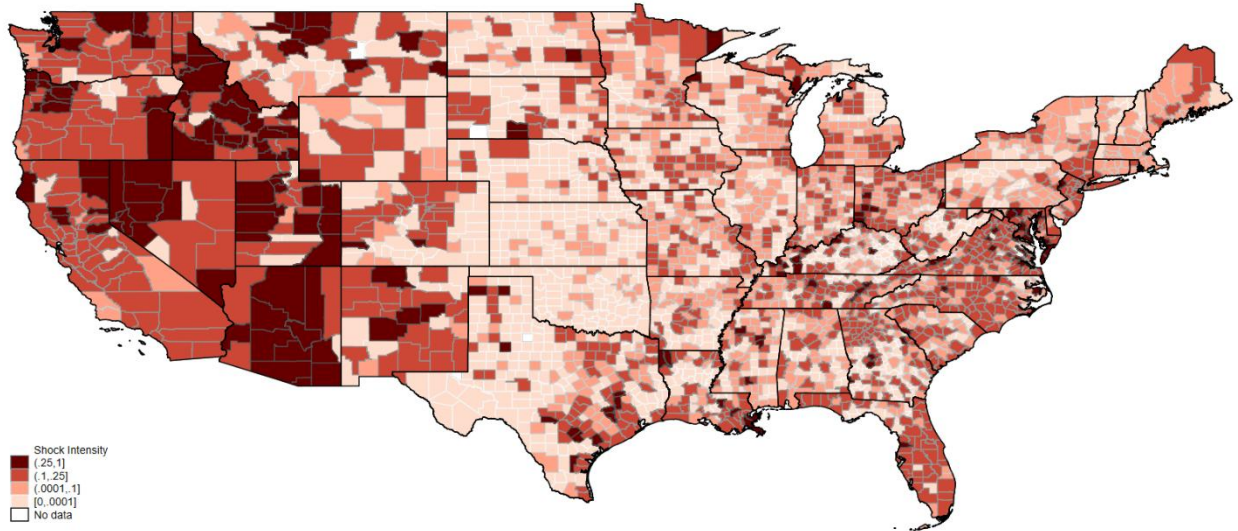
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Figure 1: Geographic Distribution of Stress Test Shocks by County

This figure illustrates the geographical distribution of county-level stress test shocks, based on *Tier1 Lev Dist*, across U.S. counties. Figure 1(A) shows the distribution of SCAP 2009, and Figure 1(B) presents the distribution of the average shocks throughout the period of 2009-2016 including SCAP 2009, CCAR 2012, DFAST 2013, DFAST 2015, and DFAST 2016. Shock intensity in the bracket of $[0, 0.001]$ is strictly equal to zero.

(A) County-level Stress Test Shocks of SCAP 2009



(B) County-level Average Stress Test Shocks of 2009-2016

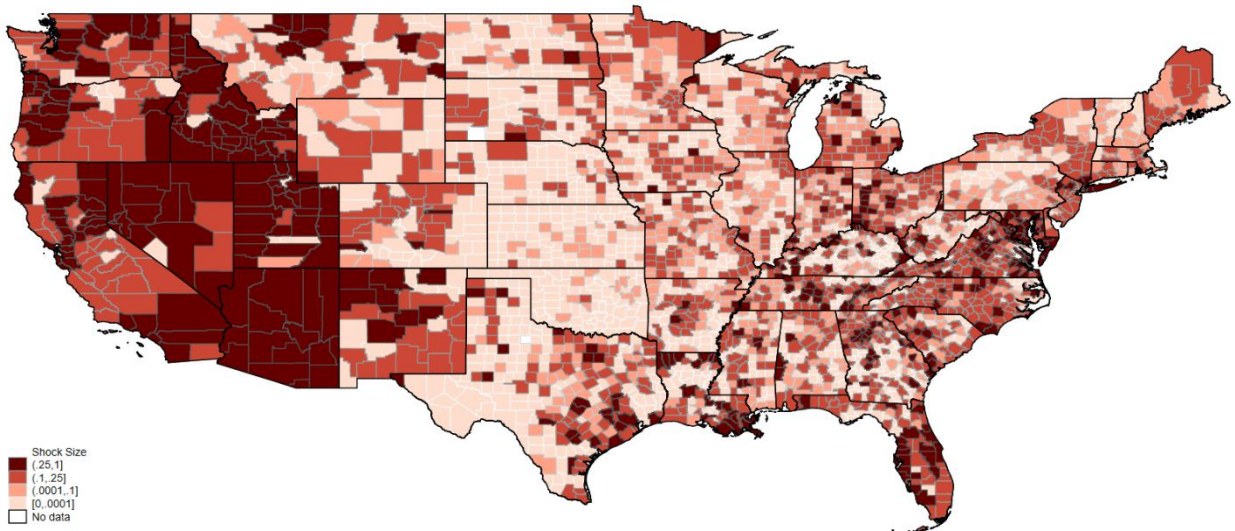
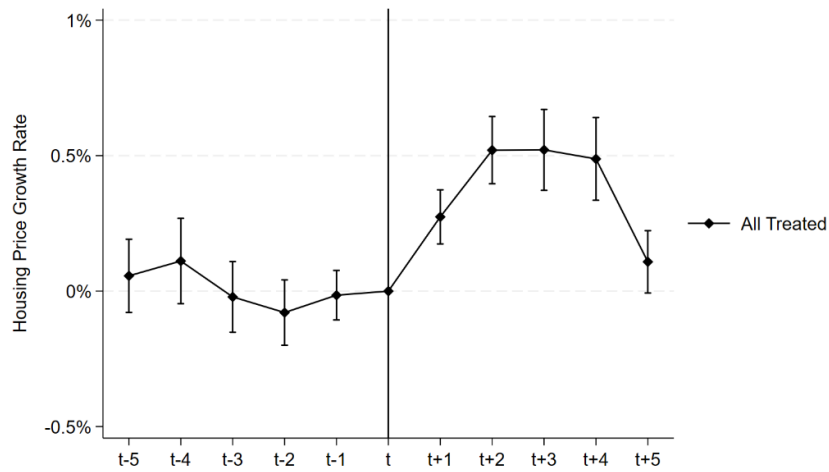


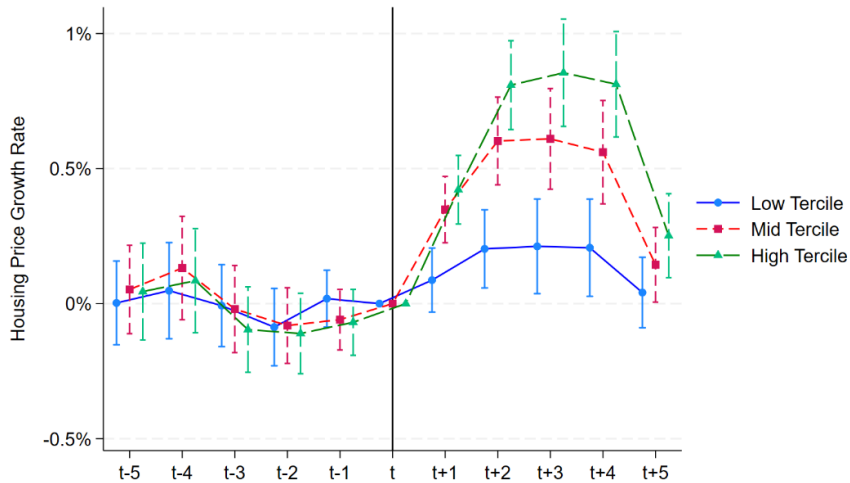
Figure 2: Dynamic Effects around SCAP 2009

This figure shows the temporal dynamic effects of county-level stress test shocks of SCAP 2009 during the periods of 2008Q1-2011Q4. Specifically, we estimate a temporal model of quarterly housing price growth rate on ten event quarter dummy variables, controlling for within-county bank characteristics, county-level demographic, economic, and political factors, county fixed effects, and quarter fixed effects, specified by Equation (2). The x-axis show the event quarters and the treatment quarter t in the graph is 2019Q2, when the SCAP 2009 results are released. On the y-axis, the graph plots the coefficient estimates of quarterly housing price growth rate on the ten event-quarter dummy variables with their 95% confidence intervals. We divide treated counties into three terciles based on the treatment intensity *Tier1 Lev Dist* from the SCAP 2009 test. Figure 2(A) presents the pre-treatment trends and the treatment effects for all treated counties vs. control counties, while Figure 2(B) presents the patterns for the three treated tercile groups sorted by treatment intensity separately. Figures (C), (D), and (E) plot the tercile groups separately. In all figures, the control group are counties that have no banks that undergo the SCAP 2009 stress test.

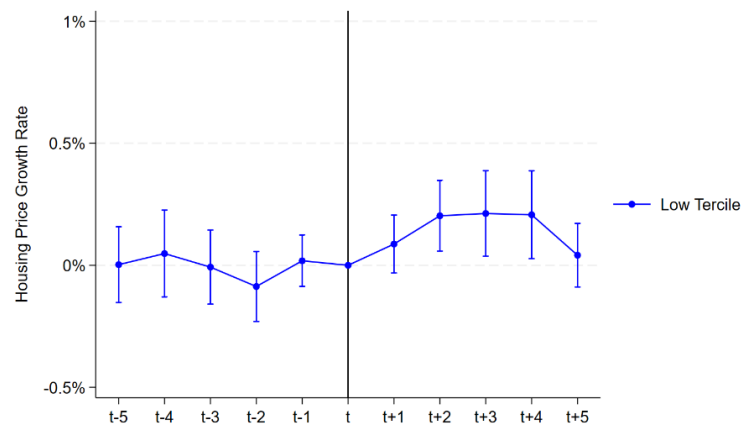
(A) All Treated Counties vs. Controls



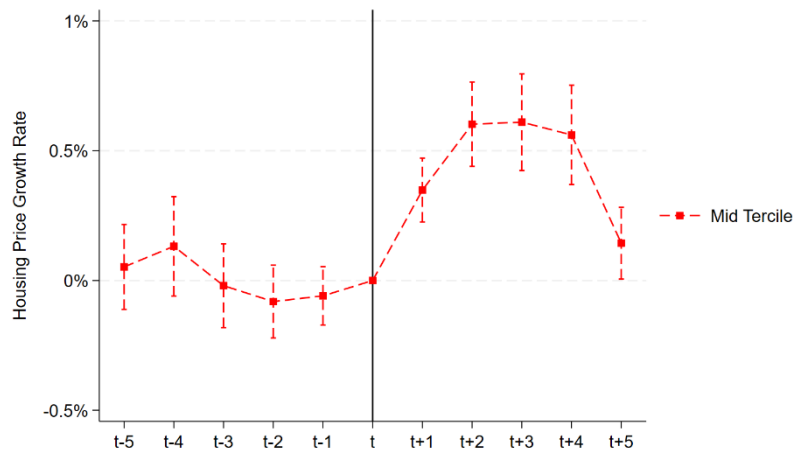
(B) Three Treated Groups sorted by Treatment Intensity vs. Controls



(C) Treated Counties with Low Treatment Intensity vs. Controls



(D) Treated Counties with Medium Treatment Intensity vs. Controls



(E) Treated Counties with High Treatment Intensity vs. Controls

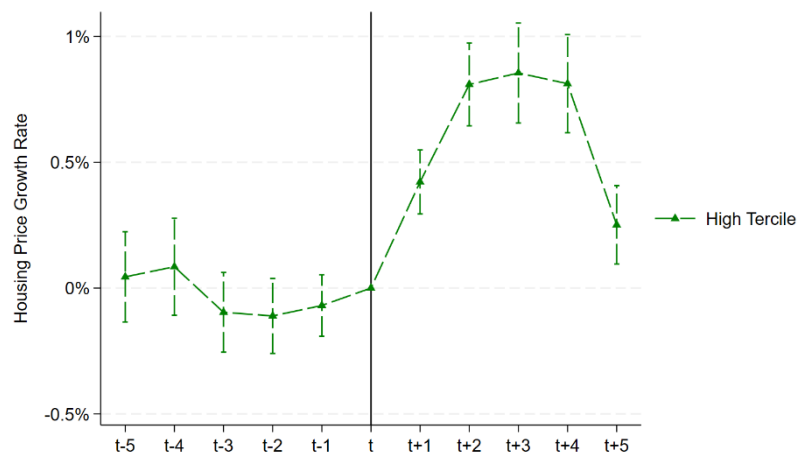


Table 1: Summary of Competing Hypotheses

This table summarizes three competing hypotheses, the underlying mechanisms, and their predictions on the sign of the relation between county-level stress test shocks and local housing price growth.

Hypothesis Name	Mechanism	Predicted Relation between Stress Test Shocks and Housing Price Growth
Credit Exclusion Hypothesis	Mortgage credit provided by stress-tested banks is shifted away from high-risk borrowers. With frictions in lender substitution, some high-risk borrowers are forced out of the housing market. Housing transactions are thus more concentrated within purchases by financially strong buyers, resulting in higher housing prices.	Positive
Uniform Credit Tightening Hypothesis	Stress-tested banks cut mortgage credit supply to all borrowers equally across the spectrum of borrower risk. Uniform credit tightening reduces overall housing demand, causing a downward pressure on housing prices.	Negative
Bank Irrelevance Hypothesis	Reductions in the mortgage credit supply by stress-tested banks do not matter, as non-stress-tested banks and non-bank institutions pick up their market shares. Housing demand is thus unaffected as overall credit supply for mortgage borrowers remains the same. Hence Housing price is not impacted by bank stress tests.	No Relation

Table 2: Stress-tested Banks

This table shows the list of the 43 stress-tested banks in U.S. after the global financial crisis until 2020, with the names of the stress tests and release quarter of stress test outcomes by the Fed. The cells are coded as one and highlighted in green if a bank participated in a stress test and otherwise coded as zero and highlighted in gray.

Bank Name	SCAP 2009	CCAR 2012	DFAST 2013	DFAST 2014	DFAST 2015	DFAST 2016	DFAST 2017	DFAST 2018	DFAST 2019	DFAST 2020
Release Quarter of Stress Test Outcomes	2009Q2	2012Q1	2013Q1	2014Q2	2015Q2	2016Q2	2017Q2	2018Q2	2019Q2	2020Q2
BancWest Corp	0	0	0	0	0	1	0	0	0	0
Zions BanCorp	0	0	0	1	1	1	1	0	0	0
Deutsche Bank Trust Corp	0	0	0	0	1	1	1	0	0	0
CIT Group	0	0	0	0	0	0	1	0	0	0
M&T Bank Corp	0	0	0	1	1	1	1	1	0	1
JPMorgan Chase & Co.	1	1	1	1	1	1	1	1	1	1
KeyCorp	1	1	1	1	1	1	1	1	0	1
Huntington Bancshares	0	0	0	1	1	1	1	1	0	1
PNC Financial Services Group	1	1	1	1	1	1	1	1	1	1
Fifth Third Bancorp	1	1	1	1	1	1	1	1	0	1
Bank of America Corp	1	1	1	1	1	1	1	1	1	1
BB&T Corp	1	1	1	1	1	1	1	1	0	1
BBVA Compass Bancshares	0	0	0	1	1	1	1	1	0	0
State Street Corp	1	1	1	1	1	1	1	1	1	1
U.S. Bancorp	1	1	1	1	1	1	1	1	1	1
Wells Fargo & Co.	1	1	1	1	1	1	1	1	1	1
SunTrust Banks	1	1	1	1	1	1	1	1	0	0
RBS Citizens Financial Group	0	0	0	1	1	1	1	1	0	1
Northern Trust Corp	0	0	0	1	1	1	1	1	1	1
Comerica Incorporated	0	0	0	1	1	1	1	0	0	0
BMO Financial Corp	0	0	0	1	1	1	1	1	0	1
American Express Co.	1	1	1	1	1	1	1	1	0	1
UnionBanCal Corp	0	0	0	1	1	1	1	1	0	1
GMAC LLC	1	1	1	1	1	1	1	1	0	1
Credit Suisse Holdings (USA)	0	0	0	0	0	0	0	1	1	1
BNP Paribas USA	0	0	0	0	0	0	0	1	0	1
Citigroup	1	1	1	1	1	1	1	1	1	1
Morgan Stanley	1	1	1	1	1	1	1	1	1	1
Capital One Financial Corp	1	1	1	1	1	1	1	1	1	1
The Goldman Sachs Group	1	1	1	1	1	1	1	1	1	1
DB USA Corp	0	0	0	0	0	0	0	1	1	1
Metlife	1	1	0	0	0	0	0	0	0	0
RBC USA Holdco Corp	0	0	0	0	0	0	0	1	0	0
HSBC North America Holdings	0	0	0	1	1	1	1	1	1	1
Regions Financial Corp	1	1	1	1	1	1	1	1	0	1
The Bank of New York Mellon	1	1	1	1	1	1	1	1	1	1
TD Group US Holdings LLC	0	0	0	0	0	1	1	1	1	1
Discover Financial Services	0	0	0	1	1	1	1	1	0	1
Santander Holdings USA	0	0	0	1	1	1	1	1	0	1
UBS Americas Holding LLC	0	0	0	0	0	0	0	1	1	1
BancWest Corp	0	0	0	0	0	0	1	0	0	0
Barclays US LLC	0	0	0	0	0	0	0	1	1	1
RBC US Group Holdings LLC	0	0	0	0	0	0	0	0	0	1
# of Participating Banks	19	19	18	30	31	33	34	35	18	33

Table 3: Summary Statistics

This table reports summary statistics of a county-quarter sample from the period of 2008Q1-2016Q2, combining house prices, bank stress test shocks, bank characteristics, local demographic, economic, and political characteristics, and inter-county migration variables. All bank-related variables are averaged at the county level with the weight equal to each bank's business share computed using the number of branches in the county in 2008Q1. The details of variable construction and data sources are described in Section 3. All variables are winsorized at 1% and 99% level.

	N	Mean	StdEv	Min	P25	P50	P75	Max
<i>Panel A: Housing Price Variables</i>								
Zillow Prc Chg 1Q	87,684	0.001	0.016	-0.050	-0.007	0.002	0.010	0.042
Zillow Prc Chg 4Q	85,862	0.002	0.054	-0.173	-0.028	0.004	0.035	0.138
Zillow Perc Prc Chg 1Q	87,684	0.000	0.005	-0.017	-0.003	0.001	0.004	0.016
FHFA Prc Chg Ann (annual)	22,356	-0.001	0.049	-0.160	-0.028	0.000	0.027	0.125
<i>Panel B: Stress Test Variables</i>								
Tier1 Lev Dist	87,684	0.105	0.125	0.000	0.000	0.066	0.176	0.531
Tier1 Lev Exp	87,684	0.095	0.112	0.000	0.000	0.060	0.159	0.481
Stress Tested	87,684	0.154	0.174	0.000	0.000	0.103	0.267	0.714
Tier1 Cap Dist	87,684	0.086	0.144	0.000	0.000	0.000	0.140	0.604
Tier1 Cap Exp	87,684	0.033	0.059	0.000	0.000	0.000	0.049	0.265
Total Cap Dist	87,684	0.083	0.139	0.000	0.000	0.000	0.135	0.584
Min Stress Dist	87,684	0.058	0.099	0.000	0.000	0.000	0.093	0.420
Total Cap Exp	87,684	0.033	0.057	0.000	0.000	0.000	0.050	0.252
Tier1 Equity Exp	87,684	0.087	0.103	0.000	0.000	0.055	0.146	0.441
Max Stress Exp	87,684	0.029	0.051	0.000	0.000	0.000	0.042	0.229
<i>Panel C: Bank Characteristics</i>								
Bank Age	87,684	76.977	24.861	3.000	61.200	77.500	93.727	136.167
No FRS District	87,684	1.623	1.156	0.111	0.946	1.256	1.950	6.875
Cap Ratio	87,684	0.084	0.023	0.012	0.070	0.086	0.100	0.138
Asset Quality	87,684	0.020	0.014	0.000	0.010	0.016	0.026	0.071
Overhead Costs	87,684	0.008	0.003	0.000	0.006	0.008	0.010	0.016
ROA	87,684	0.006	0.006	-0.026	0.004	0.006	0.009	0.017
Liquidity Ratio	87,684	0.217	0.085	0.022	0.158	0.207	0.266	0.475
Market Risk Sensitivity	87,684	0.092	0.051	0.001	0.056	0.084	0.118	0.269
Bank Size	87,684	11.737	3.051	1.362	9.964	12.104	13.758	18.317
Loan to Asset Ratio	87,684	0.488	0.140	0.049	0.396	0.498	0.593	0.752
Asset Diversity	87,684	0.534	0.155	0.063	0.434	0.536	0.640	0.881

	N	Mean	StdEv	Min	P25	P50	P75	Max
<i>Panel D: County Demographic, Economic, and Political Factors</i>								
Population Dens	87,672	4.171	1.492	0.571	3.265	4.052	4.977	8.238
Per Capita Income	87,668	10.031	0.214	9.534	9.887	10.019	10.158	10.652
Gini Index	87,684	0.434	0.034	0.360	0.410	0.432	0.456	0.528
Female Perc	87,684	0.502	0.019	0.411	0.498	0.506	0.512	0.536
Minority Perc	87,684	0.160	0.149	0.014	0.046	0.103	0.234	0.658
Age65 Perc	87,684	0.154	0.038	0.072	0.128	0.151	0.176	0.267
Low Edu Perc	87,684	0.513	0.110	0.237	0.438	0.517	0.596	0.734
Unemployment	87,684	0.081	0.030	0.024	0.060	0.077	0.098	0.171
Dem Vote	87,467	0.411	0.133	0.143	0.314	0.404	0.497	0.770
Bank HHI	87,460	0.280	0.173	0.080	0.162	0.232	0.343	1.000
Nonbank Share	87,620	0.208	0.148	0.000	0.096	0.180	0.291	0.667
<i>Panel E: Mortgage Applications</i>								
Approved	1,976,107	0.843	0.364	0.000	1.000	1.000	1.000	1.000
Originated	1,886,978	0.836	0.371	0.000	1.000	1.000	1.000	1.000
Loan Amount (Ln)	1,976,107	5.389	0.885	0.000	4.875	5.425	5.981	11.513
Low Income	1,976,107	0.497	0.500	0.000	0.000	0.000	1.000	1.000
Applicant Income (Ln)	1,976,107	4.579	0.776	0.000	4.043	4.564	5.075	10.135
High Debt to Income	1,976,107	0.497	0.500	0.000	0.000	0.000	1.000	1.000
Debt to Income	1,976,107	2.576	1.211	0.171	1.716	2.435	3.306	6.258
<i>Panel F: Migration among Counties (annual)</i>								
Net Out1	18,281	0.007	0.057	-0.138	-0.027	0.002	0.034	0.162
Out1	20,727	0.192	0.046	0.105	0.160	0.187	0.218	0.349
In1	18,281	0.185	0.051	0.089	0.149	0.179	0.215	0.338
Net Out2	18,281	0.008	0.056	-0.132	-0.025	0.002	0.032	0.174
Out2	20,727	0.184	0.055	0.091	0.147	0.175	0.210	0.397
In2	18,281	0.177	0.055	0.081	0.138	0.168	0.205	0.360

Table 4: Effects of Bank Stress Test Shocks on Local Housing Prices

This table reports the baseline regression results of Equation (1), on the relation between lagged bank stress tests and local housing prices using county-quarter observations during 2008Q1-2016Q2. The dependent variable is *Zillow Prc Chg 1Q*, which is equal to the natural logarithm of the Zillow House Price Index in the current quarter divided by that in the last quarter. The key explanatory variables are the three stress test variables: *Tier1 Lev Dist*, *Tier1 Cap Dist*, and *Stress Tested*. Control variables include bank characteristics, county-level demographic, economic, and political factors. All bank-related variables are averaged at the county level with the weight equal to each bank's branch share in 2008Q1. The details of variable construction and data sources are described in Section 3. In Column (1), (3), (5), county fixed effects and year-quarter fixed effects are included, while in Column (2), (4), (6), county fixed effects and state-year fixed effects are included. Standard errors are clustered by county. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
<i>County-Bank Stress Test Shocks</i>						
Tier1 Lev Dist	0.026*** (11.932)	0.010*** (7.247)				
Tier1 Lev Exp			0.029*** (11.987)	0.009*** (6.386)		
Stress Tested					0.016*** (11.434)	0.002** (2.488)
<i>Controls: Bank Characteristics</i>						
Bank Age	0.000*** (4.499)	-0.000 (-0.802)	0.000*** (4.667)	-0.000 (-0.750)	0.000*** (5.160)	-0.000 (-0.608)
No FRS District	-0.001*** (-5.631)	0.000** (2.265)	-0.001*** (-5.596)	0.000** (2.061)	-0.001*** (-6.558)	0.000 (1.368)
Cap Ratio	-0.046*** (-3.146)	0.015 (1.474)	-0.041*** (-2.827)	0.016 (1.594)	-0.047*** (-3.232)	0.018* (1.747)
Asset Quality	-0.075*** (-6.378)	-0.056*** (-6.878)	-0.072*** (-6.208)	-0.055*** (-6.802)	-0.085*** (-7.254)	-0.054*** (-6.596)
Overhead Costs	0.528*** (7.701)	0.205*** (4.129)	0.541*** (7.919)	0.212*** (4.284)	0.558*** (8.130)	0.219*** (4.435)
ROA	0.195*** (12.458)	0.038*** (3.437)	0.196*** (12.541)	0.041*** (3.697)	0.202*** (12.851)	0.050*** (4.495)
Liquidity Ratio	0.017*** (3.151)	0.006* (1.778)	0.017*** (3.182)	0.007* (1.875)	0.019*** (3.431)	0.007** (2.160)
Market Risk Sensitivity	-0.003 (-1.005)	0.006*** (3.048)	-0.003 (-1.047)	0.006*** (2.911)	-0.003 (-1.058)	0.005** (2.408)
Bank Size	-0.001*** (-2.582)	-0.000 (-0.279)	-0.001*** (-2.694)	-0.000 (-0.271)	-0.001*** (-3.020)	-0.000 (-0.254)
Loan to Asset Ratio	-0.003 (-0.552)	-0.001 (-0.432)	-0.003 (-0.563)	-0.001 (-0.441)	-0.000 (-0.061)	-0.001 (-0.393)
Asset Diversity	0.000 (0.084)	-0.003* (-1.951)	-0.000 (-0.162)	-0.004** (-2.108)	0.000 (0.065)	-0.004** (-2.297)
<i>Continued to the next page</i>						

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Controls: County Factors</i>						
Population Dens	0.006 (1.497)	0.003 (0.885)	0.007 (1.533)	0.003 (0.941)	0.009** (2.199)	0.004 (1.193)
Per Capita Income	-0.018*** (-5.331)	-0.005** (-2.156)	-0.018*** (-5.419)	-0.005** (-2.177)	-0.020*** (-5.837)	-0.006** (-2.320)
Gini Index	0.032*** (3.630)	0.019*** (3.147)	0.032*** (3.658)	0.019*** (3.152)	0.033*** (3.767)	0.019*** (3.178)
Female Perc	0.011 (0.543)	0.018 (1.408)	0.013 (0.632)	0.019 (1.498)	0.020 (0.963)	0.022* (1.731)
Minority Perc	-0.017** (-2.072)	0.001 (0.116)	-0.016** (-2.000)	0.001 (0.164)	-0.016** (-2.016)	0.002 (0.342)
Age65 Perc	0.056*** (3.303)	-0.002 (-0.192)	0.055*** (3.263)	-0.003 (-0.265)	0.053*** (3.171)	-0.005 (-0.453)
Low Edu Perc	-0.006 (-0.753)	-0.005 (-1.021)	-0.006 (-0.811)	-0.004 (-0.963)	-0.004 (-0.598)	-0.004 (-0.806)
Unemployment	0.071*** (6.995)	0.008 (1.267)	0.071*** (7.055)	0.007 (1.225)	0.073*** (7.190)	0.006 (1.073)
Dem Vote	0.022*** (5.997)	0.015*** (4.141)	0.023*** (6.270)	0.016*** (4.247)	0.024*** (6.501)	0.017*** (4.534)
Bank HHI	0.004 (1.506)	-0.001 (-0.662)	0.004 (1.478)	-0.001 (-0.712)	0.004 (1.338)	-0.001 (-0.828)
Nonbank Share	0.009*** (8.871)	0.002** (2.231)	0.009*** (8.972)	0.002** (2.272)	0.010*** (9.450)	0.002** (2.316)
County FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y		Y		Y	
State-Year FE		Y		Y		Y
Observations	87,153	87,153	87,153	87,153	87,153	87,153
Adjusted R-squared	0.457	0.562	0.457	0.562	0.455	0.561

Table 5: The Baseline with Alternative County-Level Stress Test Measures

This table reports the regression results of Equation (1), on the relation between lagged bank stress tests and local housing prices using county-quarter observations during 2008Q1-2016Q2 with alternative county-level stress test measures. The dependent variable is *Zillow Prc Chg 1Q*, which is equal to the natural logarithm of the Zillow House Price Index in the current quarter divided by that in the last quarter. In Panel A, we continue to use *Tier1 Lev Dist*, *Tier1 Cap Dist*, and *Stress Tested* to measure stress test shocks as in the baseline but use three alternative weights when aggregating them to county-level measures. In the first three columns, weights are branch shares lagged by one year, compared to branch shares in 2008Q1 used in the baseline; in the middle (last) three columns, the weights are deposit shares (mortgage shares) lagged by one year. In Panel B, we use seven alternative stress test variables while they are weighted by branch shares in 2008Q1: *Tier1 Cap Dist*, *Tier1 Cap Exp*, *Total Cap Dist*, *Min Stress Dist*, *Total Cap Exp*, *Tier1 Common Exp*, and *Max Stress Exp*. Control variables include county-level bank characteristics, county-level demographic, economic, and political factors, and for the sake of brevity their coefficient estimates are not presented. The details of variable construction and data sources are described in Section 3. In all specifications, county fixed effects and year-quarter fixed effects are included. Standard errors are clustered by county. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Stress Test Shocks Weighted by Alternative Bank Business Shares

Weights of banks	Branch Share			Deposit Share			Mortgage Share		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tier1 Lev Dist	0.026*** (12.963)			0.022*** (12.013)			0.018*** (7.237)		
Tier1 Lev Exp		0.027*** (12.281)			0.022*** (11.428)			0.022*** (8.045)	
Stress Tested			0.015*** (11.057)			0.013*** (10.654)			0.009*** (5.505)
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	87,145	87,145	87,145	87,145	87,145	87,145	81,653	81,653	81,653
Adjusted R-squared	0.462	0.461	0.458	0.458	0.457	0.454	0.444	0.445	0.443

Panel B: Five Alternative Measures for Stress Test Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier1 Cap Dist	0.015*** (10.643)						
Tier1 Cap Exp		0.034*** (10.771)					
Total Cap Dist			0.015*** (10.511)				
Min Stress Dist				0.023*** (11.310)			
Total Cap Exp					0.034*** (10.249)		
Tier1 Equity Exp						0.034*** (12.625)	
Max Stress Exp							0.038*** (10.395)
County FE	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y	Y
Observations	87,153	87,153	87,153	87,153	87,153	87,153	87,153
Adjusted R-squared	0.456	0.456	0.456	0.457	0.456	0.458	0.456

Table 6: The Baseline with Alternative Measures of Price Changes

This table reports the regression results of Equation (1), on the relation between lagged bank stress tests and local housing prices using county-quarter observations during 2008Q1-2016Q2 with three alternative measures for housing price changes: *Zillow Prc Chg 4Q* (Column 1-3), *Zillow Perc Prc Chg 1Q* (Column 4-6), and *FHFA Prc Chg Ann* (Column 7-9). *Zillow Prc Chg 4Q* is the natural logarithm of the Zillow House Price Index in the current quarter divided by that in the same quarter of last year. *Zillow Perc Prc Chg 1Q* is the percentage change of the Zillow index level from last quarter to the current quarter. *FHFA Prc Chg Ann* as the natural logarithm of the Federal Housing Finance Agency (FHFA) House Price Index (HPI) at the county level in the current year divided by that in last year. The key explanatory variables are the three stress test variables: *Tier1 Lev Dist*, *Tier1 Cap Dist*, and *Stress Tested*. Control variables include county-level bank characteristics, county-level demographic, economic, and political factors, and for the sake of brevity their coefficient estimates are not presented. The details of variable construction and data sources are described in Section 3. From Column (1) to (6) (Column (7) to (9)), the regressions are based on county-quarter (county-year) observations, and county fixed effects and year-quarter (year) fixed effects are included. Standard errors are clustered by county. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Dependent Variable	Zillow Prc Chg 4Q			Zillow Perc Prc Chg 1Q			FHFA Prc Chg Ann		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tier1 Lev Dist	0.090*** (10.764)			0.009*** (11.885)			0.087*** (10.289)		
Tier1 Lev Exp		0.100*** (11.146)			0.010*** (11.887)			0.096*** (10.163)	
Stress Tested			0.051*** (9.559)			0.006*** (11.548)			0.042*** (7.380)
County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y			
Year FE							Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	85,344	85,344	85,344	87,153	87,153	87,153	22,237	22,237	22,237
Adjusted R-squared	0.572	0.572	0.569	0.42	0.42	0.418	0.399	0.398	0.394

Table 7: The Baseline with Different Types of Houses

This table reports the regression results of Equation (1), on the relation between lagged bank stress tests and local housing prices using county-quarter observations during 2008Q1-2016Q2 with Zillow Home Value Index (ZHVI) for subgroups of houses. In Column (1), quarterly housing price change is calculated using the Bottom Tier ZHVI, which is the typical value for homes within the 5th to 35th percentile range for a given region. In Column (2), quarterly housing price change is calculated using the Top Tier ZHVI, which is the typical value for homes within the 65th to 95th percentile range for a given region. From Column (3) to (7), the quarterly housing price change is calculated using ZHVI one-bedroom, two-bedroom, three-bedroom, four-bedroom, and five-bedroom time series, respectively. The table also shows the difference in coefficient estimates for *Tier1 Lev Dist*, between Column (1) and (2), and between Column (3) and (7). Control variables include county-level bank characteristics, county-level demographic, economic, and political factors, and for the sake of brevity their coefficient estimates are not presented. The details of variable construction and data sources are described in Section 3. In all specifications, county fixed effects and year-quarter fixed effects are included. Standard errors are clustered by county. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Dependent Variable	Bottom Tier	Top Tier	Bottom Tier minus Top Tier	1-bedroom	2-bedroom	3-bedroom	4-bedroom	5-bedroom	1-bedroom minus 5-bedroom
	(1)	(2)		(3)	(4)	(5)	(6)	(7)	
Tier1 Lev Dist	0.032*** (10.069)	0.026*** (10.475)		0.036*** (6.569)	0.033*** (9.452)	0.030*** (10.695)	0.027*** (9.716)	0.026*** (7.986)	
Difference in Coefficients			0.006* (1.66)						0.01** (1.71)
County FE	Y	Y		Y	Y	Y	Y	Y	
Quarter FE	Y	Y		Y	Y	Y	Y		
Bank Controls	Y	Y		Y	Y	Y	Y	Y	
County Controls	Y	Y		Y	Y	Y	Y	Y	
Observations	71,668	73,476		32,619	62,921	71,036	64,354	46,425	
Adjusted R-squared	0.43	0.464		0.446	0.441	0.475	0.48	0.487	

Table 8: Effects of Bank Stress Test Shocks on Local Housing Prices around SCAP 2009

This table reports the regression results on the relation between lagged bank stress test variables based on SCAP 2009 and local housing prices using county-quarter observations during 2008Q1-2011Q4. The dependent variable is *Zillow Prc Chg 1Q*, which is equal to the natural logarithm of the Zillow House Price Index in the current quarter divided by that in the last quarter. In the first three columns, the regression specification is identical to the baseline of Equation (1), with three stress test variables (*Tier1 Lev Dist*, *Tier1 Cap Dist*, and *Stress Tested*) that are continuous variables. Column (4) and (5) show the results of Equation (3), where *Post* is a dummy variable if the housing price is in a quarter after 2009Q2, when the SCAP 2009 results are released. In Column (4), the dummy variable *Treated* is equal to one if *Tier1 Lev Dist* > 0, and zero otherwise. In Column (5), we replace the *Treated* dummy variable with three dummy variables by sorting *Tier1 Lev Dist* into three tercile groups. *Treated Low (Mid, High) Tercile* is equal to one if *Tier1 Lev Dist* > 0 and the *Tier1 Lev Dist* belongs to the lower (mid, high) tercile. Control variables include bank characteristics, county-level demographic, economic, and political factors. The details of variable construction and data sources are described in Section 3. In all specifications, county fixed effects and year-quarter fixed effects are included. Standard errors are clustered by county. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Treatment: a continuous variable			Treatment: a dummy variable	
	(1)	(2)	(3)	(4)	(5)
Tier1 Lev Dist	0.018*** (7.127)				
Tier1 Cap Dist		0.019*** (6.836)			
Stress Tested			0.011*** (8.412)		
Treated × Post				0.003*** (5.684)	
Treated Low Tercile × Post					0.001 (1.416)
Treated Mid Tercile × Post					0.003*** (4.642)
Treated High Tercile × Post					0.005*** (8.468)
County FE	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y
Observations	39,434	39,434	39,434	38,800	38,800
Adjusted R-squared	0.398	0.398	0.399	0.398	0.401

Table 9: Effects of Bank Stress Test Shocks on Bank Credit Supply in Mortgage Markets

This table reports the regression results of Equation (4), on the relation between lagged bank stress test shocks and their subsequent credit supply in mortgage markets at the mortgage application level. In Column (1) to (3), the dependent variable is a dummy variable indicating the approval of the loan; in Column (4) to (6), the dependent variable is a dummy variable indicating the loan is originated; in Column (7) to (9), the dependent variable is the natural logarithm of loan amount. The key explanatory variable is the bank-level stress test variable *Bank Tier1 Lev Dist*. Bank controls are the same as in the baseline regression in Table 4 but at the bank level. Loan and applicant controls include loan size, borrower income, co-applicant indicator, race, and gender. The details of variable construction and data sources are described in Section 3. In all specifications, county-year fixed effects and bank-county fixed effects are included. Standard errors are clustered by county. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Dependent Variable	Approved			Originated			Loan Amount		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bank Tier1 Lev Dist	-0.044*** (-5.414)	-0.032*** (-4.106)	-0.019** (-2.386)	-0.048*** (-5.697)	-0.036*** (-4.393)	-0.023*** (-2.782)	0.036*** (5.309)	0.062*** (3.880)	0.215*** (13.248)
Low Income × Bank Tier1 Lev Dist		-0.021*** (-3.984)			-0.022*** (-4.025)			0.021 (0.812)	
Low Income		-0.039*** (-9.158)			-0.041*** (-9.289)			-1.058*** (-55.697)	
High Debt to Income × Bank Tier1 Lev Dist			-0.045*** (-9.583)			-0.045*** (-9.227)			-0.304*** (-20.844)
High Debt to Income			0.047*** (11.584)			0.048*** (11.364)			0.958*** (65.624)
County-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank-County FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan Applicant Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,976,107	1,976,107	1,976,107	1,886,717	1,886,717	1,886,717	1,976,107	1,976,107	1,976,107
Adjusted R-squared	0.089	0.085	0.089	0.091	0.086	0.091	0.917	0.687	0.787

Table 10: Bank Stress Test Shocks and Aggregate Credit Supply in Mortgage Markets

This table reports the regression results of Equation (5), on the relation between lagged bank stress test shocks and the total credit supply including banks and nonbanks, and aggregated bank credit supply in the mortgage market at the county-year level. In Column (1) and (2), the dependent variable is *Loan Amount Approved*, which is the natural logarithm of the total mortgage loan amount approved in the county-year. In Column (3) and (4), the dependent variable is *Loan Amount Originated*, which is the natural logarithm of the total mortgage loan amount originated in the county-year. The key explanatory variable is the county-level stress test variable *Tier1 Lev Dist*. The details of variable construction and data sources are described in Section 3. In all specifications, county fixed effects and year fixed effects are included. Standard errors are clustered by county. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Dependent Variable	Loan Amount Approved		Loan Amount Originated	
	Banks	Total	Banks	Total
	(1)	(2)	(3)	(4)
Tier1 Lev Dist	-0.053*** (-2.757)	-0.038** (-2.019)	-0.053*** (-2.714)	-0.050** (-2.520)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County-Bank Controls	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Observations	51,777	51,839	51,764	51,837
Number of Counties	2,672	2,673	2,671	2,673
Adjusted R-squared	0.501	0.434	0.513	0.452

Table 11: Bank Stress Test Shocks and the Risk of Mortgage Loans

This table reports the regression results of Equation (6), on the relation between lagged bank stress tests and the risk of mortgage loans using county-year observations. The dependent variable is the risk of the mortgage loans measured by *Perc Delinq 90*, *Perc Delinq 30*, and *Perc Subprime*, in Column (1), (2), and (3), respectively. *Perc Delinq 90* (*Perc Delinq 30*) is the percentage of mortgage loans that are past due for over 90 (30) days in a county, and the data is from Consumer Financial Protection Bureau (CFPB) which covers 434 counties. *Perc Subprime* is the percentage of subprime mortgage loans in a county and from the Economic Data by Fed (FRED) which covers 2595 counties in our sample. The key explanatory variable is the stress test variable *Tier1 Lev Dist*. Control variables include county-level bank characteristics, county-level demographic, economic, and political factors, and for the sake of brevity their coefficient estimates are not presented. The details of variable construction and data sources are described in Section 3. In all specifications, county fixed effects and year fixed effects are included. Standard errors are clustered by county. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Perc Delinq 90 (1)	Perc Delinq 30 (2)	Perc Subprime (3)
Tier1 Lev Dist	-1.615*** (-3.545)	-1.961*** (-3.503)	-1.762** (-2.472)
County FE	Y	Y	Y
Year FE	Y	Y	Y
County-Bank Controls	Y	Y	Y
County Controls	Y	Y	Y
Observations	9,750	9,750	26,131
Number of Counties	434	434	2,595
Adjusted R-squared	0.894	0.938	0.992

Table 12: Bank Stress Test Shocks and Local Population Migration Patterns

This table reports the regression results of Equation (7), on the relation between lagged bank stress tests and local population migrations using county-year observations during from 2008 to 2016. The dependent variables are the net size of population moving out of a county, the size of population moving out of a county, and the size of population moving into a county, scaled by the total number of tax filings of the county in the first three columns and by the total population of the county in the last three columns. The key explanatory variable is the stress test variable *Tier1 Lev Dist*. Control variables include county-level bank characteristics, county-level demographic, economic, and political factors, and for the sake of brevity their coefficient estimates are not presented. The details of variable construction and data sources are described in Section 3. In all specifications, county fixed effects and year fixed effects are included. Standard errors are clustered by county. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Dependent Variable	Net Out1	Out1	In1	Net Out2	Out2	In2
	(1)	(2)	(3)	(4)	(5)	(6)
Tier1 Lev Dist	0.020** (2.496)	0.004 (1.599)	-0.015** (-2.419)	0.019** (2.542)	0.009*** (2.902)	-0.011 (-1.529)
Bank Controls	Y	Y	Y	Y	Y	Y
County Controls	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	18,117	20,550	18,117	18,117	20,550	18,117
Number of Counties	2684	2684	2684	2684	2684	2684
Adjusted R-squared	0.772	0.916	0.887	0.753	0.904	0.908

Table 13: Bank Stress Test Shocks and Local Income Distribution

This table reports the regression results on the relation between lagged bank stress tests and income distribution of residents using county-year observations. The dependent variables are *Chg Perc Below 25K*, *Chg Perc Below 25K*, *Chg Perc Below 25K*, and *Chg AGI*, in Column (1), (2), (3) and (4), respectively. *Chg Perc Below 25K* (*Chg Perc Below 50K*, *Chg Perc Below 75K*) is the natural logarithm of the percentage of tax filings with income no greater than \$25,000 (\$50,000, \$75,000) in a county in the current year divided by the percentage in the previous year. *Chg AGI* is the natural logarithm of the average taxable income of all tax filings in a county in the current year divided by its value in the previous year. All four dependent variables are constructed using data from IRS. The key explanatory variable is the stress test variable *Tier1 Lev Dist*. Control variables include county-level bank characteristics, county-level demographic, economic, and political factors, and for the sake of brevity their coefficient estimates are not presented. The details of variable construction and data sources are described in Section 3. In all specifications, county fixed effects and year fixed effects are included. Standard errors are clustered by county. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

	Chg Perc Below 25K	Chg Perc Below 50K	Chg Perc Below 75K	Chg AGI
	(1)	(2)	(3)	(4)
Tier1 Lev Dist	-0.026*** (-4.161)	-0.017*** (-4.695)	-0.008** (-1.984)	0.031* (1.922)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
County-Bank Controls	Y	Y	Y	Y
County Controls	Y	Y	Y	Y
Observations	45,447	45,447	45,447	51,797
Number of Counties	2670	2670	2670	2674
Adjusted R-squared	0.231	0.283	0.91	0.146