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Army of Mortgagors: Long-Run Evidence on Credit Externalities and the Housing Market*

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Abstract

Houses are the most important asset on American households' balance sheets, rendering the U.S. economy sensitive to house prices. There is a consensus that credit conditions affect house prices, but to what extent remains controversial, as an expansion in credit supply often coincides with changes in house price expectations. To address this long-standing question, we rely on novel microdata on the universe of mortgages guaranteed under the Veterans Administration (VA) loan program. We use the expansion of eligibility of veterans for the VA loan program following the Gulf War to estimate a long-lived effect of credit supply on house prices. We then exploit the segmentation of the conventional mortgage market from program eligibility to link this sustained house price growth to developments in the initially unaffected segment of the credit market. We uncover a net increase in credit for all other residential mortgage applicants that aligns closely with the evolution of house price growth, which supports the view that credit-induced house price shocks are amplified by beliefs.

JEL classifications: E21, G20, G21, G28
Keywords: credit supply, mortgages, beliefs, house prices, veterans

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1 Introduction

Housing and mortgage debt are the most important items on the balance sheets of U.S. households. As such, the house price fluctuations of the 21$^{\text{st}}$ century have placed the housing and mortgage markets center stage of the debate on the interplay between the financial system and the real economy. In particular, credit supply has been proposed as an important determinant of house prices and, thus, as a key channel for boom and bust cycles of the macroeconomy (Mian and Sufi, 2009). However, the empirical scrutiny of this relationship is burdened with the challenge of separating the role of credit supply from house price expectations that simultaneously govern credit demand. A causal interpretation of empirical estimates thus requires identifying credit expansions that are independent of variation in market participants' house price expectations (Kuchler, Piazzesi, and Stroebel, 2022).

This paper addresses this challenge by leveraging novel data on the universe of mortgages guaranteed under the Veterans Administration (VA) loan program over the last three decades. In August 1990 the VA loan program extended eligibility to the large group of Gulf War veterans concentrated in specific regional housing markets. This quasi-experimental variation in credit supply allows to identify the effect of more readily available credit on local house prices. Importantly, this credit supply shock originates from a segment that is separated from the remaining mortgage market only by veteran status, i.e., independent of economic conditions. This unique feature enables us to disentangle house price growth due to credit supply in one segment of the mortgage market from credit fluctuations in the other. In particular, the expansion of credit affects the VA loan segment, but simultaneously shifts house price expectations for the non-VA population in regions with high concentrations of newly eligible veterans due to higher house prices (see, e.g., Armona, Fuster, and Zafar, 2018). In this manner, we document an amplification of the initial house price increases through changes in expectations that feed back to additional credit supply (and demand).

The granularity and the long time span of our data offer two key advantages for our research design. First, we can study the housing market in the 1990s, which unlike the tumultuous 2000s saw anchored house price expectations. Second, we can identify particularly generous loans guaranteed under the VA loan program that offer conditions unmet on the ordinary mortgage market, such as loan-to-value ratios clearly in excess of one. We document a significant positive relationship between the number of generous VA loans and house price growth at the county level, which lasts up to five years, becomes weaker in counties with greater housing supply elasticity, and holds up to including county by decade fixed effects.

To achieve a causal interpretation of this result, we pursue a Bartik-like identification strategy. We construct an instrument for the provision of generous VA loans by interacting a pre-determined exposure measure at the county level with a common shock that is a function of time-varying share of veterans taking out generous VA loans. For this purpose, we exploit the fact that veterans purchase homes close to the military bases from which they were deployed to the Gulf War. Combining the microdata with hand-collected data on U.S. military bases, we distinguish VA loan recipients by their military branch (Air Force, Army, Navy, or Marine Corps) and determine, first, for each county the distance to the closest Gulf War base of the respective branch. Second, we determine the national take-up rate of generous VA loans per branch, which varies over time as veterans were deployed at different ages but purchase homes roughly around the same age (of 30). To ensure that the exclusion restriction holds, we control for any confounding house price effects associated with a county's proximity to military bases in general, as captured by the non-Gulf War equivalent of our Bartik instruments.

We show that a one-standard-deviation higher share of generous VA loans increases house prices by approximately 6% in the year following the credit supply shock. The effect is further amplified for another five years, after which it starts to reverse. We then show that the larger part of this amplification effect reflects house price reactions to developments in the mortgage market that are due to changes in house price expectations. For this purpose, we use our credit-supply-induced exogenous variation in house price growth to scrutinize its impact on the conventional mortgage, as opposed to the VA loan, market. The segmentation of the two mortgage markets allows us to capture the role of house price expectations and beliefs for mortgage market outcomes that potentially foster further house price increases. Consistent with this view, we find that lenders—including those without exposure to the VA loan market—expand credit supply in housing markets with rising prices. A one-standard-deviation larger house price increase leads to a 2.1 percentage-point higher approval rate and 2% lower average interest rates on new mortgages at the county level.

Using application-level data from the Home Mortgage Disclosure Act (HMDA), we show that this finding is robust to controlling for time-varying unobserved heterogeneity at the lender level, including overall trends in individual institutions' lending behavior that are not specific to county-level house price developments. These granular data also allow us not only to dig deeper into underlying heterogeneous effects but also to control for confounding supply and demand forces. Doing so, we establish a net relative increase in supply, which results from multiple forces on both the supply and the demand side of credit.

When we test for demand forces at the mortgage contract level, we exploit between-borrower variation by including fixed effects at the lender by county by year level, which is the most granular level at which mortgage supply can be confounded with local house price growth. In line with Bailey, Dávila, Kuchler, and Stroebel (2019), who fail to detect any effect of increased household optimism on leverage choices among owner-occupiers, we find that demand drops relatively more for owner-occupiers or, put differently, it increases relatively more for non-owner-occupiers, such as expectations-driven investors. This is reflected at the extensive margin by lower approval rates and at the intensive margin by higher loan amounts (conditional on the approval of an application) for the latter type of borrowers.

To isolate supply forces from such demand-driven effects, we incorporate county by year fixed effects, which subsume any stand-alone effect of house price growth on mortgage outcomes, and use between-lender variation in the same county and year. Lenders for whom real estate makes for a larger portion of their overall loan portfolio expand their supply by more in response to credit-supply-induced house price growth. This results in higher approval rates and larger loan amounts granted, even after additionally controlling for lender by year fixed effects. Using complementary data on interest rates from the Federal Housing Finance Agency's Monthly Interest Rate Survey (MIRS), we confirm that such specialized lenders increase their supply and subsequently offer lower interest rates.

Finally, we show that credit-induced house price growth mitigates asymmetric-information concerns in the supply of credit, as lenders charge lower interest rates for new buildings where asymmetric information about the collateral matters more. Importantly, the incorporation of county by year, and in the previous tests lender by county by year, fixed effects holds constant the average effect of *contemporaneous* house prices on households' collateral constraints, the relaxation of which matters for credit supply (see Cloyne, Huber, Ilzetzki, and Kleven, 2019, for evidence from the United Kingdom). In this manner, we test, instead, for the effect of higher *expected* future collateral value. Besides manifesting pecuniary externalities stemming from the VA loan market, these heterogeneous effects are all consistent with the view that house price growth affects mortgage market outcomes through altering beliefs.

Our paper contributes to the literature on the effects of mortgage supply on the macroeconomy. A defining question in this literature is if and how credit supply and house prices connect financial markets and the real economy. In particular, the Great Financial Crisis (GFC) has sparked research trying to model and quantify this connection. Prominently, Mian and Sufi (2009) argue that securitization in the early 2000s translated to a credit supply shock in the housing market, and that this credit supply shock was a substantial driver of the house price boom leading up to the GFC. Rising house prices have then led to increasing credit demand also by other households, further fueling household indebtedness.

In contrast, Foote, Gerardi, and Willen (2012) and Adelino, Schoar, and Severino (2016) argue in favor of a shift in expectations as the main causal mechanism for higher debt levels and house prices. Expectation-driven asset price booms can arise, for instance, from non-rational expectations (e.g., Glaeser and Nathanson, 2017; DeFusco, Nathanson, and Zwick, 2022). The main argument for such an expectation-driven boom is based on the observation that the credit expansion during the house price boom was broad-based across all income strata of the population. A broad-based increase in household debt lends support to the hypothesis that the credit expansion resulted from, rather than caused, higher house prices.[1]

Although the precise mechanism and the initial trigger of the debt and house price booms during the early 2000s are still debated, there is a consensus that the two forces amplified each other and that the resulting high debt levels exacerbated the economic downturn from the GFC. Against the backdrop of this important macroeconomic discussion, there is very little direct evidence on the transmission mechanism—in particular the role of shifting expectations and whether they precede or follow increases in credit supply—and most of the existing evidence focuses on the turbulent times of the boom-bust period surrounding the GFC. The challenge in providing direct evidence is to disentangle expanding credit supply leading to higher house prices from higher house price expectations leading to more credit demand (Adelino, Schoar, and Severino, 2018; Mian and Sufi, 2018). The segmented credit supply shock from the expansion of eligibility for the VA loan program allows us to tackle this challenge and, thus, fill a crucial gap in the literature.

The first building block of our paper is to show how an initial credit supply shock from outside the financial system affects house prices. As such, it is closely related to the strand of research purporting that exogenous credit supply expansions lead to higher house prices (Favara and Imbs, 2015; Di Maggio and Kermani, 2017; Mian, Sufi, and Verner, 2020; Blickle, 2022). Unlike our setting, these papers have in common that they rely on credit supply shocks that originate from the banking sector, e.g., due to regulation or changes affecting local bank competition. More akin to the nature of our credit supply shock is that in Tracey and Van Horen (2021), who study the "Help to Buy" program in the United Kingdom during the aftermath of the GFC. Likely because of the challenging financial market conditions,

[1] Violante (2018) discusses the opposing views on the drivers of the debt increase before the GFC.

the program provided support for potential homeowners aiming to buy houses with low downpayments who otherwise would not have received financing given the then predominant market conditions—typically young, low-income households.

By using the expansion of VA eligibility in the early 1990s, our approach is similar in that it relies on a particular historical episode to study the consequences of credit supply shocks. Importantly, however, we exploit a quasi-experimental expansion of credit that results from past geopolitical decisions of the U.S. government and is, thus, orthogonal to the financial system. Furthermore, the shock affects only a clearly defined segment of the mortgage market. As a result, our VA credit supply shock matches closely the description of a credit supply shock in Mian and Sufi (2018) as "an increased willingness of lenders to provide credit that is independent of the borrowers' income position."

The segmentation of the conventional mortgage market and the VA loan market, in conjunction with the VA eligibility shock, allows us to disentangle the initial effect of credit supply on house prices from the subsequent spillover effects on the remainder of the mortgage market due to adjusted house price expectations. Furthermore, we study the housing market during normal times, which is all the more important in light of evidence that the sensitivity of economic activity to house prices was stable (Guren, McKay, Nakamura, and Steinsson, 2020), unlike most of the existing work that considers time periods around the GFC.[2] Finally, while the Gulf War constitutes as much a singular event as those used in previous studies, we can make use of the fact that the ramifications of the Gulf War for the take-up of generous VA loans materialize even many years later due to variation in the age at which veterans are drawn into their respective military branch. This puts us in a unique position to consider long-term effects over three decades.[3]

An exception to the approach of looking at particular time periods is Jordà, Schularick, and Taylor (2015) who rely on macroeconomic cross-country panel data and an instrumental-variable approach for shifts in credit supply. They find that across countries and time, house prices and household debt increase after a credit supply shock. Adelino, Schoar, and Severino (2020) also differ from existing work as they use individual-level, rather than regional-level, data to study how changes in financing costs around the conforming loan limit (CLL) affect

[2]In contrast, Favara and Imbs (2015) study banking deregulation during the 1990s, which they argue allows them to address the potential endogeneity of credit supply to conditions in the housing market.

[3]We will discuss adjusting expectations over the long run, but this is an intricate information problem as non-veteran households have to know the joint distribution of age and eligibility of veterans in their local housing market to form expectations on future credit supply shocks from VA eligibility.

house prices. They find a positive effect on house prices stemming from lower funding costs, consistent with a positive credit supply shock.

A key advantage of our quasi-natural experiment is that it allows us to separately study and quantify the empirical relevance of the credit supply and expectation-based channels. By identifying a feedback effect of credit-supply-induced house price growth on the conventional mortgage market, we close a gap in the scrutiny of transmission mechanisms of credit supply shocks. Namely, we provide empirical evidence of a key missing link from credit supply to house prices and back to credit supply in line with the expectation-based view, which to date has been only a theoretical conjecture (Violante, 2018).

Mirroring the empirical literature, the theoretical literature also presents different attempts to pin down these two mechanisms. Favilukis, Ludvigson, and Van Nieuwerburgh (2017), Justiniano, Primiceri, and Tambalotti (2019), and Greenwald and Guren (2021) emphasize the quantitative importance of expanding credit supply for the house price boom. Kaplan, Mitman, and Violante (2020) argue that only if there is a sufficiently large group of constrained households, changing credit conditions can drive aggregate house prices. Including both the credit supply and the expectation-based channel in their quantitative model, they conclude that shifts in expectations were the main driver of the house price boom in the early 2000s. They also find a strong effect of rising house price expectations on household debt. By documenting strong pecuniary externalities due to changes in expectations following an otherwise modest credit supply shock, our empirical findings synthesize and reconcile these different theoretical mechanisms underlying the change in aggregate house prices.

Beyond the new economic insights, we also contribute to the literature a novel data source that covers 40 years of U.S. financial history. It is the granularity and extent of these novel data on the universe of VA loans that allow us to expand upon the important findings that already exist on the role of credit in the macroeconomy. The dataset that we introduce relates our work to Fieldhouse, Mertens, and Ravn (2018) who use data on changes in GSE mortgage purchases, including those by federal agencies such as the Veterans Administration. They document an increase in mortgage supply and increasing house prices, however solely based on macroeconomic data. To the best of our knowledge, the microdata on VA loan guarantees has not been exploited before for economic research.

2 Historical and Institutional Background

The U.S. Department of Veterans Affairs offers a range of services to veterans of the US military. One of the most prominent services is to support veterans in becoming homeowners by providing guarantees for home-purchase and refinancing loans, known as VA loans. The Veterans Administration does not directly grant loans to eligible veterans but, instead, offers insurance for loans of veterans obtained in the private market. Since the program's inception in 1944, more than 22 million loans have been guaranteed. The insured loans offer conditions that are typically not available in the regular mortgage market. Most importantly, the VA does not require any downpayment, making it possible for many borrowers to obtain loans they may not qualify for under other loan-guarantee programs. Eligibility for VA loans is based on veterans' military service, with specific requirements varying by type and duration of service, e.g., having served for at least 90 days on active duty in the Gulf War.[4] As a consequence, large-scale military operations expand the group of eligible veterans. Eligibility increases not automatically, though, but has to be decided by the U.S. Congress.

The Gulf War of 1990-1991 was a significant event in military history. The conflict began when Iraq, under the leadership of Saddam Hussein, invaded Kuwait in August 1990, prompting international condemnation and a military response from the United States and its allies. The role of the U.S. military in the Gulf War was central to the success of the operation, which involved a massive deployment of American troops, equipment, and logistical support to the region. The U.S.-led coalition forces launched two operations:

Operation *Desert Shield* began on August 7, 1990, when the U.S. deployed military forces to the Persian Gulf region in response to Iraq's invasion of Kuwait. The operation was focused on defending Saudi Arabia from potential Iraqi aggression and building up a coalition force to expel Iraqi forces from Kuwait. Operation *Desert Storm* began on January 17, 1991, with an aerial bombardment of Iraqi targets, and continued with a ground assault that liberated Kuwait on February 27, 1991. The success of these operations marked a turning point in the military history of the Middle East and shaped the political landscape of the region for years to come. In total, the U.S. military deployed approximately 700,000 soldiers in both operations, making it one of the largest military deployments in history. All four branches of the military—i.e., Air Force, Army, Navy, and Marine Corps—were involved.

After the war ended, on April 6, 1991, the criteria for VA loan eligibility were significantly

[4]See https://www.va.gov/housing-assistance/home-loans/eligibility/.

relaxed. As a result of Public Law 102-25, all veterans, including those on active duty during the Gulf War, became eligible. We exploit this historical expansion of the VA loan program to quantify the effect of credit supply on house prices and house price expectations in the non-VA segment of the housing market.

As soldiers that were actually deployed to the Gulf War are more likely to lack a credit history, which is a friction that the Veterans' Home Loan Program Improvement Act was designed to mitigate, we argue that previously deployed veterans are more prone to taking up VA loans. As we consider anyone who served on active duty from August 2, 1990, to present a Gulf War veteran, we see veterans become eligible for the VA loan program even decades later due to the American-led invasion of Iraq in 2003.

3 Data

Our empirical analysis relies on loan-level microdata from two sources that provide high-quality detailed information on loan and borrower characteristics. The first dataset is novel microdata from the VA loan program. The second dataset is the data collected under the Home Mortgage Disclosure Act (HMDA data). We combine a subset of the HMDA data with lender information using the so-called "Avery file." Furthermore, we combine another subset of the HMDA data with interest-rate data from the Federal Housing Finance Agency's Monthly Interest Rate Survey (MIRS). We merge the loan-level microdata with county-level data on house prices, income, unemployment rates, and housing supply elasticities from Saiz (2010). Next, we describe these different data sources in turn.

3.1 Loan-level Microdata

The VA loan program data are administered by the Department of Veterans Affairs. We obtain the microdata on the universe of mortgages guaranteed under the VA loan program for four decades from 1978 to 2017.[5] In total, the data contain 13.3 million records. On average, VA loans correspond to 5-10% of all newly issued mortgages in the U.S. mortgage market. The microdata on these loans provide detailed information on the loan, as is customary also in the HMDA data, but most importantly on the applicant, such as information on the veteran's entitlement status and military branch, which are unavailable in the HMDA data.

[5] Data have been obtained under the Freedom of Information Act request FOIA 22-03431-F.

Table 1: **Summary Statistics: VA Loans**

	Mean	SD	Min	P25	P75	Max	N
Generous loans							
Age	31.7	7.1	18.0	26.0	36.0	98.0	1,094,096
Loan amount (in thous.)	191.4	69.3	47.1	137.8	245.4	399.4	1,094,140
Income (in thous.)	69.7	70.1	8.3	49.7	82.5	51,882.4	1,080,244
LTV (in %)	100.9	2.6	79.7	100.7	101.7	102.5	1,094,013
Debt-to-income (in %)	39.7	4.5	25.0	38.1	43.0	43.0	814,675
Other loans							
Age	34.0	8.1	18.0	28.0	39.0	99.0	1,125,018
Loan amount (in thous.)	204.0	74.7	47.1	144.3	269.6	408.5	1,125,052
Income (in thous.)	80.0	195.2	6.3	53.4	95.3	180,622.9	1,114,065
LTV (in %)	97.3	5.1	79.7	95.1	100.0	102.5	1,124,442
Debt-to-income (in %)	36.0	5.4	25.0	34.1	41.5	41.5	678,514

Notes: The table reports summary statistics for VA loans to Gulf War veterans for home purchases. The upper panel comprises loans classified as generous, whereas the lower panel comprises the remainder. All dollar values are converted to 2017 dollars using the Consumer Price Index Retroactive Series.

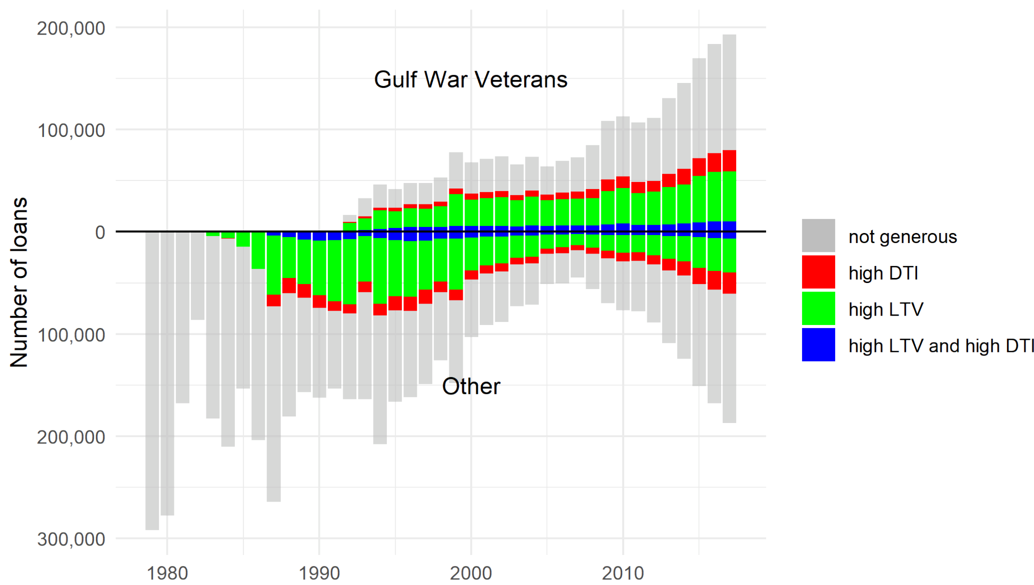
For our analysis, we focus on the period from 1991 when the first Gulf War entitlement loans are observed in the data up until the end of the sample.[6] There are 3.4 million loans with this entitlement status. Table 1 reports descriptive statistics of all VA-guaranteed loans granted to Gulf War veterans. Note that some variables such as the loan amount, the loan-to-value (LTV) ratio, or the debt-to-income ratio are only provided in bins in the raw data, and we use the midpoints of these bins to construct data moments.

The upper panel of Table 1 reports descriptive statistics for loans with particularly "generous" conditions. We will rely on this subset of loans to construct the credit supply shock. The generous VA loans capture the subset of loans insured by the VA program that would typically not be provided in the private market. Specifically, we classify a loan as generous if the debt-to-income (DTI) ratio of the loan is above 43%, which is the maximum permissible ratio given by the Federal Housing Administration (FHA), or if the loan-to-value ratio is above one, implying zero downpayment.[7] These loan conditions are typically not attainable

[6]We focus on the entitlement code "Persian Gulf," which also covers the missions in Afghanistan and Iraq in the 2000s.

[7]We additionally require that total assets amount to less than 25% of the mean annual income in the same year and county so as to safeguard that borrowers' LTV constraints are binding for conventional loans.

Figure 1: **Composition of VA Loans over Time**



Notes: For each year from 1979 to 2017, this graph plots the number of guaranteed VA loans for home purchases. Positive bars show the number of loans granted to Gulf War veterans. Negative bars show loans to all other veterans. Colored parts of the bars show the number of generous loans broken down by loan characteristics.

on the ordinary mortgage market as lenders usually require DTI ratios below 43%.[8] Hence, we consider loans with either high LTV, high DTI, or both as generous VA loans.

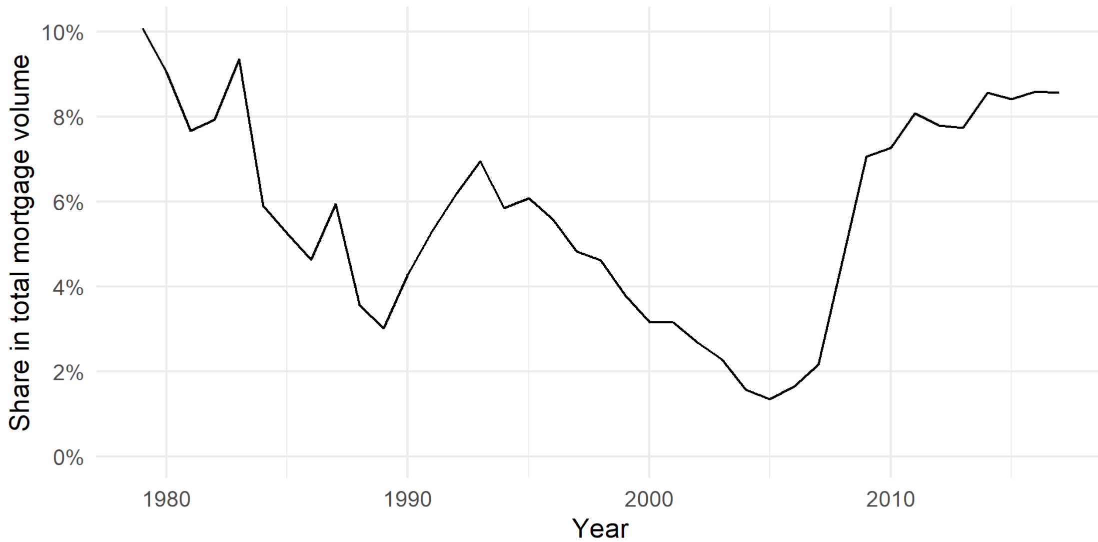
This is also reflected in the respective summary statistics, as these loans have high LTVs with an average of approximately 101%. For comparison, the average LTV ratio of non-VA mortgages in the first year this variable becomes available in the HMDA data (2018) is 81%, while the average LTV ratio across all VA loans is 97% in the same year. What is more, the average borrower of a generous VA loan is 32 years old and, thus, younger than the average person in the United States. Army veterans at 41% account for the largest share of VA loan borrowers, followed by Navy and Air Force veterans with 23%, while Marine Corps veterans (11%) are least well represented in our sample.[9]

The lower panel reports descriptive statistics for all remaining VA loans. They are broadly similar to those in the top panel, owing (at least partly) to the fact that both types of loans

[8] A key requirement for income under the VA loan program is the "residual income" of the loan applicant. There exist detailed rules for the determination of residual income, designed to correspond to disposable income of the household after taxes, mortgage payments, utility costs, and other expenditures.

[9] Coast guards and other groups account for 2.5% of all VA loans.

Figure 2: **Importance of VA Loans in the Total Mortgage Market**



Notes: For each year from 1979 to 2017, this figure shows the share of VA loans as a percentage of the total issued mortgage volume. Data from 1979 to 1989, unavailable in the HMDA dataset, are from the U.S. Department of Housing and Urban Development, and data from 1990 to 2017 are from HMDA.

are granted to Gulf War veterans. However, against the background of the binned nature of the LTV and DTI ratios, one can still infer that while all VA loans are fairly "generous" compared to ordinary mortgages, this holds in particular for those identified in the top panel. The average LTV ratio is higher for generous loans in the top panel, but the difference is understated due to the bins. Once one zooms in on the middle of the distribution, e.g., the 25^{th} percentile, the difference becomes larger. This holds also for the DTI ratios in the last row of each panel.

Figure 1 shows the number of VA loans by year of guarantee for different categories. The bars above (below) the horizontal line represent loans granted to Gulf War veterans (all other veterans). The colored bars are generous VA loans broken down by loan characteristics. Notably, generous VA loans were not available prior to the second half of the 1980s. As stated above, many loans are classified as generous because they carry an LTV larger than 100%. Starting in 1992, the number of loans accruing to Gulf War veterans increases quickly up to around 75,000 loans guaranteed each year. While the number of guaranteed VA loans decreases during the housing boom of the 2000s, the number for Gulf War veterans is roughly constant. For our analysis, we focus on home-purchase loans and exclude refinancing loans. Importantly, this implies that we have no subprime loans in our sample.

Table 2: **Summary Statistics: Conventional Mortgages**

	Mean	SD	Min	P25	P75	Max	N
All conventional-loan applications							
Application approved	0.8	0.4	0.0	1.0	1.0	1.0	87,602,221
Loan amount (in thous.)	206.6	258.0	0.0	83.3	265.0	309,000.0	87,602,077
Applicant income (in thous.)	119.9	216.1	1.0	55.0	134.8	542,821.0	87,602,221
Applicant white	0.8	0.4	0.0	1.0	1.0	1	87,602,221
Applicant male	0.7	0.4	0.0	0.0	1.0	1	87,602,221
Home not owner-occupied	0.1	0.3	0.0	0.0	0.0	1.0	87,021,913
Granted loans with interest-rate information							
Interest rate (in %)	6.7	1.2	2.6	5.9	7.5	18.4	4,854,384
Loan amount (in thous.)	225.9	146.2	11.3	126.8	284.4	1,264.2	4,854,384
Maturity (in years)	27.9	5.5	1.0	30.0	30.0	40.0	4,854,384
Loan-to-Price Ratio (in %)	76.2	17.5	2.0	70.0	90.0	100.0	4,854,384
Fixed rate	0.8	0.4	0.0	1.0	1.0	1.0	4,854,384
New building	0.2	0.4	0.0	0.0	0.0	1.0	4,854,376

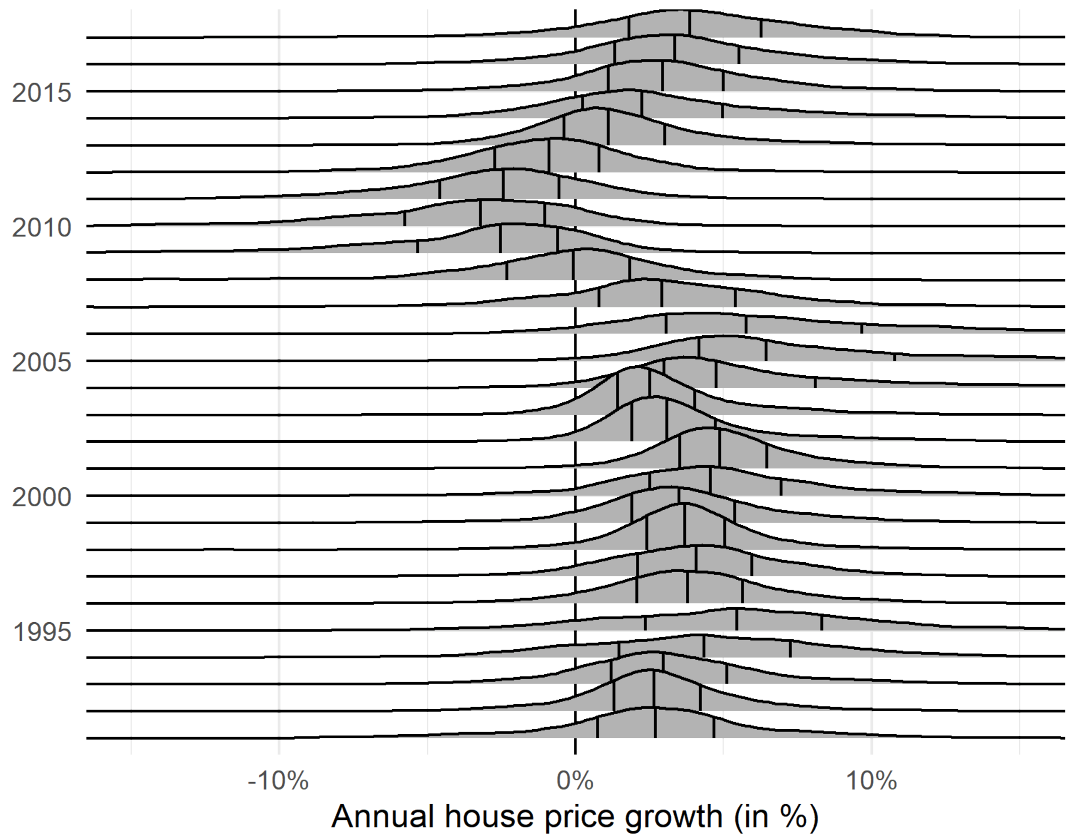
Notes: The upper panel reports summary statistics for the universe of loan applications in the conventional loan market in the HMDA data at the application level m, as used in Tables 8 to 10. The lower panel is limited to the subsample of granted mortgages for which we have data on interest rates from the MIRS dataset, as used in Tables 11 and 12. All dollar values are converted to 2017 dollars using the Consumer Price Index Retroactive Series.

Over the entire period since 1979 (the first year in the VA microdata), the VA loan program covers a substantial share of the U.S. mortgage market. As can be seen in Figure 2, up to ten percent of all newly issued mortgages are guaranteed by the VA loan program, both before (in the early 1980s) and during our sample period (especially in the 2010s). The VA loan program is, thus, sufficiently large to make it plausible that changes in the VA loan market can have an effect on prices in the housing market, especially if they give rise to amplification effects through the remaining mortgage market.

To cover the conventional mortgage market, we use the Home Mortgage Disclosure Act (HMDA) dataset. We extract for the time period from 1991 to 2017 data on 88 million loan applications, excluding all subsidized loans (FHA, VA, and FSA/RHS)[10] and, again, any refinancing loans. The upper panel of Table 2 provides summary statistics for all conventional-loan applications. 80% of all applications are approved on average. Importantly, the average

[10]See Fieldhouse, Mertens, and Ravn (2018) for a comprehensive overview of the policy changes in these programs over time.

Figure 3: **Distribution of House Price Growth**



Notes: For each year from 1991 to 2017, this graph plots the distribution of house price growth across the 2361 counties in our sample. We limit the support of the figure to [-15%;15%].

loan amount is close to the average amount of VA loans for Gulf War veterans (cf. Table 1), but applicants' income is substantially higher for conventional loans given the occupational sorting. Furthermore, the vast majority of loan applications are for owner-occupied housing, which is a characteristic that we use in our empirical analysis to capture relative demand by investment-driven borrowers vs. owner-occupiers. We also include summary statistics on other applicant characteristics, such as their gender, that we use as control variables wherever applicable.

For a subset of these conventional loans, we can add lender balance-sheet characteristics from call reports, which we obtain via Wharton Research Data Services (WRDS). To match the two datasets, we use the HMDA Lender File from the Federal Housing Finance Agency (FHFA), the so-called "Avery file." Using additional information, we determine for each lender the share of real estate loans out of its total loan portfolio and use this share to measure the degree to which the lender specializes in mortgage lending. To overcome endogeneity problems, we use the first observation in a decade for each lender. We find that the share of real estate loans varies significantly across lenders. The median loan portfolio consists of 53% real estate loans, close to the average of 54%. The interquartile range is 34.2 percentage points between 36.4% and 70.6%.

We obtain interest-rate data from a separate dataset, which cannot be merged with the HMDA data, namely the Federal Housing Finance Agency's Monthly Interest Rate Survey (MIRS) for the period from 1992 to 2010. The MIRS survey is a small-scale survey of mortgage lenders in which respondents are asked to report the terms and conditions of all conventional, single-family, fully amortized purchase-money loans closed during the last five working days of a month. Since participation decreased, the data provide comprehensive coverage only before 2010.[11]

The lower panel of Table 2 reports the summary statistics for the subsample of granted conventional mortgages with interest-rate information. We find that this subsample aligns closely with the universe of loan applications in the upper panel. The average loan amounts are close at 226 and 207 thousand dollars. Furthermore, loans have an average maturity of almost 28 years. We also include summary statistics on other mortgage characteristics, such as their interest-rate type (fixed vs. floating rate), that we use as control variables wherever applicable. Lastly, 20% of the loans with interest-rate information are used for new buildings, which is a characteristic that we use to capture the extent of asymmetric information.

3.2 County-level Data

We combine the loan-level microdata with regional house prices and local economic conditions, and focus on the county as our unit of analysis. We obtain regional data from Federal Reserve Economic Data (FRED). For each county c we compute annual local house price growth in year t from the house price index by Fannie Mae and Freddie Mac as

$$\text{House price growth}_{c,t} = 100 \times \frac{\text{House price}_{c,t} - \text{House price}_{c,t-1}}{\text{House price}_{c,t-1}}.$$

[11] For aggregation at the county level, we exclude county-year pairs with fewer than ten observations.

Table 3: **Summary Statistics: County-year Level**

	Mean	SD	Min	P25	P75	Max	N
Average county-level loan statistics							
Share Gulf War VA loans (per 100,000)	27.17	62.06	0.00	3.93	26.85	1,457.46	59,710
Share generous Gulf War VA loans (per 100,000)	12.50	34.97	0.00	0.00	11.90	962.39	59,710
Approval rate conventional loans (in %)	72.77	15.20	0.00	64.34	84.21	100.00	59,665
Mean loan amount, conventional loans (in thous.)	147.44	81.03	11.16	98.93	173.03	2,075.65	59,632
Mean interest rate (in %)	6.84	1.00	3.45	6.12	7.61	11.34	40,054
County economic conditions							
House price growth (in %)	2.89	5.08	−44.81	0.25	5.39	56.42	59,710
Change in unemployment (in pp.)	−0.07	1.22	−13.60	−0.70	0.40	13.20	59,689
Income growth (in %)	3.57	3.71	−85.67	1.85	5.37	89.31	58,421
Population growth (in %)	0.71	1.58	−145.97	−0.16	1.35	35.46	59,710
Housing supply elasticity ρ	2.36	1.24	0.60	1.45	3.00	12.15	7,541
Distance to closest Gulf War base							
Army base (in miles)	338.15	272.42	1.54	145.34	442.75	1,437.97	2,354
Navy base (in miles)	436.31	286.10	2.33	190.86	634.75	1,190.53	2,354
Air Force base (in miles)	246.29	156.04	1.54	123.70	345.31	777.84	2,354
Marine Corps base (in miles)	648.39	319.88	3.39	402.53	915.23	1,376.61	2,354

Notes: Table reports summary statistics at the county-year level ct, corresponding to the respective descriptions in Tables 5 to 7. Loan amounts are converted to 2017 dollars using the Consumer Price Index Retroactive Series.

The index is based on appraisal values and sales prices from mortgages bought or guaranteed, and is computed using the repeated-sales methodology (see Bogin, Doerner, and Larson, 2019, for details). It has an annual, rather than monthly, frequency, which in turn allows for wider geographic coverage and a longer time series than other indices can offer.

Figure 3 shows the distribution of house price growth across counties for each year from 1991 to 2017. The vertical lines at each year's density mark the 25$^{\text{th}}$, 50$^{\text{th}}$, and 75$^{\text{th}}$ percentiles of the house price growth distribution. Over the sample period, we typically observe that most counties saw positive house price growth. On average, broad-based negative house price growth occurs only after the Great Financial Crisis. Furthermore, in all years there is significant variation across counties, with a standard deviation in house price growth of 5.1 and an interquartile range of 5.1.

In addition to house price data, we use county-level population data from the Census Bureau and the unemployment rate from the U.S. Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS). We calculate mean income at the county level as the total personal income received divided by the county population.

We complement these data with housing supply elasticities at the MSA level (Saiz, 2010). To assign counties to their corresponding MSAs, we employ a crosswalk provided by the U.S. Department of Labor, and assume the same housing supply elasticity within all counties belonging to the same MSA (as in Favara and Imbs, 2015). The elasticity is available for about one-third of the counties in our sample. For this subset of counties, we have a mean elasticity of 2.36. When we rely on these elasticities in our analysis, we end the sample in 2000, consistent with the validation period in Saiz (2010). The resulting sample selection is not correlated with distance to the next military base (see Appendix Figure A1). Finally, Table 3 provides summary statistics for all county-year-level variables used in our analysis.

4 Identification Strategy

The main data source for our analysis of the effects of credit supply on the housing market is the novel administrative VA loan microdata. The VA loan program has two key features that we leverage for this purpose. First, it covers a sizable part of the U.S. mortgage market and is, thus, large enough to have an impact on regional housing markets. Second, the VA loan program only affects a clearly defined segment of the mortgage market. Finally, we exploit for our identification that following the Gulf War, thousands of U.S. veterans became eligible for the VA loan program. This expansion of eligibility of the VA loan program is orthogonal to local economic conditions and the banking sector as the Gulf War itself resulted from U.S. geopolitical decisions.

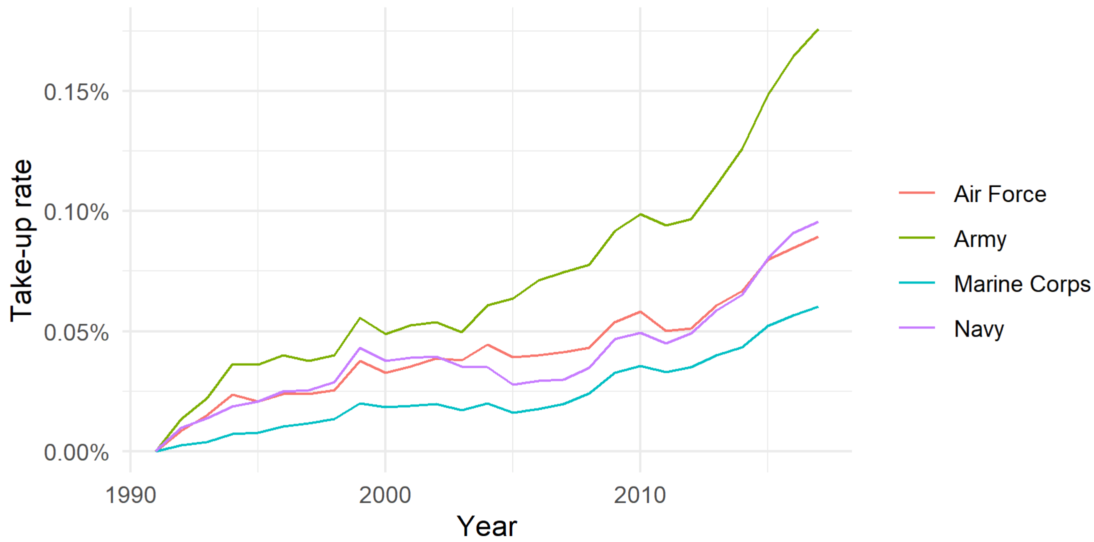
We are interested in estimating the effect of credit supply on house prices. As a measure of credit supply, we focus on the subset of generous VA loans granted after the expansion of eligibility of the VA loan program. To adjust for the size of local housing markets, we scale the number of generous VA loans by the total population in a county as follows:

$$\text{VA loans}_{c,t-1} = 100 \times \frac{\text{No. of generous VA loans to Gulf War veterans}_{c,t-1}}{\text{Population}_{c,t-1}}.$$

We then estimate the following county-year-level regression specification:

$$\text{House price growth}_{c,t} = \beta_1 \text{VA loans}_{c,t-1} + \beta_2 \mathbf{X}_{c,t} + \theta_{c,d(t)} + \nu_t + \varepsilon_{c,t}, \tag{1}$$

Figure 4: **Take-up Rates of Generous VA Loans by Gulf War Veterans**



Notes: For each year from 1991 to 2017, the graph plots the take-up rates of generous VA loans by Gulf War veterans for each military branch at the national level.

where House price growth$_{c,t}$ and VA loans$_{c,t-1}$ are measured as indicated above, c identifies a county, t indexes calendar years, and $\mathbf{X}_{c,t}$ is a vector of macroeconomic control variables, including change in unemployment, income growth, and population growth. In addition, we control for county by decade fixed effects $\theta_{c,d(t)}$ that capture, for instance, slow-moving demographic factors, and year fixed effects ν_t.

A challenge with any measure of credit supply is that the number of issued loans is an equilibrium outcome of the demand for credit and supply thereof. To address this issue, we construct an instrument for VA loans$_{c,t-1}$ at the county-year level as the product of a common shock that varies only over time and a pre-determined, time-invariant exposure measure to this shock that varies across counties. Our instrumental-variables strategy can be interpreted in the spirit of a Bartik-like identification strategy similar to Goldsmith-Pinkham, Sorkin, and Swift (2020).

We compute the common shock as the annual take-up rate of VA loans. To this end, we obtain the number of U.S. veterans from Census data and interpolate the data linearly between census years.[12] When calculating the take-up rate, we follow a leave-one-out approach. We distinguish VA loans by their military branch and construct branch-specific

[12]Note that the number of veterans is not available by their military branch.

take-up rates:

$$\text{Take-up rate}^b_{c,t} = \frac{\sum_{j\neq c} \text{No. of generous VA loans to Gulf War veterans from branch } b_{j,t}}{\text{Number of U.S. veterans}_t}, \tag{2}$$

where branch $b \in B = \{\text{Army, Navy, Air Force, Marine Corps}\}$.[13]

As indicated in Table 1, Gulf War veterans with VA loans exhibit substantial variation in their age. While eligibility for the VA loan program followed a federal decision, individual take-up by eligible Gulf War veterans varies over time as they do not all purchase homes at the same time but, rather, at the same age.

Also, the decision to take out a generous or non-generous loan is likely demand driven and depends on the borrower's financial situation. In Appendix Figure A2, we show that the share of generous VA loans out of all VA loans varies significantly across lenders. If certain lenders were predominantly issuing generous or non-generous VA loans, we would expect to see higher concentrations at the left and right ends of the distribution.[14]

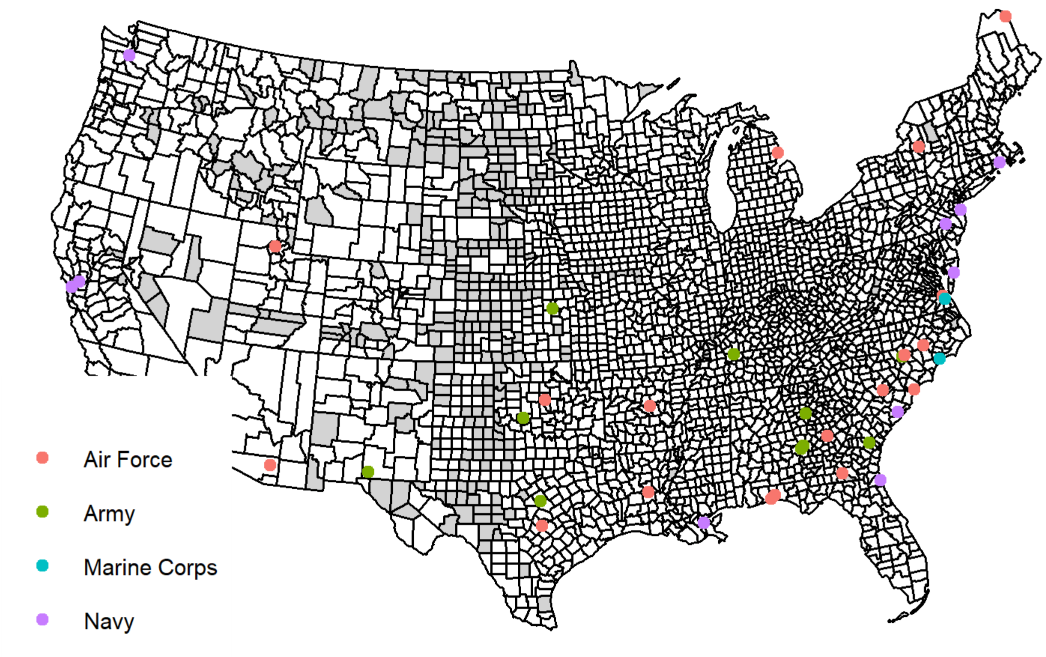
Figure 4 plots the annual take-up rates of loans accruing to Gulf War veterans by branch at the national level. Take-up rates are zero before 1992 and then increase constantly over time. In particular, there is a steep increase of take-up rates for loans to Army veterans in the early 2000s. Note that these take-up rates are downward biased due to the fact that we (are forced to) use the total number of U.S. veterans in the denominator (analogously to the county-level definition in (2)).

To identify the causal effect of VA loans on house prices, we use the variation in VA loans that is predicted by the pre-determined exposure to the take-up rates. As our exposure measure, we calculate the distance of a county to the closest military base from which soldiers were deployed to the Gulf War. We again construct branch-specific exposure measures, distance^b_c, where c denotes the county and b the military branch. This reflects the idea that a county that is closer to a Gulf War base is arguably more exposed to the common shock because de-facto deployed soldiers are more likely to take up generous VA loans given their lack of credit history. As we show below, these veterans indeed tend to buy homes close to their bases.

To compute distance^b_c, we hand-collect a list of all military bases based on the Military

[13]The denominator includes all veterans as the number of Gulf War veterans is not available.
[14]We can only perform this analysis for loans issued in 2018 because our VA loan data do not include a lender ID and earlier HMDA data lack the variables required to identify generous loans.

Figure 5: **Bases from which Soldiers were Deployed to the Gulf War**



Notes: This map shows the location of all military bases in the U.S. from which soldiers were deployed to the Gulf War. The colors represent the different military branches. Grey counties are excluded from our sample either because of missing data or because their population is below 5,000. Table B1 lists the name, branch, and coordinates of each base.

Bases dataset published by the U.S. Department of Transportation.[15] To identify bases that were active with deployable personnel during the Gulf War, we use reports from Base Realignment and Closure (BRAC) Commission (1991, 1993, 1995, and 2005).[16] We identify 46 military bases from which soldiers were deployed to the Gulf War, alongside their coordinates and military branches.[17] Figure 5 shows the locations of the Gulf War bases. While the majority of bases are in the East, they exist in all parts of the U.S. Naturally, Marine Corps and

[15]See http://public.opendatasoft.com.

[16]In cases where the nature of the use of an area is ambiguous, we rely on descriptions from Military.com, newspaper articles, or corresponding Wikipedia entries.

[17]See Appendix B for further details. We consider the list to be comprehensive, and could not receive any additional information from the Department of Defense (FOIA 23-F-0965).

Navy bases are concentrated on the coasts. We calculate for each military base its distance from a given county based on the geographical center of the respective county (using the U.S. Department of Homeland Security's Homeland Infrastructure Foundation-Level Data). As we require a valid value for this distance measure for all counties, we exclude Alaska and Hawaii, as well as counties with a population of less than 5,000 inhabitants. Appendix Figure A3 shows estimated densities for the distance to the closest military base across all counties in our sample. More counties are closer to Air Force and Army bases than to Marine Corps and Navy bases.

An important prerequisite to safeguard the exogeneity of our credit supply shock is that the location of these bases was pre-determined. Appendix Figure A4 shows the years of operation for the bases from which troops were deployed. Some bases were established as early as the mid-19th century, and most bases were established during World Wars I and II. The most recent bases began operating in the 1950s. Hence, the location of all bases was chosen at least 30 years before our sample starts.

The 46 military bases constitute a small subset of all military bases in the United States. Anecdotal evidence suggests that deployed units were chosen for military reasons unrelated to local economic conditions.[18]

Combining our measures for the common shock and exposure, we compute four instruments $Z^b_{c,t}$, one for each branch, at the county-year level:

$$Z^b_{c,t} = \log(\text{Distance to closest Gulf War base of branch } b \text{ in miles})^b_c \times \text{Take-up rate}^b_{c,t}. \quad (3)$$

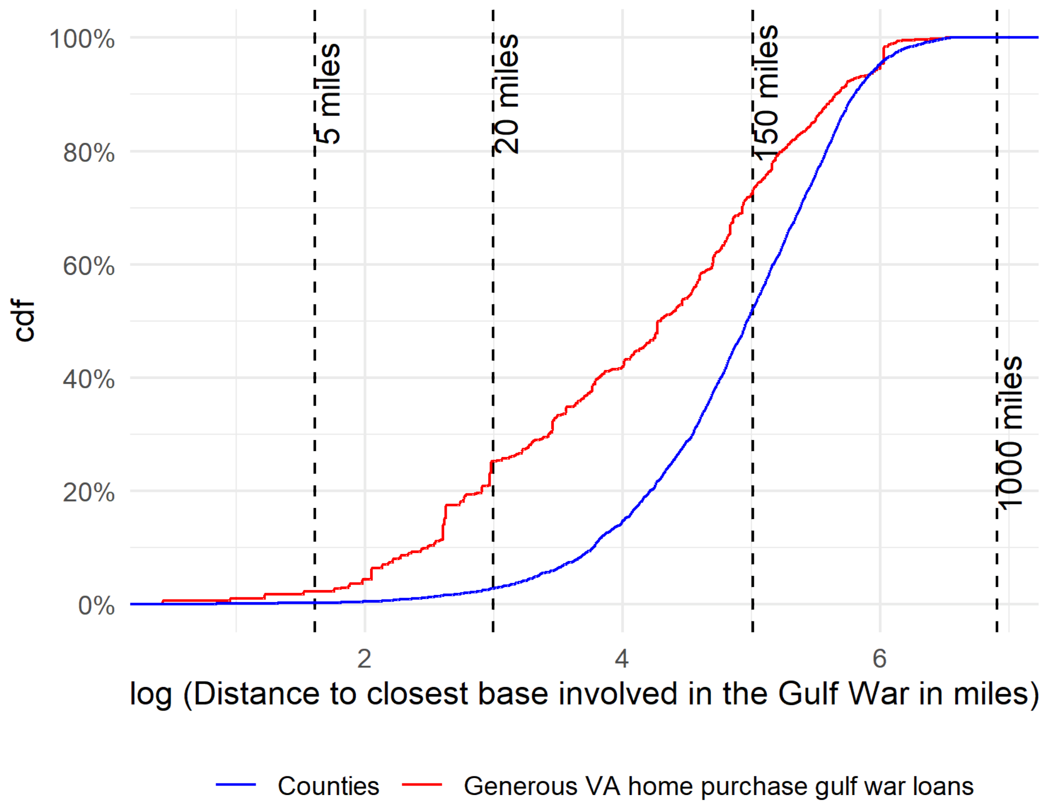
The identification rests on the exclusion restriction that the distance to military bases must be uncorrelated with the error term, after adding control variables and fixed effects

$$\text{E}[\text{Distance}^b_c \varepsilon_{c,t} | X_{c,t}, \theta_{c,d(t)}, \nu_t] = 0 \ \forall b \in B. \quad (4)$$

Thus, our identification assumption is that the distance of a county to military bases from

[18] For example: "Early on in the process, Saint and Franks had to decide which units in Germany would deploy. The chosen units would not necessarily all come from those currently part of VII Corps. Assigned to the two U.S. Corps in Germany (V and VII) were two armored and two mechanized infantry divisions, two separate brigades, and two armored cavalry regiments, among others. The need for a tank-heavy force, the status of equipment modernization, the state of training, and readiness (specifically the fact that some units were in the process of standing down as part of the downsizing of U.S. forces in Europe) affected Saint's and Franks's decisions." (Source: https://armyhistory.org/jayhawk-goes-to-war-vii-corps-in-operation-desert-storm/)

Figure 6: **Counties' Distance to Military Bases and Generous VA Loans**



Notes: This graph shows empirical cumulative distribution functions of the sum across all years of all generous VA loans to Gulf War veterans (red) and counties (blue) over the log distance to the closest military base from which soldiers were deployed to the Gulf War.

which soldiers were deployed to the Gulf War affects house prices only through VA loans, which should be valid as deployed units were chosen primarily for military reasons. Furthermore, Bruhn, Greenberg, Gudgeon, Rose, and Shem-Tov (2024) show that deployments to Iraq or Afghanistan at the beginning of the 21st century had limited effects on soldiers' financial health or education, which could otherwise affect house prices.

To further capture any confounding house price effects associated with a county's proximity to military bases in general, we also control for the interaction of the take-up rate with the log distance of county c to the closest military base from which *no* soldiers were deployed to the Gulf War. This helps control for any remaining components in the take-up rate that could be correlated with local economic conditions, in particular local housing demand.

Table 4: **First-stage IV Results**

Dependent variable:	VA loans$_{c,t-1}$		
	(1)	(2)	(3)
$Z^{\text{Army}}_{c,t-1}$	-5.86***	-5.40***	-5.36***
	(1.92)	(1.94)	(2.02)
$Z^{\text{Navy}}_{c,t-1}$	-6.54***	-5.63***	-4.77***
	(1.69)	(1.81)	(1.82)
$Z^{\text{Air Force}}_{c,t-1}$	-4.95*	-4.92	-5.00
	(3.01)	(3.04)	(3.16)
$Z^{\text{Marine Corps}}_{c,t-1}$	4.97	2.81	1.86
	(4.75)	(5.35)	(5.41)
County-Decade FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Local macroeconomic conditions	No	Yes	Yes
Local mortgage market conditions	No	No	Yes
Lagged house price growth	No	No	Yes
F-test (1st stage)	135.8	106.1	97.0
Observations	59,710	58,400	55,432
Adjusted R^2	0.85	0.85	0.85

Notes: The table reports first-stage results of the IV regression (5) with different control variables. The sample is a county-year panel ct from 1991 to 2017. The instruments are defined as $Z^b_{c,t} = \log(\text{Distance to closest Gulf War base of branch } b \text{ in miles})^b_c \times \text{Take-up rate}^b_{c,t}$ for the four military branches $b \in \{\text{Army, Navy, Air Force, Marine Corps}\}$. The endogenous variable VA loans$_{c,t-1}$ is the relative incidence of generous VA loans. Local macroeconomic conditions include the change in unemployment rates, income growth, population growth, and the product of the log distance to the closest military base from which no soldiers were deployed to the Gulf War times the Gulf War take-up rate at the county-year level. Local mortgage market conditions include the numbers of conventional loans issued and conventional-loan applications denied per capita, as well as the number of denied applications for FHA loans per capita in county c in the previous year $t-1$. Robust standard errors, clustered at the county level, are in parentheses.

For the relevance of our instrument, it is crucial that veterans tend to buy homes close to their military bases. In Figure 6, we provide empirical evidence for this assumption. The figure plots the cumulative distribution function of counties and VA loans with respect to the distance to the nearest of all Gulf War bases. The distance of a county to the closest Gulf War base is strongly correlated with the number of VA loans in a county. While only 2.8% of all counties are within 20 miles of a military base, 25.3% of all VA loans to Gulf War veterans with generous conditions were issued in these counties. Hence, the distance to the nearest Gulf War base is a relevant predictor of VA-loan incidence. Appendix Figure A5 shows that this holds also for each military branch separately. We further evaluate the relevance criterion in Appendix Figure A6a by scrutinizing the relationship between the instrument for the Army branch and the endogenous variable, VA loans$_{c,t-1}$. There is a clear negative

Table 5: **Effect of VA Loans on House Price Growth**

Dependent variable:	House price growth$_{c,t}$					
Estimation:	OLS	OLS	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
VA loans$_{c,t-1}$	14.9***	10.4***	5.6***	228.3***	207.5***	174.6***
	(2.4)	(1.9)	(1.4)	(49.0)	(49.1)	(44.7)
log(Distance to closest non-Gulf War base)$_c \times$ Take-up rate$_{c,t}^{\text{Gulf War}}$		-101.1**	-133.6***		223.0**	126.5
		(39.7)	(32.1)		(96.3)	(84.1)
County-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Local macroeconomic conditions	No	Yes	Yes	No	Yes	Yes
Local mortgage market conditions	No	No	Yes	No	No	Yes
Lagged house price growth	No	No	Yes	No	No	Yes
Observations	59,710	58,400	55,432	59,710	58,400	55,432
Adjusted R^2	0.38	0.41	0.49	0.06	0.14	0.29

Notes: The sample is a county-year panel *ct* from 1991 to 2017. Columns 1 to 3 report OLS estimates of (1) with different sets of control variables and fixed effects. Columns 4 to 6 report IV estimates of (6), based on the first-stage regression (5). The dependent variable is the one-year house price growth rate from year t to $t-1$ in %. VA loans$_{c,t-1}$ is the relative incidence of generous VA loans. Local macroeconomic conditions include the change in unemployment rates, income growth, and population growth at the county-year level. Local mortgage market conditions include the numbers of conventional loans issued and conventional-loan applications denied per capita, as well as the number of denied applications for FHA loans per capita in county c in the previous year $t-1$. Robust standard errors, clustered at the county level, are in parentheses.

relationship, supporting the relevance of our instrument. This holds also for the remaining three military branches (Appendix Figures A6b - A6d).

Finally, we present in Table 4 the results for the first-stage regression. Depending on the set of control variables, the F-statistic of the joint significance of our instruments varies between 97 and 136. Not all four coefficients on the instruments are negative, however. This is likely driven by the strong positive correlation between the distance measures.

5 Results

In the first part of our empirical analysis, we study the effect of credit on house price growth at the county level. In the second part, we consider the consequences of the credit supply shock for the remaining part of the mortgage market in response to elevated house price expectations.

5.1 Credit Supply and House Prices

Table 5 reports in the first three columns the results from estimating equation (1) using OLS as a reference point for the discussion. We find throughout a positive and significant effect of credit supply, as measured by the number of generous VA loans, on house price growth. While we always include county by decade and year fixed effects, adding more control variables reduces the coefficient somewhat across columns 1 to 3

The coefficients imply that a one-standard-deviation higher share of generous VA loans corresponds to ($5.6 \times 0.03/5.08 =$) 3.3% (column 3) to 8.8% (column 1) of a standard deviation higher house price growth (cf. Table 3). To address the potential endogeneity of these estimates, we use our credit-supply instrument based on generous VA loans, and estimate the following instrumental-variable regression:

$$\text{First stage:} \qquad \text{VA loans}_{c,t-1} = \sum_{b \in B} \gamma_1^b Z_{c,t-1}^b + \gamma_2 \mathbf{X}_{c,t} + \theta_{c,d(t)} + \nu_t + u_{c,t-1} \tag{5}$$

$$\text{Second stage:} \qquad \text{House price growth}_{c,t} = \beta_1 \text{VA } \widehat{\text{loans}}_{c,t-1} + \beta_2 \mathbf{X}_{c,t} + \theta_{c,d(t)} + \nu_t + \varepsilon_{c,t}, \tag{6}$$

where $Z_{c,t-1}^b$ is the logged distance to the closest Gulf War base of county c associated with branch b (Army, Navy, Air Force, or Marine Corps) multiplied by the take-up rate in year t, and the remaining variables are defined as in the endogenous regression specification (1).

The IV results analogous to the OLS specifications in the first three columns are reported in columns 4 to 6 of Table 5. The IV estimates exceed the OLS estimates by an order of magnitude, and are statistically significant irrespective of the set of control variables and fixed effects. The estimate in column 5 implies that a one-standard-deviation higher share of generous VA loans increases house prices by ($207.5 \times 0.03 =$) 6.2%, which corresponds to a bit more than one standard deviation in house price growth—a stronger effect than those documented in Di Maggio and Kermani (2017) (3.2%) or Blickle (2022) (3.5%).

The coefficient on the non-Gulf War Bartik instrument is negative in the OLS specifications, corresponding to the negative sign of the respective first-stage coefficients in Table 4. After instrumenting for generous VA loans, our coefficient of interest remains robust, and any negative (positive) effect of the exposure of distant (close) non-Gulf War bases to the take-up rate is explained away as the sign of the respective coefficient flips and eventually becomes insignificant. In Appendix Table A1, we show that the coefficient of interest is furthermore robust to, first, not controlling for the effect of non-Gulf War bases, second,

Table 6: **Impact of Housing Supply Elasticity on the Effect of VA Loans on House Price Growth**

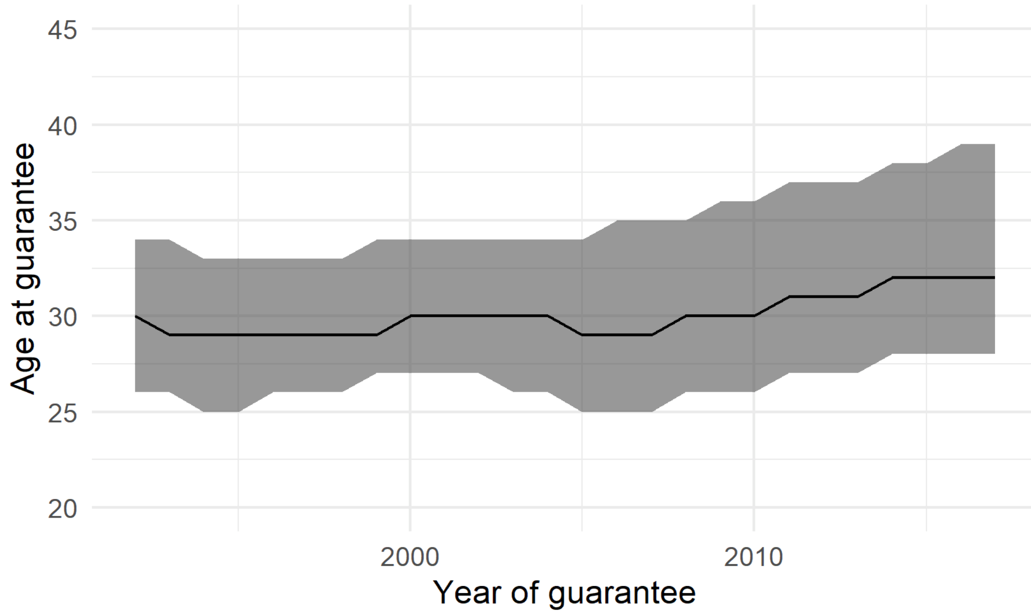
Dependent variable:	House price growth$_{c,t}$		
	(1)	(2)	(3)
VA loans$_{c,t-1}$	113.1***	86.8***	62.9***
	(32.7)	(27.4)	(21.3)
VA loans$_{c,t-1} \times \rho_{msa(c)}$	-33.1***	-29.3***	-18.1***
	(10.2)	(8.9)	(6.7)
County-Decade FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Local macroeconomic conditions	No	Yes	Yes
Local mortgage market conditions	No	No	Yes
Lagged house price growth	No	No	Yes
Observations	7,541	7,294	7,064
Adjusted R^2	0.30	0.40	0.50

Notes: The table reports IV estimates of (7) with different sets of control variables. The sample is a county-year panel ct from 1991 to 2000, consistent with the validation period in Saiz (2010). The dependent variable is the one-year house price growth rate from year t to $t-1$ in %. The endogenous variables are VA loans$_{c,t-1}$, the relative incidence of generous VA loans, and its interaction with $\rho_{msa(c)}$, the housing supply elasticity measure from Saiz (2010) for the MSA corresponding to county c. Local macroeconomic conditions include the change in unemployment rates, income growth, population growth, and the product of the log distance to the closest military base from which no soldiers were deployed to the Gulf War times the Gulf War take-up rate at the county-year level. Local mortgage market conditions include the numbers of conventional loans issued and conventional-loan applications denied per capita, as well as the number of denied applications for FHA loans per capita in county c in the previous year $t-1$. Robust standard errors, clustered at the county level, are in parentheses.

including year-specific coefficients for the log distance to the closest non-Gulf War base, and, third, interacting this distance with the non-Gulf War instead of the Gulf War take-up rate.

Our results suggest that increasing credit supply to veterans leads to elevated demand for housing, which in turn drives up prices. The increase in prices will depend on the elasticity of the supply of housing, and should be smaller if the supply of housing is more responsive to an increase in demand. To test this, we modify the second-stage specification (6) by introducing an interaction term between VA loans and the local (MSA-level) housing supply

Figure 7: **Age of VA Borrowers at Guarantee**



Notes: This figure plots the age at which Gulf War veterans with a generous VA loan receive the guarantee. The solid line shows the median age, and the shaded area depicts the interquartile range.

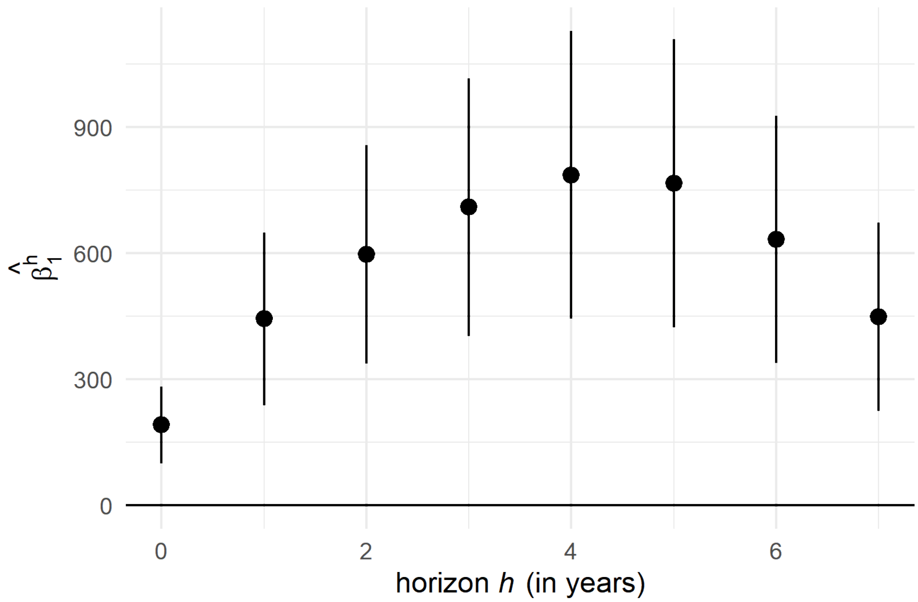
elasticity $\rho_{msa(c)}$ from Saiz (2010) for the MSA corresponding to county c:

$$\begin{aligned}\text{House price growth}_{c,t} = {} & \beta_1 \widehat{\text{VA loans}_{c,t-1}} \times \rho_{msa(c)} + \beta_2 \text{VA } \widehat{\text{loans}}_{c,t-1} \\ & + \beta_3 \mathbf{X}_{c,t} + \theta_{c,d(t)} + \nu_t + \varepsilon_{c,t}.\end{aligned} \tag{7}$$

We expect the effect of an increase in credit supply on house prices to be attenuated when the housing supply elasticity is larger, i.e., $\beta_1 < 0$. Table 6 presents the results. Across all specifications, the estimated coefficient β_1 is negative and statistically significant. That is, the estimated house price effect is mitigated in counties with greater housing supply elasticity. Given that the average value for $\rho_{msa(c)}$ is 2.36 (cf. second panel of Table 3), the mitigation effect accounts economically for at least two-thirds of the baseline effect. Hence, we find that in counties where the supply of housing can expand easily the supply of credit leads to less price pressure and, thus, a smaller increase in house prices.

Thus far, we have considered only immediate effects on house prices. It is, however, possible that adjustments in the housing market build up over time and could revert back if, for example, the housing stock adjusts appropriately. That is why in the next step we

Figure 8: **Dynamic Effect of VA Loans on Cumulative House Price Growth**



Notes: The dots in this figure are the point estimates for β_1^h in (8), i.e., local projections of cumulative house price growth on the change in credit supply, for $h \in \{0, 1, 2, ..., 7\}$. The bars represent 95% confidence intervals. Robust standard errors are clustered at the county level.

analyze the dynamic effect of our credit supply shock on house prices.

5.2 The Dynamic Response of House Prices

In Figure 1, we have shown the increasing number of VA loans accruing to veterans of the Gulf War over time. This reflects the idea that not all veterans applied for a mortgage upon becoming eligible. Thus, while the initial credit supply shock expands the availability of credit for many borrowers, not all borrowers demand credit at the same time. An important reason why the one-off expansion in credit supply materializes only over time is that eligible veterans reach the appropriate age for a home purchase in different years. Indeed, most veterans take out a VA loan around the age of 30 (Figure 7).[19]

To explore the dynamic response of house prices, we estimate local projections of cumulative house price growth on our credit supply shock (Jordà, Schularick, and Taylor, 2020):

[19] It is also important to note that not all of the loans in the VA data that have "Persian Gulf" as entitlement were actually issued to veterans who were deployed to the Middle East in 1990-1991.

$$
\begin{aligned}
100 \times \frac{\text{House price}_{c,t+h} - \text{House price}_{c,t-1}}{\text{House price}_{c,t-1}} = {} & \beta_1^h \text{VA } \widehat{\text{loans}}_{c,t-1} \\
& + \beta_2^h 100 \times \frac{\text{House price}_{c,t-1} - \text{House price}_{c,t-2}}{\text{House price}_{c,t-2}} \\
& + \beta_3^h \mathbf{X}_{c,t} + \theta^h_{c,d(t)} + \nu^h_t + \varepsilon^h_{c,t}. \qquad (8)
\end{aligned}
$$

We estimate separate regressions for horizon $h \in \{0, 1, 2, ..., 7\}$, controlling for lagged house price growth. β_1^h captures the cumulative impact of VA loans issued in period $t-1$ on house price growth between $t+h$ and $t-1$.

Figure 8 shows that generous VA loans have a persistent positive effect on house price growth. The coefficient at $h = 0$ is similar to our IV estimates in columns 4 to 6 of Table 5. The effect is amplified further thereafter and reverses slowly after five years.

Longer-lived effects beyond $h = 0$ could constitute delayed amplification effects of the initial credit supply shock on house price growth. They could also, however, capture the potential amplification stemming from the reaction of the conventional loan market, to which we turn next.

5.3 Mortgage-market Responses to House Price Expectations

Increased eligibility for the VA loan program constitutes a credit supply shock to a segment of the U.S. mortgage market. In the previous section, we have shown that this segmented shock affects house prices at the county level. We can now exploit this credit-supply-induced exogenous variation in house price growth to analyze its impact, stemming from changes in expectations as a result of pecuniary externalities, on the conventional mortgage market that does not experience a credit supply shock due to Gulf War veterans' eligibility over time.

5.3.1 Macro-level Effects

We start out by estimating aggregate effects of (credit-supply-induced) house price growth at the county level. In particular, we wish to analyze the effects of house price growth on (conventional) mortgage applications and loan terms. Since house prices are potentially endogenous to mortgage market decisions, we again employ an IV strategy and use the same set of instruments as in the previous analysis.

Building on the relevance of our instruments based on credit conditions for U.S. veterans from their deployment to the Gulf War, we directly instrument house price growth, rather than VA loans. The full segmentation of the VA and conventional mortgage markets, in turn, safeguards that the exclusion restriction holds and our instruments affect decisions in the conventional mortgage market only through their effect on house price growth. This justifies the use of the reduced-form equation from the IV strategy in (5) and (6) as our new first stage:

$$\begin{aligned}\text{First stage:} \quad & \text{House price growth}_{c,t} = \sum_{b \in B} \gamma_1^b Z_{c,t-1}^b \\ & +\gamma_2 \mathbf{X}_{c,t} + \theta_{c,d(t)} + \nu_t + u_{c,t} \qquad (9)\\ \text{Second stage:} \quad & y_{c,t} = \beta_1 \widehat{\text{House price growth}}_{c,t} \\ & +\beta_2 \mathbf{X}_{c,t} + \theta_{c,d(t)} + \nu_t + \varepsilon_{c,t}, \qquad (10)\end{aligned}$$

where $y_{c,t}$ denotes outcome variables from data on the conventional mortgage market (HMDA or MIRS), namely the approval rate, defined as $100 \times \frac{\text{No. of issued loans}}{\text{No. of issued loans+No. of denied applications}}$, the first difference (between year t and $t-1$) of the logged total number of loans issued or of the logged total loan amount issued, and the average interest rate charged on granted mortgages in county c and year t.

Table 7 presents the results. As house prices increase, so does the approval rate (column 1). This implies that supply increases relative to demand. The number of loans issued and the total volume thereof grow as well (columns 2 and 3). Consistent with a relative increase in supply, the mean interest rate on issued mortgage loans decreases (columns 4 to 6). A one-standard-deviation higher house price growth leads to a 2.1 percentage-point higher approval rate, while it leads to around 14 basis points or 2% lower interest rates.

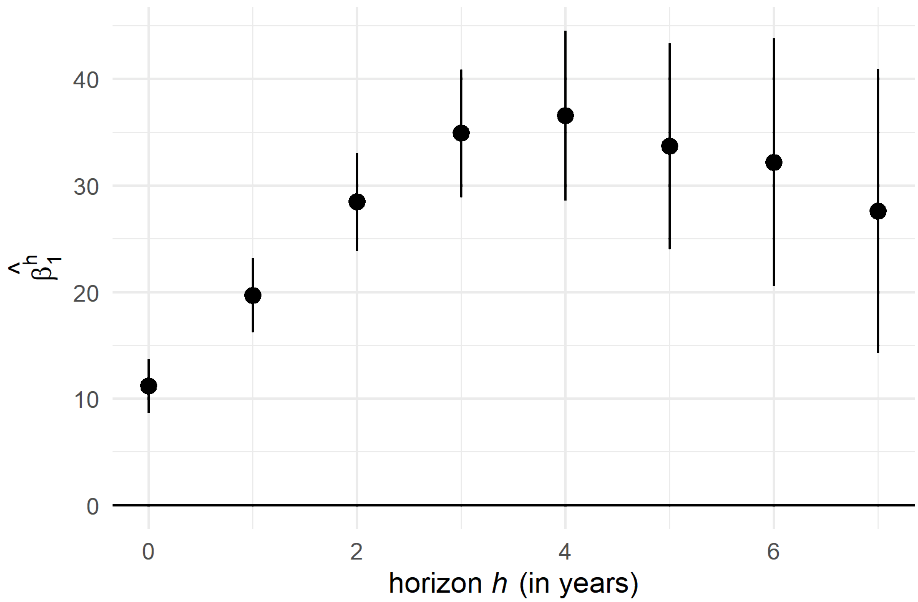
Based on this empirical strategy, we revisit the dynamic response of house price growth to our initial credit supply shock in Figure 8. To analyze whether it is driven by an amplification effect within the market for VA loans or due to spillovers to the conventional mortgage market, i.e., an expansion of credit supply in said market that feeds back to higher house prices, we estimate the dynamic effect of (instrumented) house price growth on the growth

Table 7: **Effect of House Price Growth on the Conventional Loan Market**

Dependent variable:	Approval rate (1)	Δ log(N issued) (2)	Δ log(Loan amount) (3)	Mean interest rate (4)	log(Mean interest rate) (5)	Mean purged interest rate (6)
House price growth$_{c,t}$	0.407***	0.025***	0.029***	-0.027***	-0.004***	-0.024***
	(0.125)	(0.004)	(0.004)	(0.003)	(0.000)	(0.003)
County-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Local macroeconomic conditions	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,359	58,222	58,222	26,779	26,779	26,779
Adjusted R^2	0.79	0.26	0.22	0.94	0.95	0.91

Notes: The sample is a county-year panel ct. The sample period is 1991 to 2017 in columns 1 to 3 and 1992 to 2010 in columns 4 to 6. The table reports IV estimates of (10). The dependent variable is the approval rate $= 100 \times \frac{\text{No. of issued loans}}{\text{No. of issued loans+No. of denied applications}}$ in column 1, the first difference (between year t and $t-1$) of the logged total number of loans issued in column 2, the first difference (between year t and $t-1$) of the logged total loan amount issued in column 3, the mean interest rate on issued mortgages in levels and logs in columns 4 and 5, and the mean purged interest rate on issued mortgages in column 6. The purged interest rate is the residual from a regression of the interest rate on the logged loan amount, the logged maturity, the LTV, and dummies for the purpose, the lender type, the interest-rate type, and jumbo loans. The endogenous variable is the one-year house price growth rate from year t to $t-1$ in %. The first-stage regression is defined in (9). Local macroeconomic conditions include the change in unemployment rates, income growth, population growth, and the product of the log distance to the closest military base from which no soldiers were deployed to the Gulf War times the Gulf War take-up rate at the county-year level. Robust standard errors, clustered at the county level, are in parentheses.

Figure 9: **Amplification of Credit-supply-induced House Price Growth**



Notes: The dots in this figure are the point estimates for β_1^h in (11), i.e., local projections of the difference in growth rates between conventional and VA loans on instrumented house price growth, for $h \in \{0, 1, 2, ..., 7\}$. The bars represent 95% confidence intervals. Robust standard errors are clustered at the county level.

rate of conventional loans relative to the growth rate of VA loans analogously to (8):

$$\begin{aligned}
&100\left(\frac{\text{Conventional loans}_{c,t+h} - \text{Conventional loans}_{c,t-1}}{\text{Conventional loans}_{c,t-1}} - \frac{\text{VA loans}_{c,t+h} - \text{VA loans}_{c,t-1}}{\text{VA loans}_{c,t-1}}\right) \\
=&\beta_1^h 100 \times \frac{\widehat{\text{House price}_{c,t} - \text{House price}_{c,t-1}}}{\text{House price}_{c,t-1}} \\
&+ \beta_2^h 100 \times \left(\frac{\text{Conventional loans}_{c,t-1} - \text{Conventional loans}_{c,t-2}}{\text{Conventional loans}_{c,t-2}} - \frac{\text{VA loans}_{c,t-1} - \text{VA loans}_{c,t-2}}{\text{VA loans}_{c,t-2}}\right) \\
&+ \beta_3^h \mathbf{X}_{c,t} + \theta_{c,d(t)}^h + \nu_t^h + \varepsilon_{c,t}^h, \qquad (11)
\end{aligned}$$

where Conventional loans$_{c,t}$ and VA loans$_{c,t}$ refer to the total loan amount issued in the respective market in county c and year t.

As before, we run separate regressions for horizon $h \in \{0, 1, 2, ..., 7\}$. Furthermore, we winsorize the dependent variable (and its lag on the right-hand side) at the 1st and 99th percentiles.

Figure 9 shows the results. As instrumented house price growth is measured between t

and $t-1$, and the initial credit supply shock is measured in $t-1$, it follows that for $h=0$ we measure growth in the respective credit market in the first year after the shock stemming from greater eligibility for VA loans (as part of our dependent variable). This corresponds to a house price effect in $t+1$ (i.e., $h=1$) in Figure 8.

Against this background, we can interpret the positive and significant coefficients as indicating that growth in the conventional loan market is greater than in the VA loan market, and that the expansion of credit in the conventional loan market is the stronger force that explains persistent house price growth. This is also reflected in the fact that the local projections exhibit the same pattern. The effect on house price growth reverses after (four to) five years in Figure 8, which corresponds to the peak at $h=4$ in Figure 9.

The dynamic pattern is consistent with the idea that the initial credit supply shock stemming from the VA loan market affects house prices on impact, and this effect is amplified by developments in the conventional mortgage market. We next use more granular, application-level data to distill whether these developments stem from higher house price expectations.

5.3.2 Transaction-level Results

In Table 8, we estimate application-level variants of (10) (cf. (12) below), and use as dependent variable an indicator variable for whether a mortgage application is approved. As house prices rise, the approval probability increases (column 1), consistent with a relative increase in supply. This also holds when we control for (time-varying) unobserved heterogeneity at the lender level by means of lender (by year) fixed effects (columns 2 and 3).

The effect of house prices on the approval probability is asymmetric: when house prices increase, so does the approval probability. However, when house prices fall, as they do for one-seventh of loan applications, the approval probability also *increases* (cf. negative coefficient on House $\widehat{\text{price growth}}_{c,t}$ in columns 4 to 6). Since lenders are unlikely to respond to falling house prices by increasing the supply of mortgages, this suggests a decline in demand. As house prices fall, households' beliefs change, and the demand for houses due to the speculative motive (Kaplan, Mitman, and Violante, 2020) weakens. When we take this asymmetry into account, the effect of positive house price growth doubles compared to the estimates in the first three columns: when house prices grow by one percentage point, the average approval rate increases by 0.6 percentage points (based on column 6).

Table 8: **Effect of House Price Growth on Approval Rates in the Conventional Loan Market**

Dependent variable:	Application approved								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
House price growth$_{c,t}$	0.009***	0.005***	0.003***	-0.016*	-0.011*	-0.005*	0.008***	0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.009)	(0.006)	(0.003)	(0.001)	(0.001)	(0.000)
$\mathbb{1}_{\text{House price growth}>0,c,t}$				0.016***	0.000	0.000			
				(0.005)	(0.004)	(0.002)			
House price growth$_{c,t}$ × $\mathbb{1}_{\text{House price growth}>0,c,t}$				0.028**	0.022**	0.011**			
				(0.013)	(0.009)	(0.004)			
1990s$_t$ × House price growth$_{c,t}$							0.009***	0.003***	0.003***
							(0.001)	(0.001)	(0.001)
2010s$_t$ × House price growth$_{c,t}$							-0.022***	-0.009***	-0.005***
							(0.005)	(0.002)	(0.001)
County-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Year FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Lender FE	No	Yes	No	No	Yes	No	No	Yes	No
Lender-Year FE	No	No	Yes	No	No	Yes	No	No	Yes
County FE	No	No	No	No	No	No	Yes	Yes	Yes
Local macroeconomic conditions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Applicant characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decade-specific distance controls	No	No	No	No	No	No	Yes	Yes	Yes
Observations	86,519,961	86,519,961	86,519,961	86,519,961	86,519,961	86,519,961	86,519,961	86,519,961	86,519,961
Adjusted R^2	0.10	0.26	0.29	0.10	0.25	0.28	0.09	0.26	0.29

Notes: The sample is the universe of all mortgage applications in the conventional loan market at the transaction level m from 1991 to 2017. The table reports IV estimates of (12). The dependent variable is a dummy for whether the application was granted. The endogenous variable is the one-year house price growth rate from year t to $t-1$ in %. The dummy $\mathbb{1}_{House\ price\ growth>0,c,t}$ is 1 when house price growth is positive. *1990s*$_t$ and *2010s*$_t$ are dummies for the respective decades. Local macroeconomic conditions include the change in unemployment rates, income growth, population growth, and the product of the log distance to the closest military base from which no soldiers were deployed to the Gulf War times the Gulf War take-up rate at the county-year level. Applicant characteristics include a dummy for white applicants, a dummy for male applicants, and the log income of the applicant. Decade-specific distance controls include all interactions of the 1990s and 2010s dummies with the log distance to the closest Gulf War base of each branch. Robust standard errors, clustered at the county level, are in parentheses.

The impact of house price growth on the approval probability of loan applications varies strongly over time (columns 7 to 9). The relative increase in supply is largest in the 1990s. In the 2000s, the effect is about half as large (as the coefficient on the intercept effect corresponds roughly to the coefficient on the respective interaction effect). While in the 1990s higher house prices likely led to a decrease in demand through price effects, the housing boom of the 2000s affected households' beliefs and dampened the price effect. Following the Great Financial Crisis, in the 2010s we find no significant effect of house price growth on the approval probability (as the sum of the two respective coefficients is less than zero). This may suggest that borrowers and lenders have become more cautious about house price growth after the experience of the bursting of the housing bubble. Alternatively, supply and demand effects could also offset each other.

To better disentangle the response of supply and demand to house price growth, and provide evidence in line with the view that house price growth affects mortgage market outcomes through altering beliefs, we use the granularity of our data, which allows us to control for confounding supply and demand forces. At the level of mortgage applications m—or at the level of actually granted mortgages when considering their volumes and rates—we estimate the following second-stage regression specification, with the first stage being specified analogously to (9) with twice as many instruments (as the interaction term is also instrumented for):

$$\begin{aligned} y_m \;=\;& \beta_1 \text{House price} \ \widehat{\text{growth}}_{c(m),t(m)} \times \text{Characteristic}_{f(m)} + \beta_2 \text{House price} \ \widehat{\text{growth}}_{c(m),t(m)} \\ & + \beta_3 \mathbf{X}_{f(m)} + \omega_{f(m)} + \varepsilon_m, \end{aligned} \tag{12}$$

where $\omega_{f(m)}$ denotes fixed effects at levels that are a function $f(\cdot)$ of the mortgage m itself, always including county (pertaining to the borrower of mortgage m) by decade and year (as determined by the application date of m) fixed effects, and Characteristic$_{f(m)}$ and $\mathbf{X}_{f(m)}$ are a characteristic and control variables measured at a level that is a function of the mortgage as well.

Higher relative demand should lead to lower application acceptance rates, higher interest rates, but also larger loan volumes. When testing for demand forces, we include interaction effects of House price $\widehat{\text{growth}}_{c(m),t(m)}$ with mortgage- or borrower-specific characteristics, and estimate the following specification:

$$y_m = \beta_1 \text{House price} \ \widehat{\text{growth}}_{c(m),t(m)} \times \text{Characteristic}_m + \beta_2 \mathbf{X}_{f(m)} + \delta_{l(m),c(m),t(m)} + \varepsilon_m, \tag{13}$$

where Characteristic_m is a characteristic of the borrower of mortgage m, and $\delta_{l(m),c(m),t(m)}$ denotes fixed effects at the lender by county by year level, which is the most granular level at which mortgage supply can be confounded with local house price growth.

As such, β_1 captures relative demand. When testing for supply forces, we control for demand by including county by year fixed effects, which subsume any stand-alone effect of house price growth on mortgage outcomes, while at the same time controlling for time-varying unobserved heterogeneity at the lender level that may govern mortgage outcomes across counties, such as regulatory changes affecting lenders differentially:

$$y_m = \beta_1 \text{House } \widehat{\text{price growth}}_{c(m),t(m)} \times \text{Characteristic}_{l(m)} + \beta_2 \mathbf{X}_{f(m)} + \theta_{c(m),t(m)} + \psi_{l(m),t(m)} + \varepsilon_m, \tag{14}$$

where $\text{Characteristic}_{l(m)}$ is a characteristic of mortgage m that relates, e.g., to lender l, and $\theta_{c(m),t(m)}$ and $\psi_{l(m),t(m)}$ denote county by year and lender by year fixed effects, respectively.

To identify relative supply effects and estimate β_1 in (14), we use variation at the lender-county-year level. The inclusion of lender by year fixed effects absorbs time-varying unobserved heterogeneity at the lender level that could otherwise bias our estimate. For instance, it precludes that β_1 potentially reflects fluctuations in lenders' net worth due to their exposure to house price developments in a particular county, which may, in turn, affect their lending decisions in other counties.

Thus far, we cannot rule out that our estimates in Tables 7 and 8 are driven by the relaxation of collateral constraints—an important credit-supply response due to higher contemporaneous house prices (Cloyne, Huber, Ilzetzki, and Kleven, 2019). In the above-mentioned tests, we control for these collateral effects by means of county by year fixed effects, if lenders' response is homogeneous, and at times lender by county by year fixed effects, capturing such heterogeneity across lenders. The remaining variation used to estimate our coefficients of interest should stem from altered beliefs, e.g., about expected future collateral values.

Furthermore, if there are lenders that issue both VA loans and conventional mortgages, higher supply of one type of mortgage can crowd out supply of the other (Fieldhouse, 2022) despite the perfect segmentation of the two markets. Besides controlling for this possibility by incorporating lender by year fixed effects, we can more crudely drop lenders that are active in both mortgage markets. In Appendix Table A2, we show that our results are robust to, first, excluding all loan applications where the lender has issued a VA loan in the year of the application and, second, reducing the sample further by excluding all observations where the

Table 9: **Heterogeneous Effect of House Price Growth on Investment-driven Borrowers**

Sample	All applications			Issued mortgages		
Dependent variable:	Application approved			log(Loan amount)		
	(1)	(2)	(3)	(4)	(5)	(6)
House price growth$_{c,t}$	0.010***			-0.019***		
	(0.001)			(0.003)		
Home not owner-occupied$_m$ × House price growth$_{c,t}$	-0.007***	-0.002***	-0.001***	0.018***	0.015***	0.015***
	(0.001)	(0.000)	(0.000)	(0.003)	(0.002)	(0.002)
Home not owner-occupied$_m$	0.019***	-0.012***	-0.012***	-0.558***	-0.537***	-0.537***
	(0.005)	(0.002)	(0.002)	(0.017)	(0.016)	(0.016)
County-Decade FE	Yes	No	No	Yes	No	No
Year FE	Yes	No	No	Yes	No	No
County-Year FE	No	Yes	No	No	Yes	No
Lender-Year FE	No	Yes	No	No	Yes	No
Lender-County-Year FE	No	No	Yes	No	No	Yes
Local macroeconomic conditions	Yes	No	No	Yes	No	No
Applicant characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85,945,436	87,021,913	87,021,913	69,115,665	70,036,044	70,036,044
Adjusted R^2	0.10	0.29	0.32	0.45	0.54	0.56

Notes: The sample in columns 1 to 3 is the universe of all mortgage applications in the conventional loan market at the transaction level m from 1991 to 2017. The sample in columns 4 to 7 is the subset of all issued mortgages, i.e., accepted applications. The table reports IV estimates of (13). The dependent variable in columns 1 to 3 is a dummy for whether the application was granted and the logged loan amount issued in columns 4 to 6. The endogenous variable is the one-year house price growth rate from year t to $t-1$ in %. Home not owner-occupied$_i$ is a dummy for applicants that will not occupy the home for which they take out the mortgage. Local macroeconomic conditions include the change in unemployment rates, income growth, population growth, and the product of the log distance to the closest military base from which no soldiers were deployed to the Gulf War times the Gulf War take-up rate at the county-year level. Applicant characteristics include a dummy for white applicants, a dummy for male applicants, and the log income of the applicant. Robust standard errors, clustered at the county level, are in parentheses.

lender received an application for a VA loan in any year during our sample period.

In the following, we show heterogeneous supply and demand responses along three dimensions: borrowers' (investment) motives for purchasing a house, lender specialization, and asymmetric information about the underlying collateral value.

Credit demand of investment-driven borrowers 12% of loan applications are for the purchase of non-owner occupied homes. On average, these borrowers are less constrained because they have higher incomes, both in absolute terms and relative to the loan amount (see Appendix Table A3 for related summary statistics). As such, their house purchase is more likely to be motivated by investment motives compared to other borrowers, and variation in their beliefs should carry more weight for their mortgage demand than price changes.

In Table 9, we estimate specifications in the spirit of (13), and use as the relevant mortgage-level characteristic whether borrowers will not occupy the home (and arguably purchase it as an investment). In this manner, we find that the demand of such borrowers increases at the extensive margin, leading to lower approval rates, in response to rising house prices relative to other borrowers, even after holding constant mortgage supply by adding lender-county-year fixed effects (columns 1 to 3). The demand of borrowers who will not occupy the home increases also at the intensive margin as the loan amount conditional on the approval of an application is larger (columns 4 to 6). Thus, current house prices impact borrowers' demand not only through prices but also through beliefs.

Credit supply by specialized lenders We can match lenders' balance-sheet characteristics to 16 out of 88 million conventional loan applications. If house price growth encapsulates any valuable information about the state of the housing market in general, lenders that specialize in mortgages should be more prone to updating their beliefs in response to it and adjust their credit supply by more than non-specialized lenders.

In Table 10, we estimate specifications as in (14), with House $\widehat{\text{price growth}}_{c,t}$ interacted with lenders' proportion of real estate loans in their total loan portfolio. In line with our hypothesis, the approval probability and the loan amount conditional on issuance increase more for such specialized lenders with a higher share of real estate loans in their loan portfolio. Thus, specialized lenders increase their credit supply more, and should also be less likely to reduce non-housing credit (Martín, Moral-Benito, and Schmitz, 2021), in response to house

Table 10: **Heterogeneous Effect of House Price Growth on Specialized Lenders**

Sample	All applications			Issued mortgages		
Dependent variable:	Application approved			log(Loan amount)		
	(1)	(2)	(3)	(4)	(5)	(6)
House price growth$_{c,t}$	-0.002			-0.015***		
	(0.002)			(0.005)		
$\frac{\text{real estate loans}}{\text{total loans}}_{l(m),t(m)} \times$ House price growth$_{c,t}$	0.011***	0.012***	0.023***	0.017***	0.015**	0.052***
	(0.002)	(0.002)	(0.007)	(0.006)	(0.006)	(0.017)
$\frac{\text{real estate loans}}{\text{total loans}}_{l(m),t(m)}$	-0.037***	-0.047***		-0.028	-0.005	
	(0.008)	(0.009)		(0.024)	(0.024)	
County-Decade FE	Yes	No	No	Yes	No	No
Year FE	Yes	No	No	Yes	No	No
Lender FE	Yes	Yes	No	Yes	Yes	No
County-Year FE	No	Yes	Yes	No	Yes	Yes
Lender-Year FE	No	No	Yes	No	No	Yes
Local macroeconomic conditions	Yes	No	No	Yes	Yes	Yes
Applicant characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,499,369	15,669,527	15,669,527	13,129,241	13,281,921	13,281,921
Adjusted R^2	0.18	0.19	0.22	0.48	0.49	0.51

Notes: The sample in columns 1 to 3 consists of all mortgage applications in the conventional loan market at the transaction level m from 1991 to 2017 for which we can match lender characteristics. The sample in columns 4 to 7 is the subset of issued mortgages, i.e., accepted applications. The table reports IV estimates of (14). The dependent variable in columns 1 to 3 is a dummy for whether the application was granted and the logged loan amount issued in columns 4 to 6. The endogenous variable is the one-year house price growth rate from year t to $t-1$ in %. $\frac{\text{real estate loans}}{\text{total loans}}_{l(m),t(m)}$ is measured at the beginning of each decade. Local macroeconomic conditions include the change in unemployment rates, income growth, population growth, and the product of the log distance to the closest military base from which no soldiers were deployed to the Gulf War times the Gulf War take-up rate at the county-year level. Applicant characteristics include a dummy for white applicants, a dummy for male applicants, and the log income of the applicant. Robust standard errors, clustered at the county level, are in parentheses.

Table 11: **Heterogeneous Effect of House Price Growth on Interest Rates by Specialized Lenders**

Dependent variable:	log(Interest rate)			
	(1)	(2)	(3)	(4)
House price growth$_{c,t}$	-0.005***	-0.001		
	(0.001)	(0.001)		
Specialized lender$_{l(m)}\times$ House price growth$_{c,t}$		-0.005***	-0.008***	-0.007***
		(0.001)	(0.001)	(0.001)
County-Decade FE	Yes	Yes	No	No
Lender type-Year FE	Yes	Yes	Yes	Yes
ZIP code FE	Yes	Yes	Yes	No
County-Year FE	No	No	Yes	Yes
ZIP code-Year FE	No	No	No	Yes
Local macroeconomic conditions	Yes	Yes	No	No
Mortgage characteristics	Yes	Yes	Yes	Yes
Observations	4,684,931	4,684,931	4,778,933	4,778,933
Adjusted R^2	0.57	0.57	0.59	0.60

Notes: The sample is a survey of issued mortgages in the conventional loan market at the transaction level m from 1992 to 2010. The table presents IV estimates of a variant of specification (14), replacing lender with lender-type fixed effects due to the unavailability of lender identities in the MIRS dataset. The dependent variable is the log interest rate. The endogenous variable is the one-year house price growth rate from year t to $t-1$ in %. Specialized lenders$_{l(m)}$ is a dummy for mortgages that are issued by lenders that specialize in mortgages, i.e., mortgage companies and thrifts, as opposed to mortgages issued by commercial banks. Local macroeconomic conditions include the change in unemployment rates, income growth, population growth, and the product of the log distance to the closest military base from which no soldiers were deployed to the Gulf War times the Gulf War take-up rate at the county-year level. Mortgage characteristics include the loan-to-price ratio, the log loan amount, the log maturity, a dummy for the interest-rate type (fixed vs. floating), and a dummy for new buildings. Robust standard errors, clustered at the county level, are in parentheses.

price growth, along both the extensive and the intensive margin. This holds also when we control for demand through county by year fixed effects.

In our separate dataset on interest rates, we do not have identifiers for lenders and, thus, can neither include lender-identity-based fixed effects nor merge the data with lenders' balance sheets but, instead, have indicators for three different types of lenders: thrifts, mortgage companies, and commercial banks. While thrifts and mortgage companies specialize in mortgages, commercial banks offer a variety of products. This allows us to examine the differential supply response of specialized lenders as reflected by their loan pricing. A greater relative supply effect should be reflected in lower rates. We first show our baseline effect that

Table 12: **Heterogeneous Effect of House Price Growth on Interest Rates and Asymmetric Information**

Dependent variable:	log(Interest rate)		
	(1)	(2)	(3)
House price growth$_{c,t}$	-0.005***		
	(0.001)		
New building$_m \times$ House price growth$_{c,t}$	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
New building$_m$	0.028***	0.030***	0.032***
	(0.003)	(0.002)	(0.002)
County-Decade FE	Yes	No	No
Lender type-Year FE	Yes	Yes	Yes
ZIP code FE	Yes	Yes	No
County-Year FE	No	Yes	Yes
ZIP code-Year FE	No	No	Yes
Local macroeconomic conditions	Yes	No	No
Mortgage characteristics	Yes	Yes	Yes
Observations	4,684,931	4,778,933	4,778,933
Adjusted R^2	0.57	0.59	0.60

Notes: The sample is a survey of issued mortgages in the conventional loan market at the transaction level m from 1992 to 2010. The table presents IV estimates of a variant of specification (14), replacing lender with lender-type fixed effects due to the unavailability of lender identities in the MIRS dataset. The dependent variable is the one-year house price growth rate from year t to $t-1$ in %. New building$_m$ is a dummy for new as opposed to existing buildings. Local macroeconomic conditions include the change in unemployment rates, income growth, population growth, and the product of the log distance to the closest military base from which no soldiers were deployed to the Gulf War times the Gulf War take-up rate at the county-year level. Mortgage characteristics include the loan-to-price ratio, the log loan amount, the log maturity, and a dummy for the interest-rate type (fixed vs. floating). Robust standard errors, clustered at the county level, are in parentheses.

relative credit supply net-increases in response to higher house price growth in column 1 of Table 11. In columns 2 to 4, we test for differential credit-supply responses by specialized lenders, and find that they indeed charge lower interest rates in response to higher house price growth, even after controlling for credit demand by including not only county by year (column 3) but also more granular zip code by year fixed effects (column 4).[20] In both columns, specialized lenders charge almost 1% lower interest rates for each percentage point in house price growth.

Credit supply and asymmetric information Finally, future house prices should matter more for mortgage supply decisions with higher asymmetric information about the collateral value. To test this, we exploit the fact that in our interest-rate data, 18% of the mortgages are for the purchase of new buildings as opposed to existing buildings, and labeled as such.[21]

When house prices are higher, the marginal borrower's loan-to-price ratio may exceed lenders' thresholds and she may, thus, be unable to obtain a mortgage. However, as house prices rise and lenders extrapolate from this into the future, the *expected* future collateral value rises, which can result in lower loan-to-value (LTV) ratios since the value used to calculate regulatory LTV ratios can deviate from the market value of the house at the time of purchase.[22]

Such an increase in expected collateral values can, and—as we find on average—does, counteract a reduction in credit supply. Since this effect is stronger for mortgages where asymmetric information about the collateral value (Stroebel, 2016) is more severe, i.e., new buildings, we expect credit supply to increase by more for new, rather than existing, buildings in response to higher house price growth.

The evidence in Table 12 lends support to this view. First, we find—in line with Stroebel (2016)—that mortgages used to finance the purchase of new buildings carry a higher interest rate. Second, interest rates decrease more for new buildings as house prices rise. Thus, supply increases relative to demand as house prices rise, and more so for mortgages sought for the purchase of new buildings. This holds also when we control for credit demand by means of county by year or zip code by year fixed effects (in column 2 and column 3, respectively).

[20] Note that there are some ZIP codes belonging to more than one county.
[21] We use this information as a control variable already in Table 11.
[22] For example, banks often use the "long-term sustainable value" to calculate LTV ratios.

6 Conclusion

This paper revisits the long-standing question on how credit conditions affect house prices and the macroeconomy. We leverage novel and unexplored data from the universe of the Veterans Administration (VA) loan program. The data allow us to construct an instrument for a credit supply shock at the regional housing market level that is independent of economic conditions as it results from the geopolitical decisions of the U.S. government. We find that an expansion of credit supply increases house prices, and then exploit the segmentation of the VA and ordinary mortgage market to trace out the effects of this credit-supply-induced house price growth on the remaining mortgage market. Consistent with the idea that house price growth affects expectations, much akin to diagnostic expectations (Bordalo, Gennaioli, and Shleifer, 2018), lenders expand their supply of ordinary mortgages more than demand for credit increases. We show that specialized lenders react more strongly to house price growth and expand their credit supply by more. Future house prices also matter more for mortgage supply decisions with higher asymmetric information about the collateral value such as new buildings as opposed to existing buildings, and for borrowers who mainly purchase a house as an investment such as borrowers who will not occupy the house they purchase.

Our long-run evidence rules in roles for both credit and beliefs in shaping house price cycles, and connects the two by showing that house price growth induced by a credit supply shock affects expectations in the housing market that feed back not only to further credit demand and supply but also contribute to the long-lived nature of house price growth. This opens up the possibility that credit supply can interact with more fundamental forces, which Chodorow-Reich, Guren, and McQuade (2024) highlight in their analysis of the 2000s housing cycle, by steering the path of beliefs.

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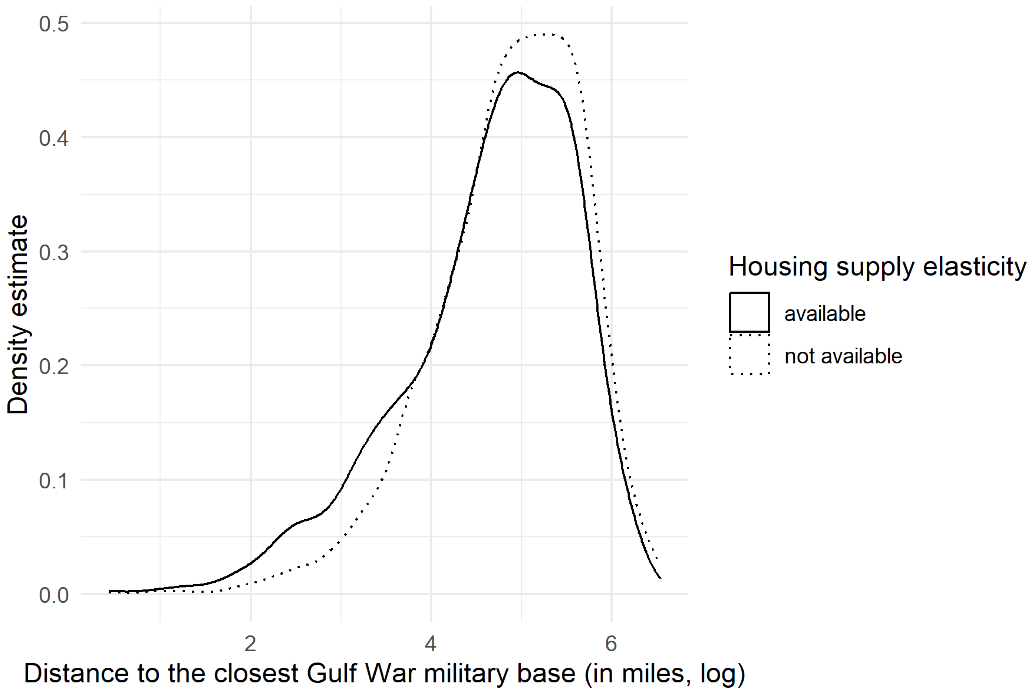
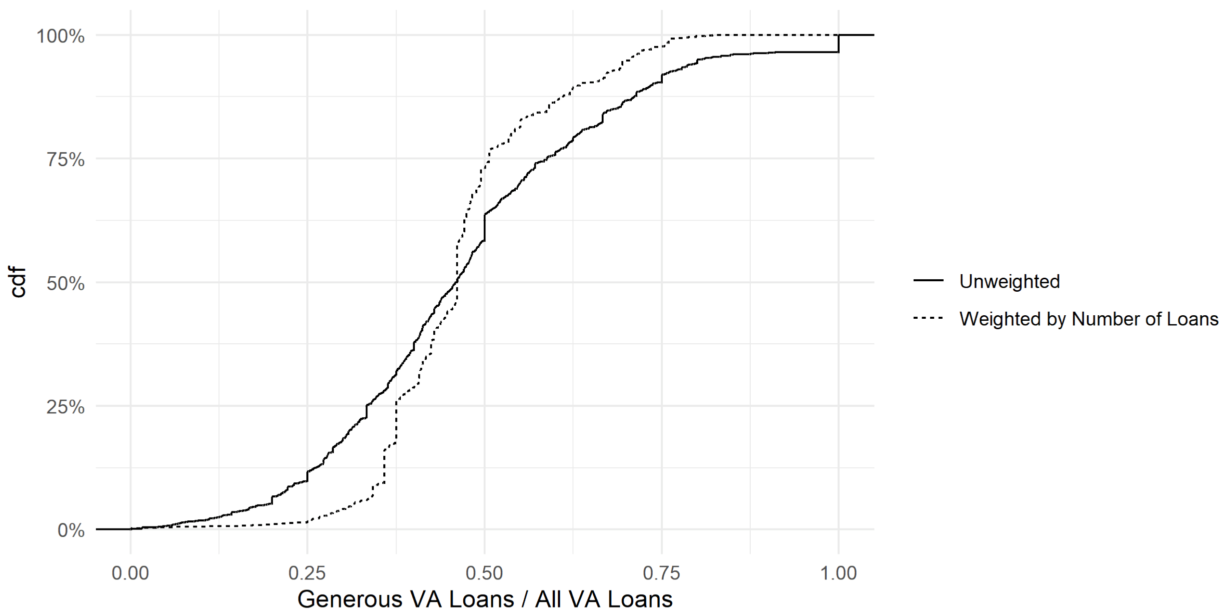
A Supplementary Figures and Tables

Figure A1: **Distance to Bases and Housing Supply Elasticity**



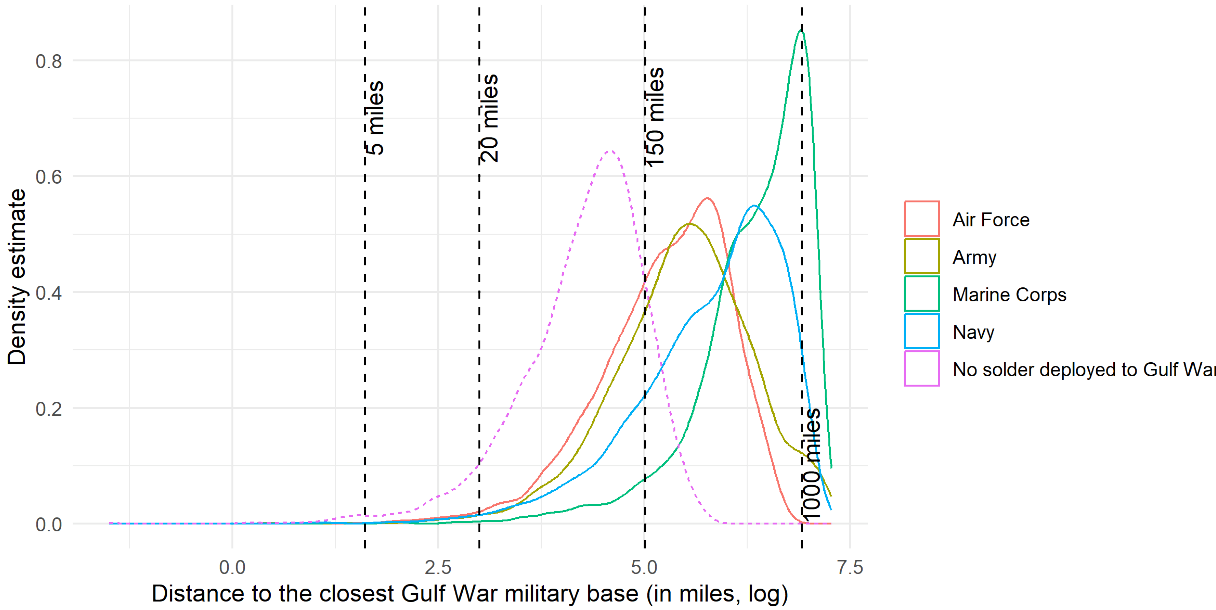
Notes: This figure plots the empirical distribution of the distance to the closest military base across all counties in our sample. The solid line represents counties for which the housing supply elasticity measure $\rho_{msa(c)}$ from Saiz (2010) is available, and the dashed line represents counties for which it is not available.

Figure A2: **Share of Generous VA Loans across Lenders**



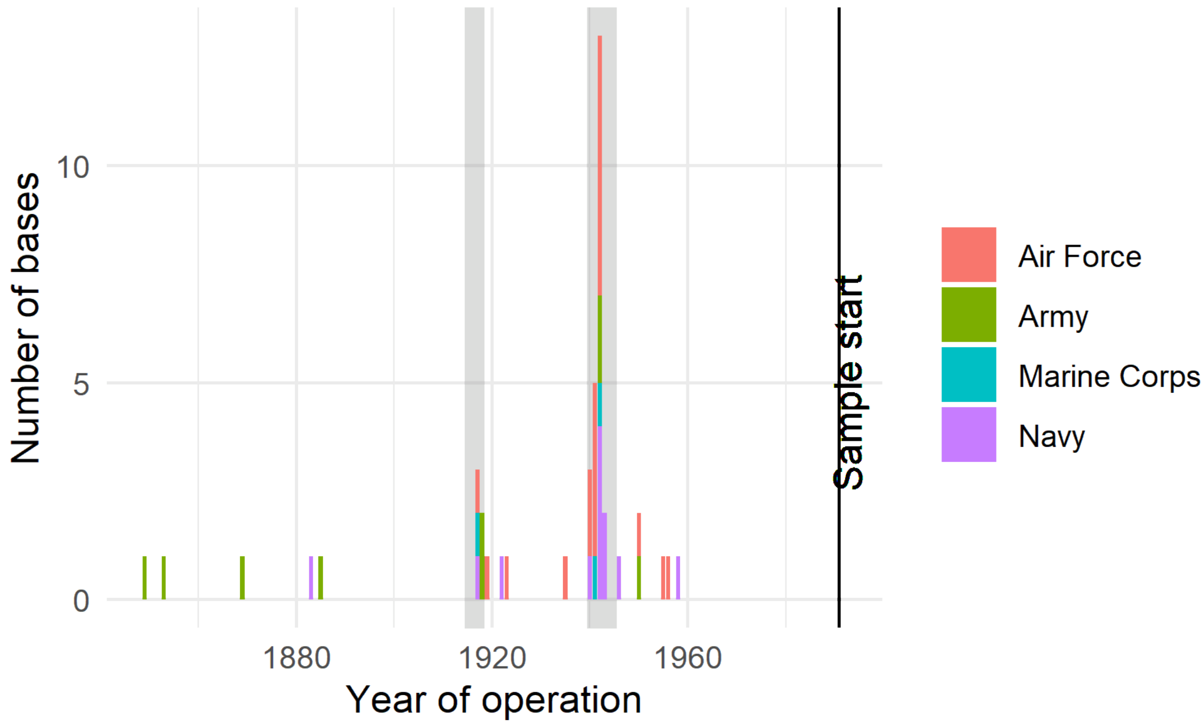
Notes: This graph shows empirical cumulative distribution functions of the share of generous VA loans out of all issued VA loans, across all lenders that reported issued VA loans in HMDA in 2018. Generous loans are defined as loans with an LTV greater than 100% or a DTI greater than 43%.

Figure A3: **Counties' Distance to Military Bases by Branch**



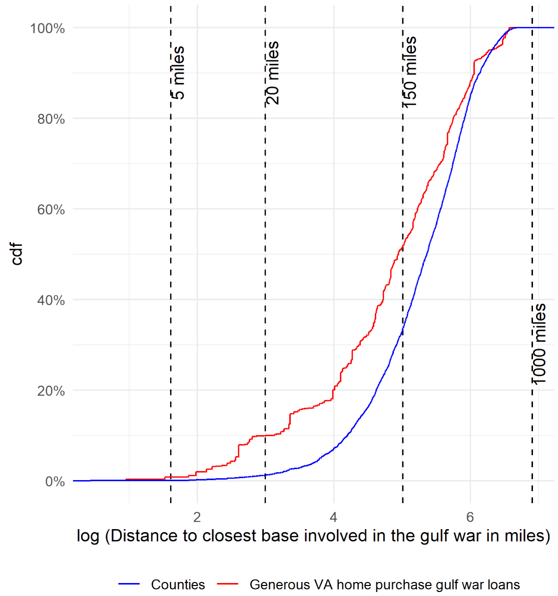
Notes: This figure plots the empirical distribution of distance to the closest military base for each of the four branches across all counties in our sample.

Figure A4: **Years of Operation of Gulf War Military Bases**

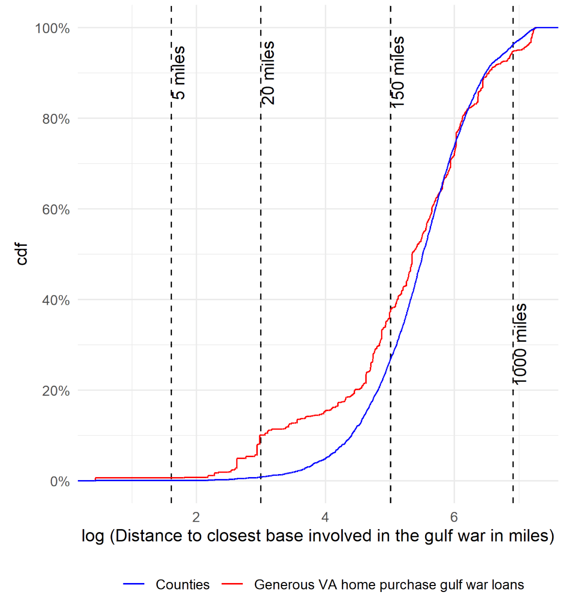


Notes: For each Gulf War military base in our sample, this figure shows the year in which the base began operations. The shaded areas mark World Wars I and II ,and the solid line marks the start of our sample period in 1991.

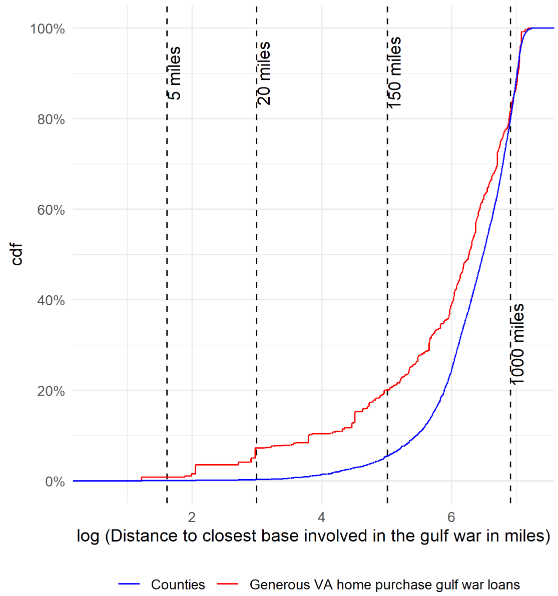
Figure A5: **Counties' Distance to Military Bases and Generous VA Loans by Branch**



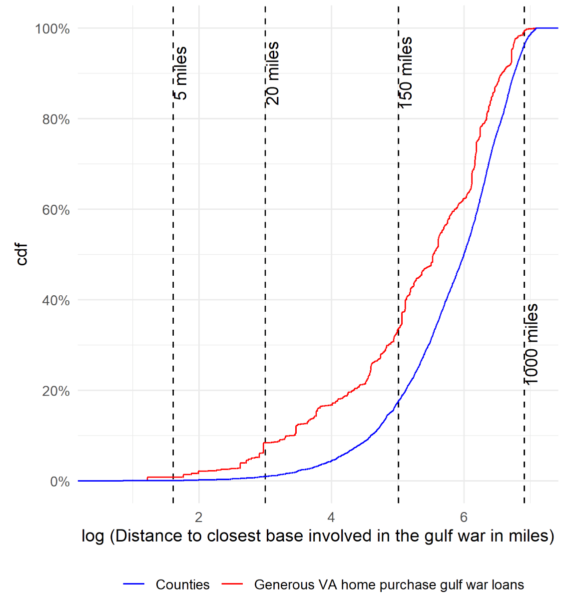
(a) Air Force



(b) Army



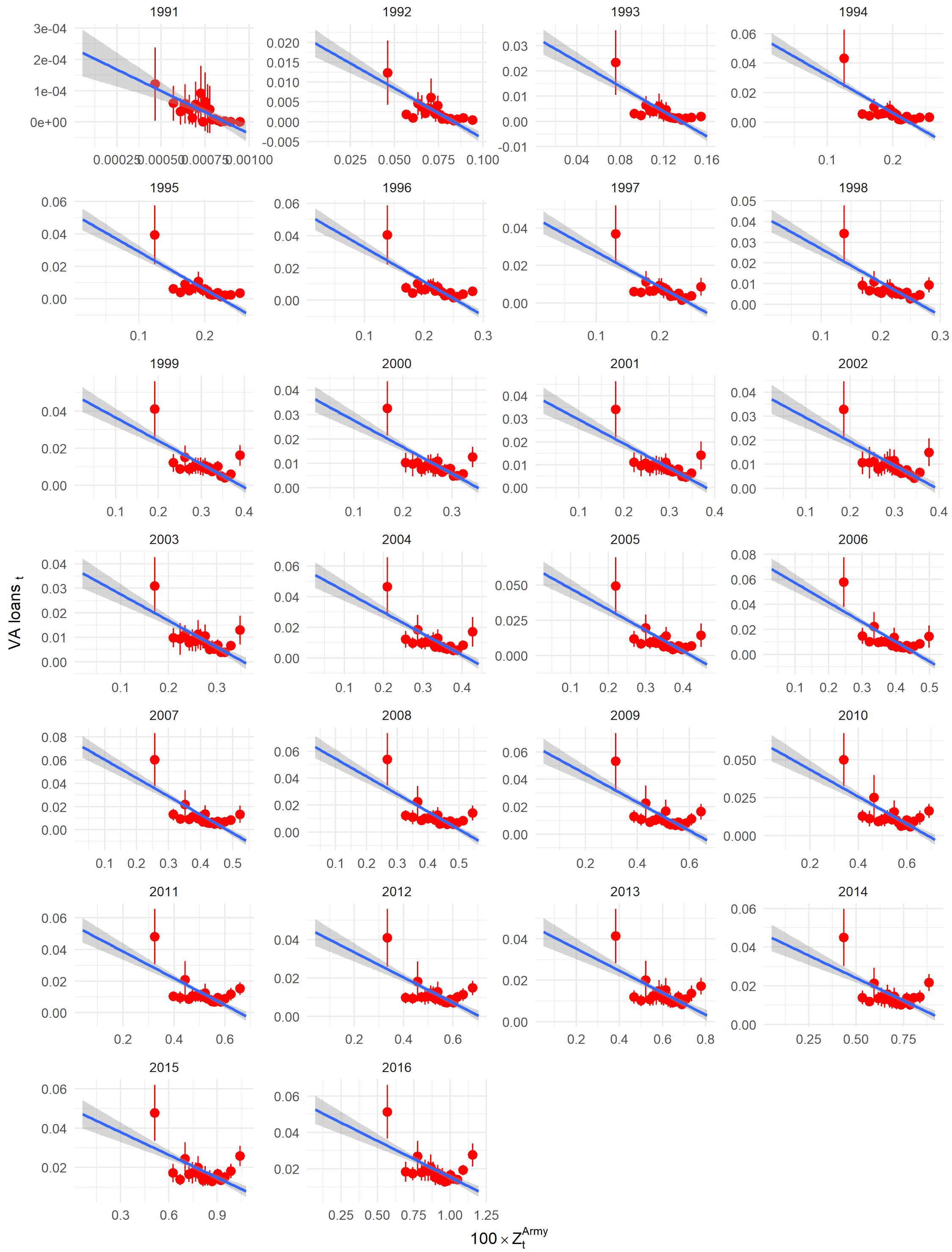
(c) Marine Corps



(d) Navy

Notes: For each of the four military branches, this graph shows empirical cumulative distribution functions of the sum across all years of all generous VA loans to Gulf War veterans (red) and counties (blue) over the log distance to the closest military base from which soldiers were deployed to the Gulf War.

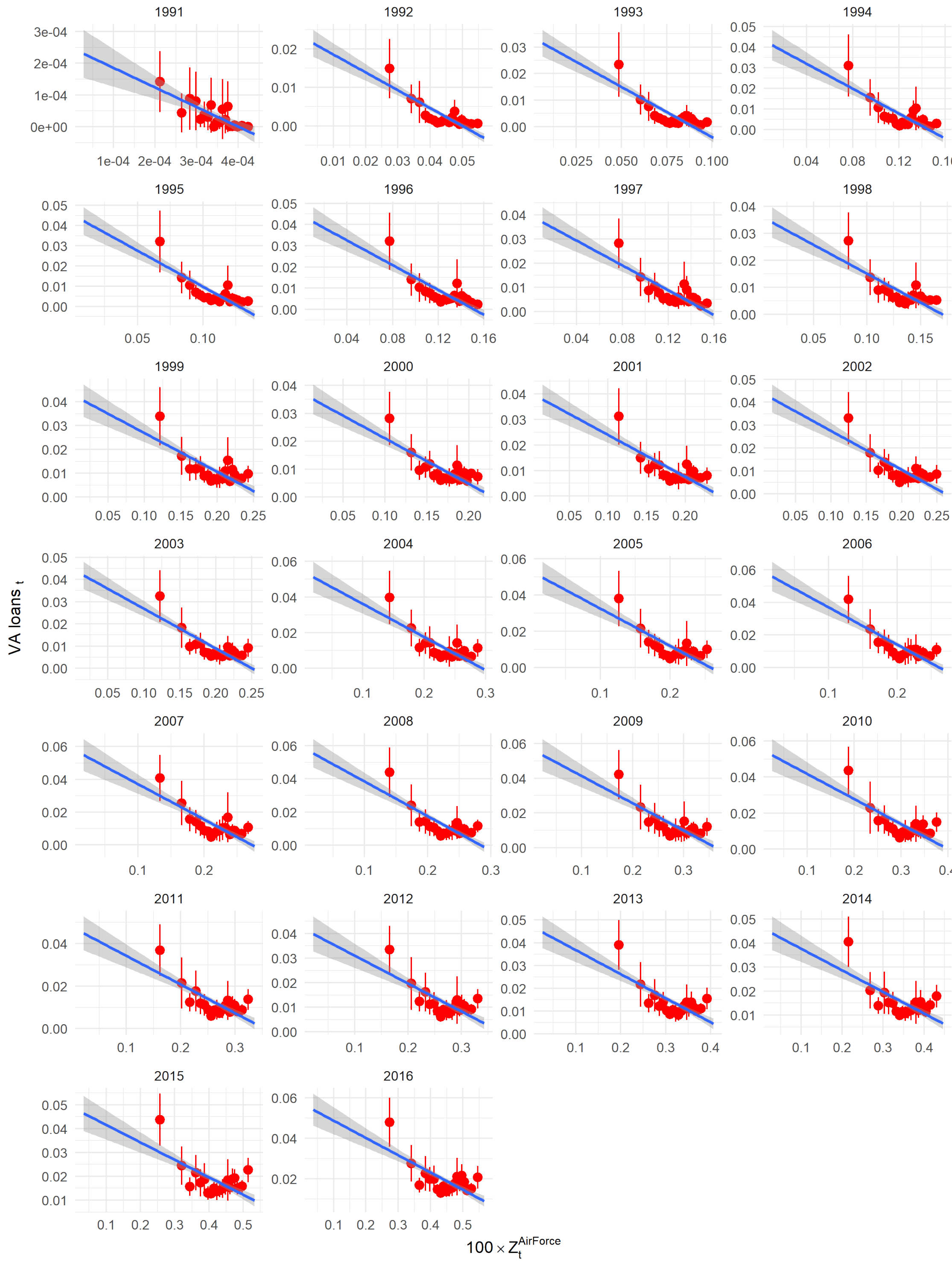
Figure A6: **Instrument for the Different Branches and the Endogenous Variable**



(a) Army

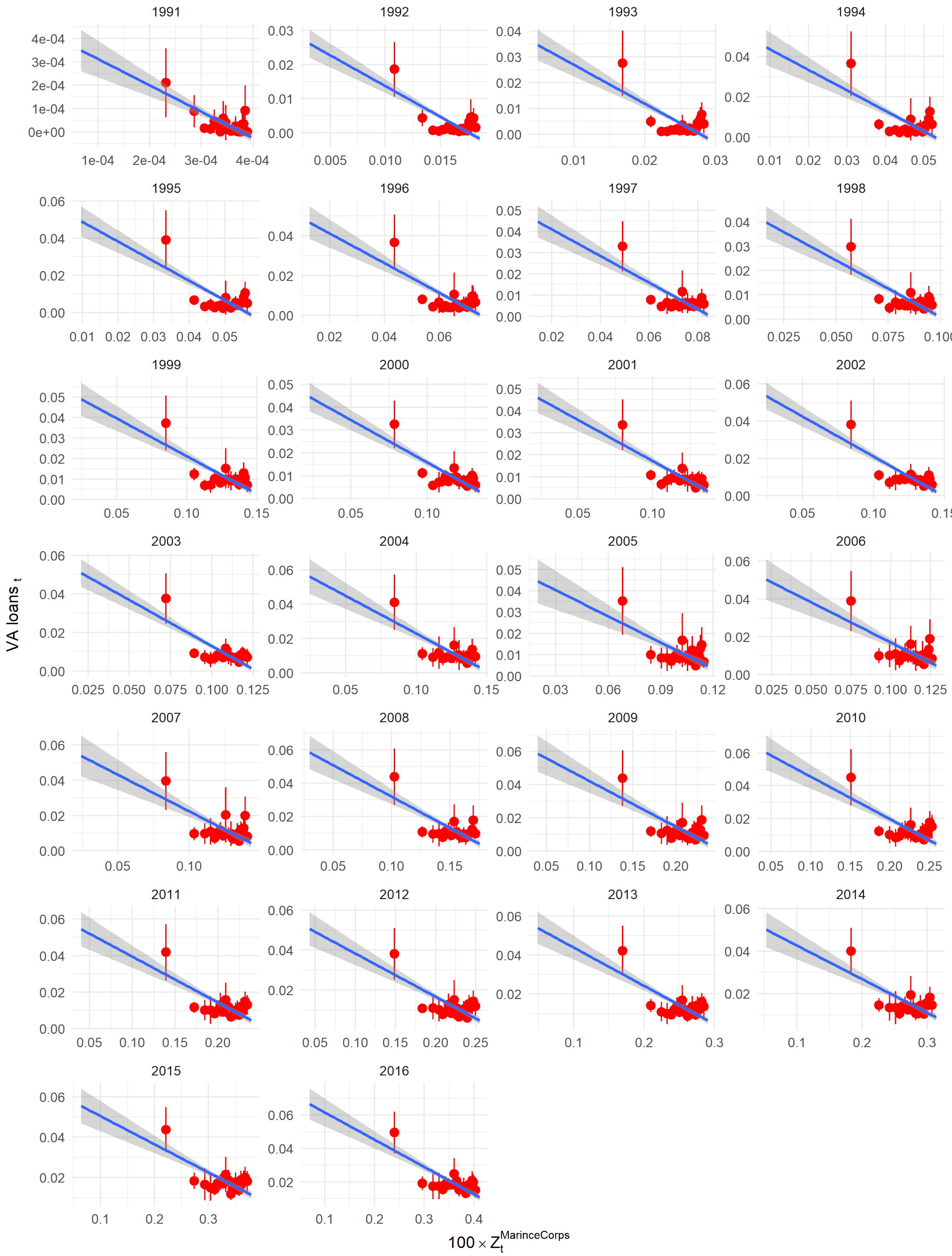
Notes: For each year, this graph shows the relationship between the endogenous variable, VA loans$_{c,t-1}$, which is the relative incidence of generous VA loans, and the instrument for the different branches. The instrument is defined as $Z^b_{c,t} = \log(\text{Distance to closest Gulf War base of branch } b \text{ in miles})^b_c \times \text{Take-up rate}^b_{c,t}$ where $b \in$ {Army, Air Force, Marine Corps, Navy}. The 20 red bins represent local means, and the blue line represents the best linear fit of all observations.

Figure A6: **Instrument for the Different Branches and the Endogenous Variable (ctd.)**



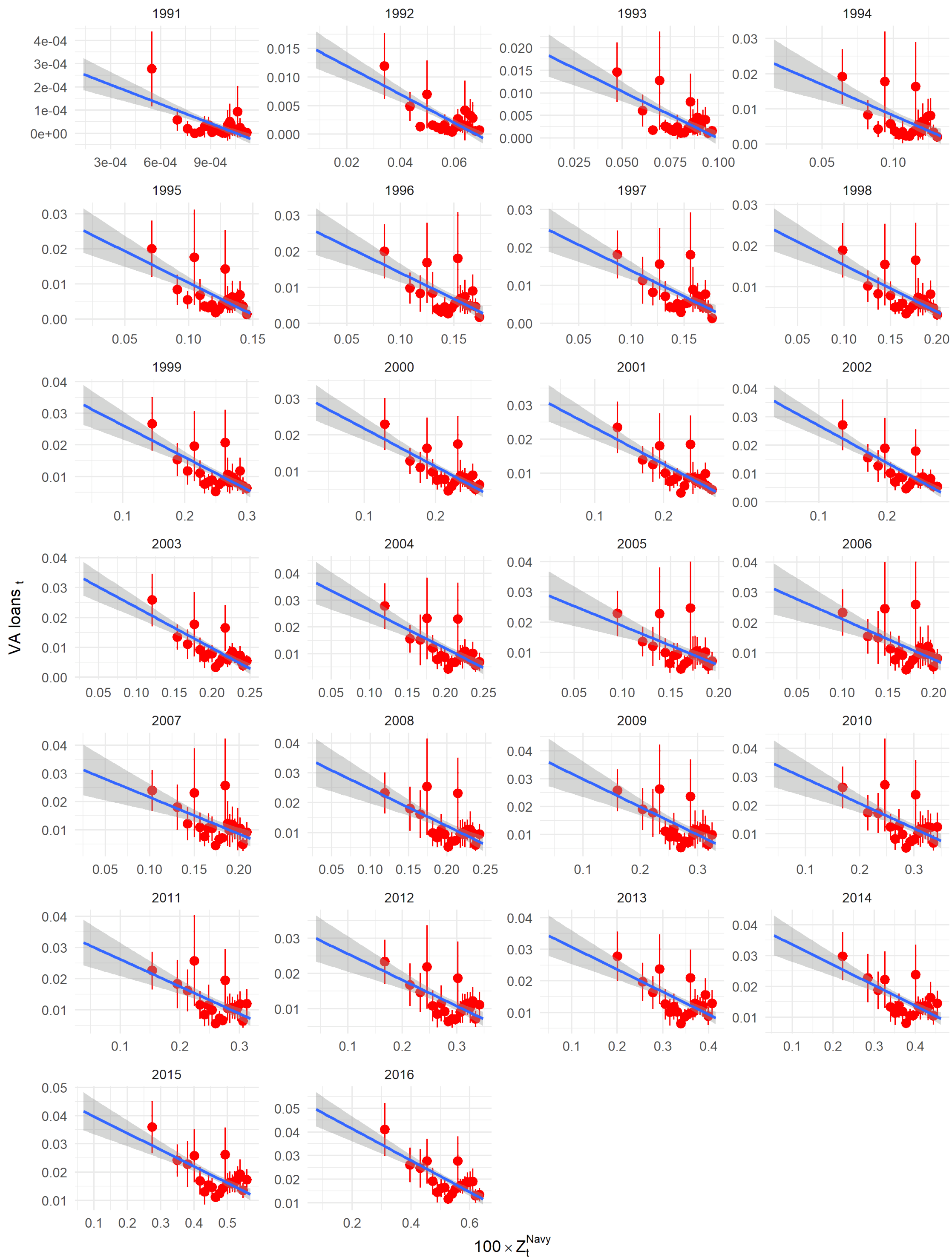
(b) Air Force

Figure A6: **Instrument for the Different Branches and the Endogenous Variable (ctd.)**



(c) Marine Corps

Figure A6: **Instrument for the Different Branches and the Endogenous Variable, (ctd.)**



(d) Navy

Table A1: **Effect of VA Loans on House Price Growth: Robustness**

Dependent variable:	House price growth$_{c,t}$		
	(1)	(2)	(3)
VA loans$_{c,t-1}$	191.2***	205.5***	163.1***
	(41.4)	(52.4)	(33.9)
log(Distance to closest non-Gulf War base)$_c \times$ Take-up rate$_t^{\text{non-Gulf War}}$			-552.1***
			(98.2)
County-Decade FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Year FE $\times$ log(Distance to closest non-Gulf War base)	No	Yes	No
Local macroeconomic conditions	Yes	Yes	Yes
Observations	58,400	58,400	58,400
Adjusted R^2	0.18	0.17	0.25

Notes: The sample is a county-year panel ct from 1991 to 2017. The Table reports estimates of (6) with different ways of controlling for the effect of non-Gulf War bases on house prices. In column 1, we do not control for this potentially confounding effect. In column 2, we include year-specific coefficients for the log distance to the closest non-Gulf War base. In column 3, we interact this distance with the non-Gulf War take-up rate, which is based on generous VA loans of non-Gulf War veterans. The dependent variable is the one-year house price growth rate from year t to $t-1$ in %. VA loans$_{c,t-1}$ is the relative incidence of generous VA loans. Local macroeconomic conditions include the change in unemployment rates, income growth, and population growth at the county-year level. Local mortgage market conditions include the numbers of conventional loans issued and conventional-loan applications denied per capita, as well as the number of denied applications for FHA loans per capita in county c in the previous year $t-1$. Robust standard errors, clustered at the county level, are in parentheses.

Table A2: **Effect of House Price Growth on Approval Rates in the Conventional Loan Market: Restricted Samples**

Sample	No VA loan issued in this year			No VA application in whole sample period		
Dependent variable:	Application approved					
	(1)	(2)	(3)	(4)	(5)	(6)
House price growth$_{c,t}$	0.019***	0.009***	0.007***	0.018***	0.008***	0.007***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
County-Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	No	Yes	Yes	No
Lender FE	No	Yes	No	No	Yes	No
Lender-Year FE	No	No	Yes	No	No	Yes
Local macroeconomic conditions	Yes	Yes	Yes	Yes	Yes	Yes
Applicant characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,381,326	30,381,326	30,381,326	15,306,516	15,306,516	15,306,516
Adjusted R^2	0.15	0.32	0.35	0.14	0.32	0.35

Notes: In columns 1 to 3, the sample consists of all mortgage applications in the conventional loan market at the transaction level m from 1991 to 2017 to lenders that did not originate a VA loan in the same year. In columns 4 to 6, we further restrict the sample to applications to lenders that did not receive an application for a VA loan during the entire sample period. The table reports IV estimates of (12). The dependent variable is a dummy for whether the application was granted. The endogenous variable is the one-year house price growth rate from year t to $t-1$ in %. Local macroeconomic conditions include the change in unemployment rates, income growth, population growth, and the product of the log distance to the closest military base from which no soldiers were deployed to the Gulf War times the Gulf War take-up rate at the county-year level. Applicant characteristics include a dummy for white applicants, a dummy for male applicants, and the log income of the applicant. Robust standard errors, clustered at the county level, are in parentheses.

Table A3: **Summary Statistics: Conventional Mortgages by Owner-occupied Status**

		Mean	SD	Min	P25	P75	Max	N
Not owner-occupied	Application approved	0.8	0.4	0.0	1.0	1.0	1.0	10,418,551
	Loan amount (in thous.)	189.5	268.3	0.0	75.4	234.0	15,9637.4	10,418,543
	Applicant income (in thous.)	194.0	322.8	1.0	81.0	212.0	180,000.0	10,418,551
	Loan-to-income	1.4	4.8	0.0	0.6	1.7	5,000.0	10,418,543
Owner-occupied	Application approved	0.8	0.4	0.0	1.0	1.0	1.0	76,603,362
	Loan amount (in thous.)	209.3	256.7	0.0	85.3	269.1	309,000.0	76,603,226
	Applicant income (in thous.)	109.8	195.4	1.0	53.1	126.5	542,821.0	76,603,362
	Loan-to-income	2.2	5.5	0.0	1.3	2.8	19,618.0	76,603,226

Notes: The table reports summary statistics for the universe of loan applications in the conventional loan market in the HMDA data at the application level m, separately for applications where the applicants will and will not occupy the home for which they take out the mortgage, as used in Table 9. All dollar values are converted to 2017 dollars using the Consumer Price Index Retroactive Series.

B List of Military Bases

In this section, we describe how we construct Table B1, a list of U.S. military bases from which soldiers were deployed during the Gulf War. The U.S. military includes four branches: the Army, the Navy, the Air Force, and the Marine Corps.[23] First, we hand-collect a list of all units that served in operations Desert Shield and Desert Storm.[24] Next, we match all units to their home bases, which gives us the required list of all bases. Finally, we retrieve the coordinates of those bases.[25] In particular, we use five sources that provide information on U.S. military units involved in these operations. Below, we describe these sources, how we extract the deployed units and their corresponding home bases, and how we assign coordinates to these bases.

B.1 Sources

We gather information from five sources. Four of them are official documents, namely the Association of the United States Army's Special Report (West and Byrne, 1991), the Department of the Navy's Summary Report (Chief of Naval Operations, 1991), the study by Cohen (1993) on the U.S. Air Force, and the publication by Westermeyer (2014) on the U.S. Marine Corps. Finally, we use the private website desert-storm.com.

B.2 Compiling a List of Units and Bases

Army report Two tables on pages 7 and 8 of West and Byrne (1991)'s Special Report list the U.S. Army units deployed during Operation Desert Shield. The tables cover each of the two phases of deployment during the operation. From these tables, we extract the names of the units and their respective home bases. This results in a list of 14 Army units with nine bases in the United States.

[23] We exclude National Guard and Reserve forces from our considerations. Although they are generally eligible for VA loans, our data show that few VA loans were issued to veterans who had served in the National Guard or Reserve forces.

[24] Note that all military branches are further organized in entities, e.g., Corps, Divisions, etc. For pragmatic reasons, we adhere to the level of granularity provided by each of the sources we analyze, as a result of which we use the same term "unit" across different military entities.

[25] We disregard units with home bases outside the U.S.

Navy report Pages B-1 through B-9 of Chief of Naval Operations (1991)'s Appendix B list the participating naval units. However, the report does not provide the respective home ports. Thus, we use the Navy report to corroborate information about naval units available from other sources, particularly desert-storm.com. This results in a loss of information if some naval units do not appear in the other sources. However, with this report we can already confirm the deployment of 102 U.S. Navy units that we extracted from desert-storm.com.

Air Force report The survey by Cohen (1993) is extensive in terms of the number of Air Force units listed, and includes detailed information on the corresponding home bases. In particular, pages 58 to 64 of this survey are relevant for the Air Force deployment. From the respective tables therein, we extract the participating units and their respective home bases. Note that information on some reported units is marked as "unknown." In particular, if a unit's home base is marked as "unknown," we do not include it in our list. This results in 79 units deployed from 52 Air Force bases.[26]

The Air Force report also includes data on participating Army and Navy units, but without reference to their home bases. Thus, we use this information only to corroborate information on deployed units from other sources.

Marine Corps report Appendix A, i.e., pages 241 to 250, in Westermeyer (2014) lays out in detail the involvement of the Marine Corps in the Gulf War. However, it only lists units without their home bases. Therefore, we proceed analogously to the Navy report, and use this source to corroborate the information on Marine Corps units available from desert-storm.com. As a result, we are able to confirm six of the ten Marine Corps units listed on the aforementioned website and three unique bases.[27]

desert-storm.com desert-storm.com is a private website, which, according to its own disclosure, was initiated by a student in 1997 to collect information about the Gulf War operations, make it available to the public, and support veterans of the war. We use the URL desert-storm.com/soldiers/units.html and the subsequent links therein.[28] The site provides

[26]We noticed that some of these bases may have actually been Air National Guard bases, which we disregard in our analysis. However, these cases are not relevant for our estimations as they only appear in one of our sources. As we describe below, we use only those bases that appear in at least two of our sources. Thus, the fact that some Air National Guard bases are present in our sample does not affect our results.

[27]One of these bases is also a Navy base, namely Norfolk, Virginia.

[28]Last retrieved on December 14, 2022.

lists of Army, Navy, Air Force, and Marine Corps units.

From these lists, we extract all Army, Navy, Air Force, and Marine Corps units that were deployed from a base in the United States. In all but two cases, the website lists the home bases of the units.[29] This procedure yields a large number of units assigned to bases. Specifically, the total includes 196 units. These units are assigned to 61 unique bases. There is a large overlap between the bases gathered from this unofficial source and those obtained from the official sources.

B.3 Assigning Coordinates to Bases

Finally, we assign coordinates to the 94 unique bases involved in the Gulf War deployment. To do this, we rely on the National Transportation Atlas Database, published by the U.S. Department of Transportation in 2019: "The dataset depicts the authoritative boundaries of the most commonly known Department of Defense (DoD) sites, installations, ranges, and training areas in the United States and Territories. (...) Sites were selected from the 2010 Base Structure Report." We attain the list from public.opendatasoft.com/explore/dataset/military-bases/table/. It contains the coordinates of the bases.[30] We hand-match our list of Gulf War bases to this list using the name of the site and the military branch.

Around 22% of the bases in our list do not appear in this official dataset. In many cases, this is due to base closures in the period from the Gulf War to 2010, when the Base Structure Report was published. In these cases, whenever possible, we obtain the coordinates from a manual web search, mainly using Wikipedia and Google Maps. With this approach, we match 15 more bases to exact locations. For the remaining six bases we were unable to find any coordinates.

B.4 Quality Assurance

Since we cannot match all Navy and Marine Corps units with home bases through official reports, and to ensure data quality, we only use those bases that we find in at least two of our five sources.[31]

[29] Units for which the home bases were unknown are omitted.

[30] Last retrieved on December 14, 2022.

[31] Note that with this approach, only two bases which we would like to use in our estimations could not be matched to coordinates.

Table B1: **List of Military Bases**

#	Branch	Base name	lat	lon
1	Air Force	Bergstrom AFB	30.17630	-97.67209
2	Air Force	Davis-Monthan AFB	32.16080	-110.84872
3	Air Force	Eglin AFB	30.57594	-86.52837
4	Air Force	England AFB	31.33467	-92.54034
5	Air Force	George AFB	34.58522	-117.37325
6	Air Force	Griffiss AFB	43.23000	-75.41000
7	Air Force	Hill AFB	41.12808	-111.99125
8	Air Force	Hurlburt	30.42919	-86.69871
9	Air Force	Langley AFB	37.08557	-76.36437
10	Air Force	Little Rock AFB	34.90400	-92.13847
11	Air Force	Loring AFB	46.94972	-67.88889
12	Air Force	Moody AFB	30.97253	-83.16469
13	Air Force	Myrtle Beach	33.67972	-78.92833
14	Air Force	Pope AFB	35.17083	-79.01444
15	Air Force	Robins AFB	32.61755	-83.58158
16	Air Force	Seymour-Johnson AFB	35.34790	-77.96258
17	Air Force	Shaw AFB	33.97486	-80.47042
18	Air Force	Tinker AFB	35.41919	-97.39293
19	Air Force	Wurtsmith AFB	44.45250	-83.38028
20	Army	Fort Benning	32.39995	-84.80062
21	Army	Fort Benning	32.28387	-84.95484
22	Army	Fort Bliss	32.26208	-106.07540
23	Army	Fort Bragg	35.13624	-79.14397
24	Army	Fort Campbell	36.59649	-87.59905
25	Army	Fort Hood	31.21569	-97.73703
26	Army	Fort McPherson	33.70621	-84.43328
27	Army	Fort Riley	39.18668	-96.82087
28	Army	Fort Sill	34.68226	-98.48341
29	Army	Fort Stewart	31.99357	-81.61677
30	Marine Corps	Camp Lejeune	34.64336	-77.30510
31	Marine Corps	Camp Pendleton	33.36176	-117.42357
32	Marine Corps	Norfolk	36.94331	-76.30151
33	Navy	Bremerton	47.55559	-122.65236
34	Navy	Charleston	32.96293	-79.96357
35	Navy	Concord	38.05140	-122.01880
36	Navy	Earle	40.25386	-74.16085
37	Navy	Little Creek	37.88615	-75.46864
38	Navy	Long Beach	33.74202	-118.23341
39	Navy	Mayport	30.38159	-81.42483
40	Navy	New Orleans	29.83136	-90.02087
41	Navy	Newport	41.53528	-71.30964
42	Navy	Norfolk	36.94331	-76.30151
43	Navy	Oakland	37.78611	-122.31861
44	Navy	Pearl Harbour	21.33657	-157.94791
45	Navy	Philadelphia	39.89111	-75.17861
46	Navy	San Diego	32.67576	-117.12275

Notes: This table lists all military bases from which soldiers were deployed to the Gulf War and their location, by military branch and name.