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The Role of Mortgage Supply on Rents in the United States

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Abstract

This paper examines the role of banking deregulation on mortgage supply from 1995-2005 and its subsequent effect on rents in the United States. We use instrumental variable estimation where, in the first stage, we estimate the effect of a deregulation index on six different mortgage supply measures. In the second stage, we use the instrumented mortgage supply measures as a treatment variable for the rent growth rate. The primary source of the mortgage data is the Home Mortgage Disclosure Act. We use fair market rents provided by the Office of Policy Development And Research for the rent data. The results indicate that the IBBEA constituted an exogenous shock to the supply of mortgages in the total sample of counties. However, the evidence was lacking for the reduced sample of counties for which we had rent data available. As the latter is necessary to research the effect on rents, we could not obtain valid results regarding the role of mortgage supply on rents.

1 Introduction

In this paper, we aim to answer the following research question: How did an exogenous shock to the supply of mortgages during 1995-2005 impact rents in the United States?

To address this research question, we will explore the following sub-questions:

- Did the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 (IBBEA) cause an exogenous shock to the supply of mortgages?
- If so, how did this shock affect rents for single-family households?
- Is the effect on rents similar to the effect documented in the paper by Gete & Reher (2018)?

To answer the first research question, we will replicate the methodology of our reference paper by Favara & Imbs (2015) and also use the same database. This means we use a specification where the dependent variable can denote the growth rate of six different mortgage supply measures. The treatment variable is an index capturing the degree of deregulation a state implements. The control variables account for some traditional factors affecting the mortgage supply measures. County and year-fixed effects are also accounted for to reduce the probability that other unobserved variables drive the results. The previous specification considers the immediate effect of the deregulation variable on the mortgage supply variables, but it is also interesting how this effect changes over time. A second specification is introduced for this purpose with the same variables as the previous specification but with the dependent variable shifted forward in time. We consider two control groups unaffected by the deregulation to see whether their mortgage supply responds significantly to the deregulation. If this is not the case, we know the shock is exogenous. Next, we will perform a two-stage least squares estimation (2SLS) of a specification that aims to capture the effect of mortgage supply on rents. In this specification, the dependent variable is the growth rate in rents, the treatment variable is an instrumented mortgage supply measure, and the control variables include factors affecting rent growth. Similar to the earlier specifications, we will include county fixed effects and year fixed effects and introduce a specification that evaluates how the effect of our mortgage supply variables on rents changes over time. We construct Anderson Rubin (AR) confidence intervals to obtain weak instrument robust inference. For the rent data, we use a database containing the fair market rent (FMR) metric, which the Office of Policy Development and Research provides.

The results of our study indicate that the IBBEA caused an exogenous shock to the supply of credit in the total sample of counties we considered and in the reduced sample of contiguous counties traversed by a state border. However, the evidence for a mortgage supply shock almost entirely disappeared for the reduced sample of counties where we had rent data available. Only one of the six mortgage supply variables was significantly affected at the 10% level in this sample. Because of this, we encountered identification issues in the second stage regression, so we could not effectively answer the second and third sub-questions.

Because the results of the deregulation on mortgage supply in our reference paper were robust to a sub-sample, we assumed that the shock would also be present for the sub-sample of counties for which we had rent data available. If we learned in an earlier stage of the research that the evidence for this fact was not available, then we likely would not have pursued this research as a mortgage supply shock is a necessary component to answer the second and third sub-questions.

As mentioned already, the foundation of this paper is the reference paper Favara & Imbs (2015). The difference is that after establishing an exogenous shock to the supply of mortgages, the authors investigate its effect on house prices instead of rents.

To our knowledge, the paper by Gete & Reher (2018) is the only other study in the literature that also researched the effect of a mortgage supply shock on US rents. They use an instrumental variable regression where they define the instruments as "the 2008 mortgage application share of lenders that underwent a capital stress test between 2011 and 2015" and "MSA exposure to the Big-4 banks using a predetermined measure of bank distribution across markets, the branch deposit share in 2008 from the FDIC's Summary of Deposits" (Gete & Reher, 2018, p. 2). They estimate the following specification:

$$Avg.rentgrowth_{m,10-14} = \beta \times Avg.\widehat{denialrate}_{m,10-14} + \gamma X_m + u_m, \tag{1}$$

where $Avg.\widehat{denialrate}_{m,10-14}$ is the instrumented shock to the average mortgage denial rate in the first stage regression, $Avg.rentgrowth_{m,10-14}$ is the average growth in rent in MSA m during the years 2010 to 2014, and X_m contains additional control variables for the growth in rent. Using this research methodology, they find that, on average, a 1% increase in mortgage denial rates increased an MSA's average rent growth during the studied period by 1.3%.

The remaining structure of this paper is as follows: Section 2 explains the data used, Section 3 presents the methodology, Section 4 contains the numerical results, and Section 5 provides a conclusion.

2 Data

Before we provide a more detailed explanation of the data, first, some general remarks. We use the dataset by Favara & Imbs (2015) to answer the first sub-question. We summarize their data section in Section 2.1 and 2.2. The dataset contains some variables that we do not use in the paper. If we do not discuss a variable, we do not use it.We inspected the dataset for outliers and found that the maximum and minimum were reasonable compared to the other values in the distribution. We thus did not alter the dataset concerning outliers. The dataset contains panel data from 1994 to 2005, with the Federal Information Processing Standard (FIPS) code serving as the group identifier. We will omit a county-year instance from the regressions explained in the methodology if either the dependent variable or one of the independent variables is missing. We will merge the dataset with Fair Market Rents (FMR) data explained in Section 2.3. Table 9 in the Appendix contains summary statistics of all variables. Figures 5, 6, and 7 in the Appendix contain empirical distributions of the mortgage supply variables for commercial banks, the control variables, and the fair market rent (FMR) data.

2.1 Bank Branching Deregulation since 1994

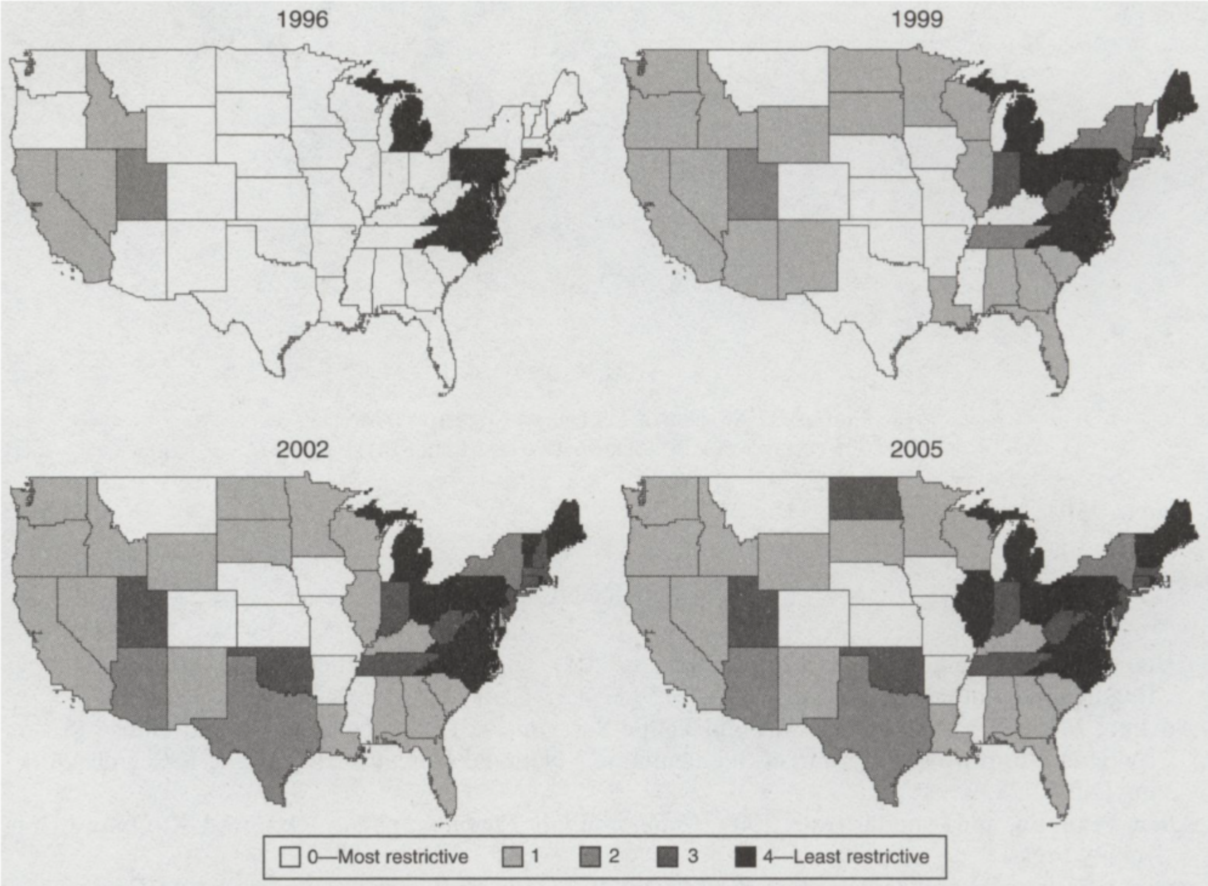
Before the passing of the Interstate Banking and Branching Efficiency Act (IBBEA) in 1994, banks needed formal authorization from state authorities to open new branches across borders. According to (Favara & Imbs, 2015, p. 962), the IBBEA removed this requirement but allowed states to implement restrictions regarding "(i) de novo branching without explicit agreement by state authorities; (ii) the minimum age of the target institution in case of mergers; (iii) the acquisition of individual branches without acquiring the entire bank; (iv) the total amount of statewide deposits controlled by a single bank or bank holding company". Johnson & Rice (2008) note that most states initially exercised these rights to some degree, but over the years, more states began deregulating. Rice & Strahan (2010) created an index to track the level of deregulation implemented by states from 1994 to 2005. The index ranges from zero to four, where four corresponds to states that have not deregulated. The index decreases by one for each deregulation measure a state implements. To investigate the effect of deregulation on mortgage supply, we use this index as our treatment variable, but in a reversed manner. This means that zero belongs to states that have not deregulated, and four belongs to states that have completely deregulated.

Figure 1 shows the geographic dispersion of deregulation measures over time. As in Rice & Strahan (2010), we assume that all states were entirely restricted in 1994.[1] The figure shows that many states lifted several restrictions within a short period, making it difficult to distinguish between the individual effects of these restrictions on mortgages supply. Therefore, we only investigate the effect of the number of restrictions lifted on mortgage supply, not the individual effects.

Kroszner & Strahan (2014) provide a comprehensive literature review on the timing of banking deregulation. The main conclusion from this review is that deregulation happens fastest in states where large banks are located, as these banks have more lobbying power. This conclusion aligns with Figure 1: states in coastal areas with large banks deregulate quickest, while states in the Midwest with smaller banks deregulate slower. In coastal areas, housing prices rose quickly from 1994 onwards. This raises the question of whether deregulation was an exogenous shock or was triggered by local demand conditions. We will examine two control groups to argue that deregulation was an exogenous shock.

[1] According to Johnson & Rice (2008), there were on average only 1.22 out-of-state branches per state before the passing of the IBBEA.

Figure 1: Geographic Dispersion of the Rice & Strahan (2010) Deregulation Index in Three-Year Intervals
Source: Favara & Imbs (2015)



2.2 Mortgage Data and Mortgage Supply Control Variables

An overview of the mortgage supply and control variables alongside a variable description and the source of the data can be found in Table 1. (BEA) is an abbreviation for the Bureau Of Economic Analysis and (Call Reports) for the Reports of Conditions and Income for Commercial Banks, which keeps track of various financial performance measures of commercial banks.

The data on mortgage supply is based on the Home Mortgage Disclosure Act (HMDA) database. This database contains detailed information on mortgages originated by depository institutions and independent mortgage companies (IMCs). The main difference between banks and IMCs is that banks rely on branches to collect deposits, while IMCs use wholesale funding and mortgage brokers. This means IMCs should not react to deregulation, as they do not open new branches across states to access new borrowers or sources of funds. Although thrifts and credit unions (TCUs) also use deposits as their primary funding source, deregulation only applies to banks. Therefore, the lending behavior of TCUs should not react to the implemented deregulation measures. TCUs and IMCs thus form the first suitable control group.

Table 2 shows mean values for mortgages originated by commercial banks, IMCs, and TCUs from 1994-2005. Commercial Banks possess the largest market share, followed by IMCs, while TCUs come in last place. The average mortgage size and applicant's income are similar for

Table 1: Overview of Mortgage Supply Variables and Relevant Control Variables
Source: Favara & Imbs (2015)

Variable name	Variable description	Source
	Mortgage supply variables	
number of mortgages	Number of mortgages originated for purchase of single family owner occupied houses.	HMDA
volume of mortgages	Dollar amount of mortgages originated for purchase of single family owner occupied houses.	HMDA
number of denials	The number of mortgage applications minus the number originated.	HMDA
denial rate	The *denial rate* equals the *number of denials* divided by the number of applications.	HMDA
mortgage to income ratio	*Volume of mortgages* divided by total income at the county level sourced from the Internal Revenue Service (IRS).	HMDA/IRS
number sold	Number of mortgages originated for purchase of single family owner occupied houses sold within the year of origination to other non-affiliated financial institutions or government-sponsored housing enterprises.	Call Reports
	Control variables	
house price index	Median house price of existing single family properties for urban counties. The series uses data from the US Census Bureau, regional and national associations of Realtors, and the house price index computed by the Federal Housing Finance Agency (FHFA).	Moody's Economy.com
income per capita	County personal income per capita.	BEA
population	County population (in thousands).	BEA
Herfindahl index	Calculated as the sum of the squared mortgage market shares of all lenders active in a county.	HMDA

Notes: All variables are measured in log changes. Mortgages are for purchase of single-family owner-occupied houses. All mortgage data is aggregated at the county level based on the location of the purchased property. Control variables are also at the county level. The denial rate variable is not present in the original Table of Favara & Imbs (2015).

commercial banks and TCUs, while these are slightly lower for IMCs. However, the magnitude of these differences is not so large that we expect significant differences in the customer bases of these lending institutions.

Table 2: Mortgage Related Summary Statistics for Commercial Banks, IMCs, and TCUs from 1994-2005
Source: Favara & Imbs (2015)

	1994-2005	**1995**	**2000**	**2005**
Number of Applications Received				
Commercial Banks	1,777	1,027	1,830	2,468
Independent Mortgage Companies	1,324	749	1,086	2,137
Thrifts and mortgages Unions	738	534	740	921
Number of mortgages Originated				
Commercial Banks	1,437	865	1,361	2,083
Independent Mortgage Companies	973	526	734	1,659
Thrifts and mortgages Unions	610	456	632	727
Average mortgage Size (thousand of dollars)				
Commercial Banks	111	85	103	144
Independent Mortgage Companies	95	71	94	121
Thrifts and mortgages Unions	114	83	115	143
Average Applicant's Income (thousand of dollars)				
Commercial Banks	65	56	64	75
Independent Mortgage Companies	58	47	58	69
Thrifts and mortgages Unions	67	54	70	75

Notes: The table displays mean values of county-year pooled data. The mortgages are for buying single-family owner-occupied houses. The sample includes US counties in urban areas where mortgage data is available from 1994-2005.

We obtain Information about the existence and geographic locations of commercial bank branches by merging data from HMDA with the Summary of Deposits collected by the Federal Deposit Insurance Corporation (FDIC). This integration allows us to determine whether each bank mortgage in HMDA is issued by a lending institution that owns a branch in the county where the property is purchased. This information enables us to construct a second control group based on the geographic location of a bank. If a state deregulates, a bank can have one of three roles relative to the deregulating state: (1) headquartered in the deregulating state, (2) headquartered outside the deregulating state without local branches in the deregulating state, or (3) headquartered outside the deregulating state with local branches in the deregulating state. Banks in the first and second roles are unaffected by deregulation, so we should observe no mortgage expansion for these banks. Banks in the third role are affected by deregulation, so we should observe mortgage expansion for these banks. As a bank can take on any of these three roles depending on which state deregulates, there can be no systematic differences in the characteristics of these three types of banks. Therefore, banks taking on the first two roles form a second control group.

From Table 9 in the Appendix, we see that in the group of IMCs and TCUs, the number of observations for the *denial rate* is significantly lower than that of the other mortgage supply measures. The reason for this is that the log change in the denial rate was not initially present in the dataset of Favara & Imbs (2015)İn order to construct this variable, we need the *number of mortgages* and the *number of denials* in 2005 for the group of IMCs and TCUs. Together with the log changes in these variables, this enables us to calculate the *number of mortgages* and the *number of denials* for every year following 2005, which enables us to calculate denial rates and log changes in denial rates. The problem is that the *number of mortgages* and the *number of denials* in 2005 for the group of IMCs and TCUs are not available in many instances, which leads to the reduced sample size [2]. The number of times the previous variables are unavailable for commercial banks is limited such that a significant decrease in sample size is not present for this group.

2.3 Rent Data

For the rent data, we use FMR data provided by the Office of Policy Development and Research (PD&R). This metric estimates the 40th percentile of the rent distribution in a particular area and is available during the years 1983-2024 on the website of the PD$R. We refer to this website for anyone interested in a detailed explanation of how FMRs are estimated. The metric also differentiates between house sizes. Separate time series data are available for houses with differing bedrooms ranging from zero to four.

We implement a few cleaning procedures to obtain data suitable for analysis, which we will explain now. For the most part, the FMR data is available at the county level, but in a few instances, the data is only available at the level of a county subdivision. We took the average of the FMRs of these subdivisions to obtain data at the county level. Another option is to take the weighted average of the subdivisions based on population sizes, which better reflects the rent distribution of a county. We do not do this as the number of times we take the average of county subdivisions is limited, so the eventual effect on parameter estimates is negligible. Additionally, from 2001 onward, FMRs were calculated at the 50th percentile level for specific counties. We exclude the counties corresponding to these areas from the dataset to avoid biased results due to the percentile change. We also delete counties where FMR values are missing from 1995-2005, as the subsequent calculation of log changes is more complicated in this case. After these procedures, we merge the data based on the county and year variables with the dataset used by Favara & Imbs (2015).

The fact that the FMR tracks the 40th percentile is important, as changes in the overall rent distribution might not reflect changes at the 40th percentile. This introduces a potential source of bias that we can not avoid since, to our knowledge, no alternative rent index covering the entire rent distribution at the county level was available during our research period.

Another potential bias source arises from the inclusion of utility costs in the FMR. Unfortunately, we can not control for this cost as no county-level data on utility costs is available for our research period. The closest alternative is a national aggregate electricity price index, but incorporating this would not be appropriate since the specification we use already accounts for nationwide trends in unobserved factors. Only log changes in the number of mortgages and the number of denials are present in the dataset used byFavara & Imbs (2015), not the actual levels, except for the years 1995, 2000, and 2005 when they are available

[2]Only log changes of the *number of mortgages* and the *number of denials* are present in the dataset of Favara & Imbs (2015), not the actual levels, except for the years 1995, 2000, and 2005 when they are available

3 Methodology

3.1 Effect of Deregulation on Mortgage Supply

To estimate the effect of deregulation on mortgage supply, we use fixed effects estimation on the following specification where c denotes counties and t denotes time periods:

$$\Delta L_{c,t} = \beta^0_{mortgages} D_{s,t-1} + \beta_1 X_{c,t} + \alpha_c + \gamma_t + \epsilon_{c,t}. \tag{2}$$

In this specification, $L_{c,t}$ represents one of the six mortgage supply variables discussed in the data section. $D_{s,t-1}$ denotes the reversed Rice & Strahan (2010) deregulation index. $X_{c,t}$ includes the following control variables: a lagged dependent variable, the current and lagged log changes in *income per capita*, *population*, *house price index*, and the *Herfindahl index* of mortgage origination. Incorporation of these control variables accounts for traditional factors affecting mortgage supply, which reduces the probability that $\beta^0_{mortgages}$ is significant due to an omitted variable bias. We take first differences of the variables as the dependent variable and control variables display heterogeneous trends over time. This is the most parsimonious way to incorporate these trends according to Paravisini (2008). It is possible that other time-invariant county-specific effects or state-level regulations influence the results. We incorporate the parameter α_c to control for these effects. It is also possible that certain year-specific factors influence the results. An example of this could be a change in the federal funds rate. We incorporate the parameter γ_t to control for these effects. With the previously discussed variables included, the parameter $\beta^0_{mortgages}$ captures the immediate effect of deregulation on the growth rate in the mortgage supply variables.

Because we observe mortgages at the county level and deregulation is state-specific, the error terms may include a time-varying state component, leading to correlation of the error terms within states. Therefore, we do not assume that the error terms are independently identically distributed (IID). To address this in our estimation, we cluster the error terms across states as Bertrand et al. (2004) and Angrist & Pischke (2009) suggest. This allows the error terms to be correlated within states, which results in robust standard errors.

The previous specification only estimates the immediate effect of deregulation on mortgages growth. We are also interested in how the effect changes over time. Jordà (2005) introduces a method that allows us to estimate this effect without specifying the underlying vector autoregression (VAR). The method is robust to misspecification of the data-generating process (DGP), can account for non-linearities, and can be estimated in a univariate specification. We estimate the following specification for $i = 0, 1, 2, 3, 4$:

$$\Delta L_{c,t+i} = \beta^i_{mortgages} D_{s,t-1} + \beta_2 X_{c,t} + \alpha_c + \gamma_t + \epsilon_{c,t}, \tag{3}$$

where each estimate of β^i_1 denotes the effect of deregulation on mortgage supply at horizon i. In the case of $i = 0$, the specification reduces to specification (2).

3.2 Effect of Mortgage Supply on Rents

Once we have identified an exogenous shock to the supply of mortgages, we can investigate whether this shock caused a difference in the growth rate of rents. To do this, we use instrumental variable estimation (IV) for the following specification:

$$\Delta R_{c,t} = \beta^0_{rents}\widehat{\Delta L_{c,t}} + \beta_2 X_{c,t} + \alpha_c + \gamma_t + \epsilon_{c,t}, \tag{4}$$

where $\widehat{\Delta L_{c,t}}$ is the in-sample prediction of one of the mortgage supply variables significantly affected by deregulation in specification (2). The control variables used for house price index by Favara & Imbs (2015) include a lagged dependent variable, the contemporaneous and lagged growth rate in *income per capita*, *population*, and the *Herfindahl index* of mortgage origination. We will assume that these variables are also relevant for rents. We made this assumption, because we could not do an extensive literature search for control variables related to rent growth due to time constraints. This inaccuracy may lead to a biased $\beta^0_{mortgages}$ due to omitted variables.

Because the effect of our mortgage supply shocks on rents is likely heterogeneous across counties, we estimate specification (4) using weighted least squares (WLS). If we apply ordinary least squares (OLS), states with many counties would disproportionately influence the final estimation results. By weighting observations by the inverse of the number of counties per state, we ensure that each state has an equal influence on the final estimation results. Finally, we estimate standard errors robust to heteroskedasticity and serial correlation.

After estimating the direct effect of a mortgage supply shock on rents using specification (4), we use the same approach as in Section 3.1 to examine how the effect of a mortgage supply shock changes over time. We do this by estimating the following specification:

$$\Delta R_{c,t+i} = \beta^i_{rents}\widehat{\Delta L_{c,t}} + \beta_2 X_{c,t} + \alpha_c + \gamma_t + \epsilon_{c,t}, \tag{5}$$

where each estimate of β^i_1 denotes the effect of a mortgages supply shock on rents at horizon i for $i = 0, 1, 2, 3, 4$.

3.3 Robust Two-Stage Least Squares Inference

Nelson & Startz (1990) and Bound et al. (1995) show that issues can arise in 2SLS inference when instruments are weakly correlated with the endogenous variable. J. H. Stock & Yogo (2002) define instruments as being weak when a conventional t-test at size α in reality has a size that can exceed a threshold T. In order to test whether this definition applies to an instrument, Olea & Pflueger (2013) propose a test statistic F^{eff} to detect weak instruments that is robust to non-homoskedastic errors. According to Andrews et al. (2019), in the case of a single endogenous variable and instrument, this test statistic reduces to the Kleibergen & Paap (2006) Wald statistic W and can be used with the J. Stock & Yogo (2005) critical values. This test statistic and its corresponding critical value are shown in Stata when using the ivreg2 command. For example, If $\hat{W} > 8.96$, then we know with 95% confidence that a two-sided t-test at the 5% level rejects a true null hypothesis at a rate no higher than 15%. If $\hat{W} > 16.38$, then a two-sided t-test has a maximum rejection rate of 10% with 95% confidence.

Even though the previous test for weak instruments allows us to determine the actual size of our two-sided 5% test with greater confidence, another problem remains even when instruments are relatively strong ($10 \leq \hat{W} \leq 20$). Keane & Neal (2023) note that 2SLS estimates generate significantly lower standard errors in the direction of the OLS bias. The consequence is that the t-test has inflated power to judge estimates in the direction of the OLS bias significant and deflated power for the direction opposite of the OLS bias. This problem is called power asymmetry.

Instead of the t-test, we will make use of the Anderson-Rubin (AR) test by Anderson & Rubin (1949), which offers a range of advantages. In exactly identified models, Moreira (2009) shows that the AR test is the uniformly most accurate unbiased test. Furthermore, Keane & Neal (2023) show that the AR test still suffers from the power asymmetry problem but that this problem quickly vanishes when instrument strength increases. Finally, they show that the benefits of the AR test are not limited to independently identically distributed (IID) normal data, such that the test is suitable in our case.

The composite null hypothesis of the AR test is as follows: $\beta^0 = b_0$, and the exogeneity condition for weak instruments is satisfied. In this null hypothesis, b_0 is a hypothesized value for β^0 and the "exogeneity condition is satisfied" means that the instruments used are uncorrelated with the error terms of the first-stage regression. A 95% confidence interval then contains all the values b_0 for which we can not reject the composite null hypothesis at the 5% level. If the 95% confidence interval contains a wide range of hypothesized b_0 values, then the parameter β^0_{rents} is poorly identified or unidentified. To conclude that β^0_{rents} is significantly different from zero, we thus need a narrow 95% confidence interval which does not contain zero.

4 Numerical Results

4.1 Effect of Deregulation on Mortgage Supply

4.1.1 Results for Sample Including all Urban Counties

Table 3 provides estimates of $\beta^0_{mortgages}$ in specification (2). The table distinguishes between the sample of commercial banks and IMCs and TCUs. From the table, we see that for the sample of commercial banks, the *number of mortgages*, *volume of mortgages*, and *mortgage to income ratio* all respond significantly to deregulation. A state that completely deregulates can expect an immediate increase in the growth rate of mortgages originated by commercial banks of around 12%. We also see that the *number of denials*, the *number sold*, and the *denial rate* do not respond significantly to deregulation. None of the dependent variables respond significantly to deregulation for the control group consisting of IMCs and TCUs. This differential effect suggests that the mortgage supply shock is exogenous.[3] If the mortgage supply shock were endogenous, meaning it resulted from increased demand for mortgages, then β_1 should be significant for both groups. Next, Figure 2 shows impulse response functions based on estimates of specification (3). For all variables except the *denial rate*, the estimates of $\beta^i_{mortgages}$ are highest on impact and gradually decrease until they become insignificant at the 90% level.

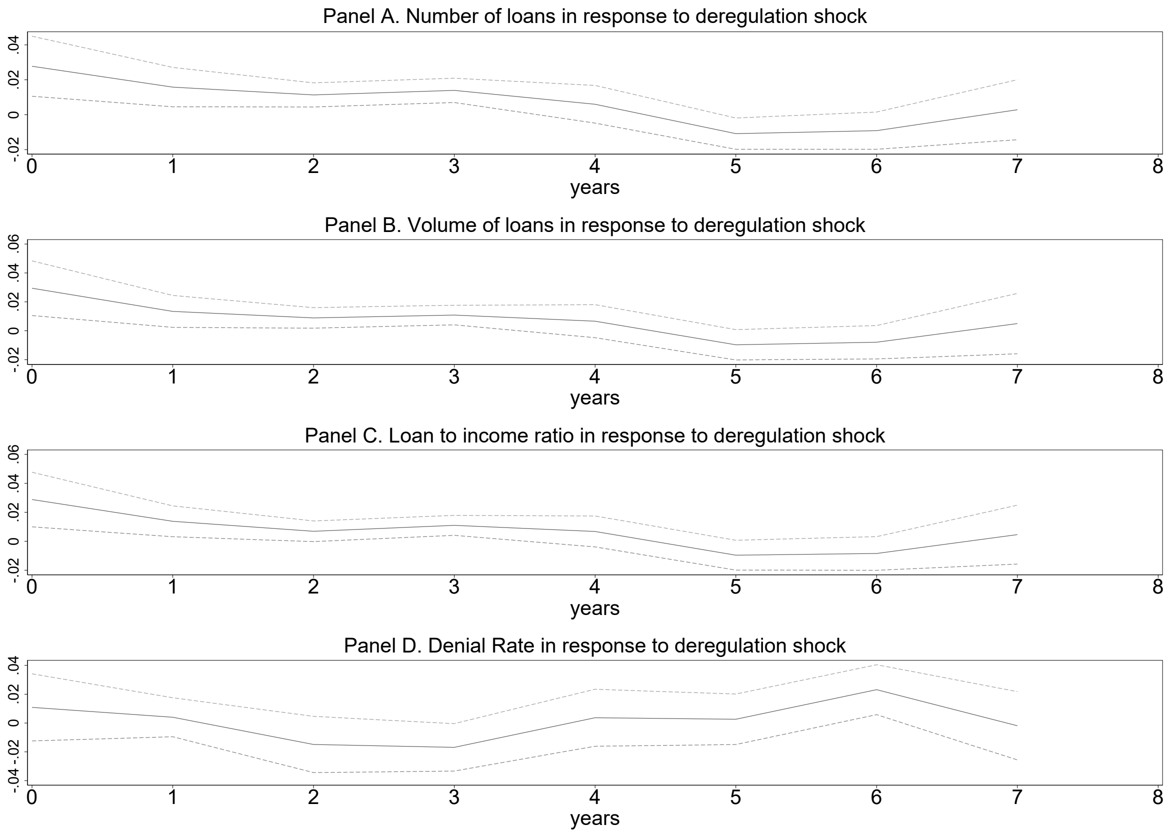
[3] Favara et al. (2010) show that the estimates of β_1 are still insignificant if we look at IMCs or TCUs separately.

Table 3: Estimation Results specification (2) for Commercial Banks and IMC and TCUs

	number of mortgages	*volume of mortgages*	*number of denials*	*mortgage to income ratio*	*number sold*	*denial rate*
Panel A. Commercial banks						
Deregulation	0.028**	0.029**	0.013	0.029**	0.008	0.109
	(0.010)	(0.012)	(0.018)	(0.011)	(0.012)	(0.014)
Observations	10,992	10,992	10,923	10,922	10,689	9047
Number of counties	1,018	1,018	1,018	1,018	1,018	1013
Number of states	50	50	50	50	50	50
R^2 within	0.122	0.132	0.389	0.124	0.112	0.443
Panel B. Independent mortgage companies, thrifts, and mortgages unions						
Deregulation	0.002	0.001	0.011	0.001	-0.015	-0.009
	(0.008)	(0.008)	(0.015)	(0.008)	(0.011)	(0.013)
Test	[0.029]	[0.038]	[0.721]	[0.042]	[0.268]	[0.447]
Observations	10,580	10,580	10,566	10,579	9,859	2853
Number of counties	1,017	1,017	1,016	1,017	1,006	317
Number of states	50	50	50	50	50	47
R^2 within	0.406	0.315	0.613	0.295	0.427	0.381

Dependent variables are the *number of mortgages*, *volume of mortgages*, *number of denials*, *mortgage to income ratio*, *number sold*, and *denial rate*. The treatment variable is the Rice & Strahan (2010) index of interstate branching deregulation. Control variables include a lagged dependent variable, the contemporaneous and lagged log change in a county's *income per capita*, *population*, *house price index*, and the *Herfindahl index* of mortgage origination. The sample includes urban counties for which mortgage data is available during 1994-2005. Standard errors are clustered by state. "Test" denotes p values related to the null hypothesis that the coefficients in panel A are zero and equal to those in panel B. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

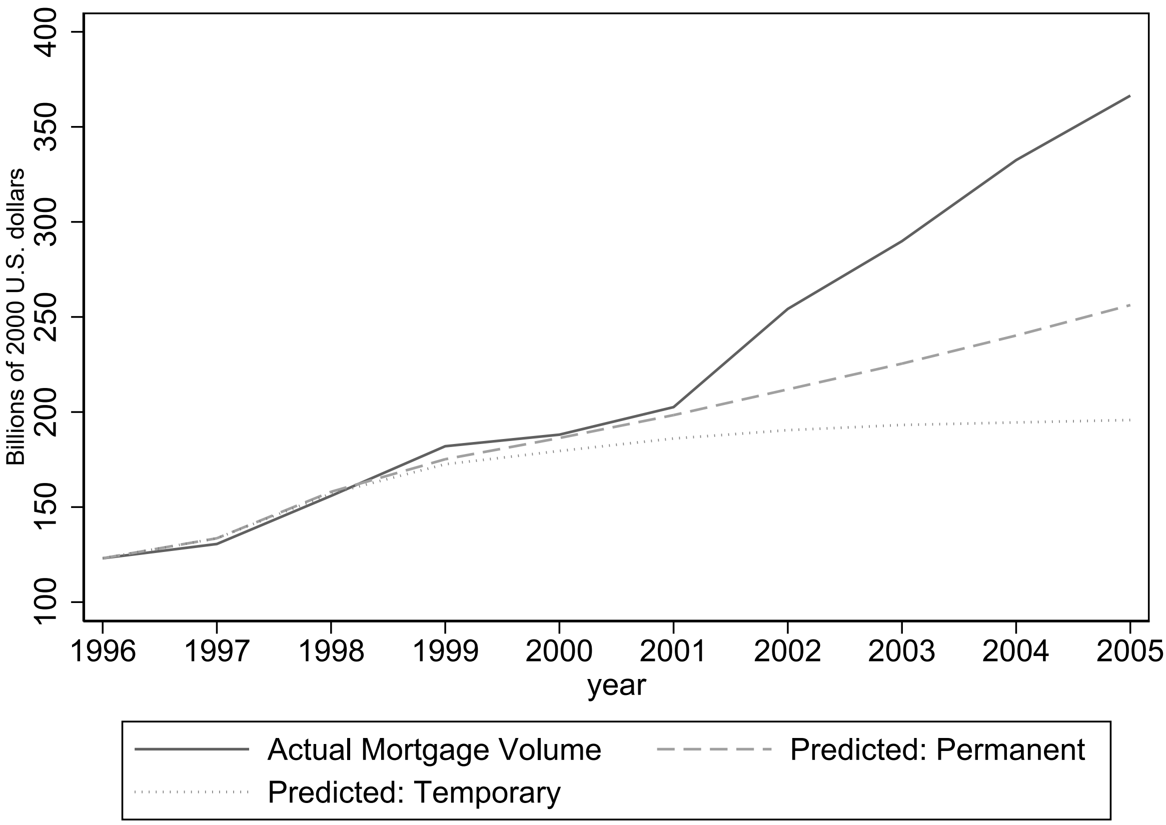
Figure 2: Impulse Response Function for Deregulation on Mortgage Supply by Commercial Banks



Note: The dashed lines indicate 90% confidence bands.

We use two in-sample predictions to quantify how much of the increase in mortgage volumes we can attribute to deregulation. The first prediction assumes that the increase in mortgage volume is permanent, with the growth rate of mortgages increasing by 2.8% for each observed deregulation measure, resulting in an upper bound. The second prediction assumes that the increase in mortgage volume is temporary, starting at 2.8% and decreasing over time according to the impulse response function in Figure 2. Additionally, the effect of a given deregulation measure stops when another deregulation is implemented so that the effects are not compounded. This provides a lower bound. The results are shown in Figure3. Deregulation explains between one-third and one-half of the increase in mortgages supply from 1994 until 2005.

Figure 3: Actual and Predicted Mortgage Volume in the US from 1996-2005
Source: Favara & Imbs (2015)

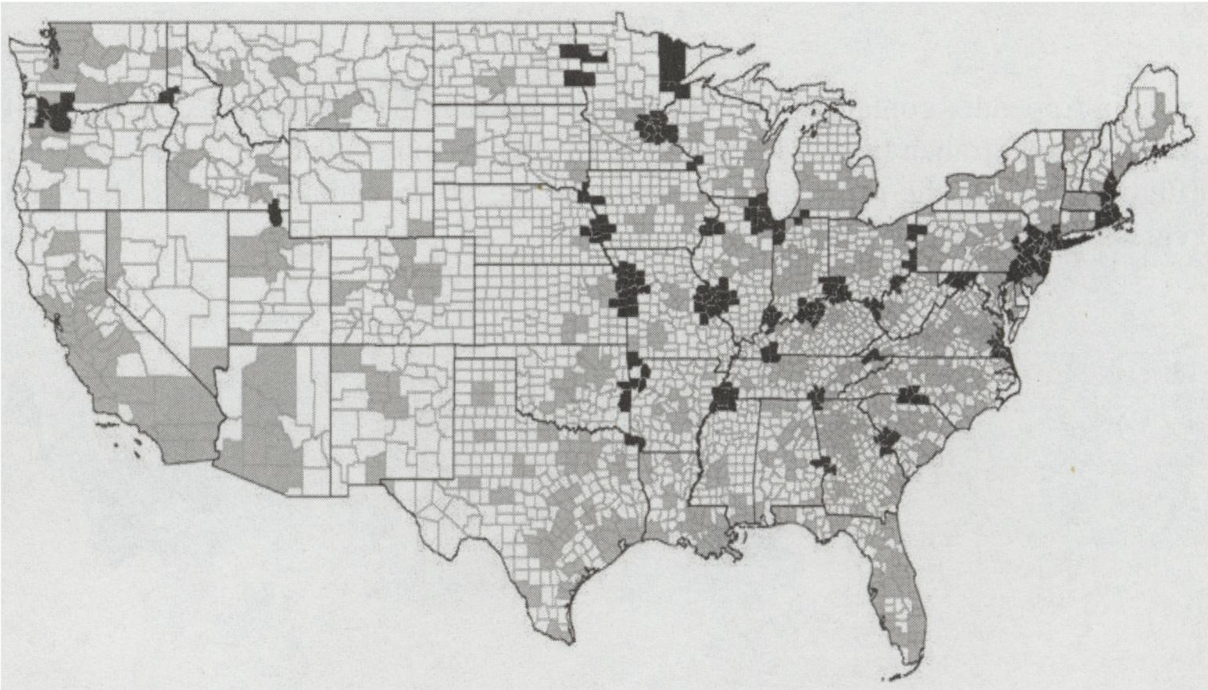


4.1.2 Reduced Sample of Contiguous Counties

Next, we focus on the sample of counties in a Metropolitan Statistical Area (MSA) traversed by a state border. This sample is visualized in Figure 4. We assume that the control variables in specification (2) do not differ substantially between two adjacent counties, given the high degree of social and economic integration.

In theory, an unobserved variable could influence both deregulation and mortgage supply, such as lobbying by banks anticipating increased mortgage demand. However, the explanation for a significant estimate of $\beta^0_{mortgages}$ would require that the increase in mortgage demand is

Figure 4: Sample of US Urban Counties (Grey) and Counties in an MSA Bordering two or more states (Black)
Source: Figure obtained from Favara & Imbs (2015). Figure is based on data from HMDA and Moody's.



only present on one side of the state border, which seems unlikely given our assumption.

Table 4 provides estimation results of specification (2) for the sample of counties in one of 36 MSAs traversed by a state border. The *number of mortgages*, *volume of mortgages*, and *mortgage to income ratio* are significantly affected by deregulation for commercial banks, and to a greater degree than in the full sample. Once again, there is no significant response for the control group.

As the data section describes, only banks taking on the first role should respond to the deregulation. The estimation results for the sample, divided according to the different roles a bank can take on, are presented in Table 5. For banks assuming the first role, the deregulation significantly affects the *number of mortgages*, *volume of mortgages*, and *mortgage to income ratio*. This is consistent with our earlier findings that the mortgage supply shock caused by deregulation was exogenous and not driven by increased demand for mortgages. If the demand for mortgages had increased, we would expect the other two types of banks to also react to the deregulation.

Interestingly, the *number of local branches* operated by out-of-state banks rises as deregulation is implemented. This expansion in local branches enables out-of-state banks to increase their mortgage supply. The establishment of more branches appears to be a strategic move to to enhance market presence and lending capacity.

Table 4: Estimation Results Specification (2) for the Sample of Contiguous Counties in an MSA Traversed by a State Border

	Panel A. Commercial banks					
	number of mortgages	*volume of mortgages*	*number of denials*	*mortgage to income ratio*	*number sold*	*denial rate*
Deregulation	0.038***	0.042***	-0.003	0.043***	0.020**	-0.002
	(0.010)	(0.012)	(0.018)	(0.012)	(0.010)	(0.013)
Observations	2,885	2,885	2,866	2,885	2,829	2377
Number of counties	267	267	267	267	267	266
Number of states	35	35	35	35	35	35
R^2 within	0.106	0.119	0.378	0.112	0.117	0.458

	Panel B. Independent mortgage companies, thrifts, and mortgages unions					
	number of mortgages	*volume of mortgages*	*number of denials*	*mortgage to income ratio*	*number sold*	*denial rate*
Deregulation	0.008	0.010	0.006	0.011*	-0.006	-0.029
	(0.005)	(0.006)	(0.017)	(0.007)	(0.010)	(0.022)
Test	[0.000]	[0.001]	[0.920]	[0.000]	[0.113]	[0.854]
Observations	2,796	2,796	2,796	2,796	2,630	819
Number of counties	266	266	266	266	265	91
Number of states	35	35	35	35	35	29
R^2 within	0.345	0.262	0.605	0.257	0.382	0.467

Notes: Dependent variables are the *number of mortgages*, *volume of mortgages*, *number of denials*, *mortgage to income ratio*, *number sold*, *denial rate*. The treatment variable is the Rice & Strahan (2010) index of interstate branching deregulation. Control variables include a lagged dependent variable, the contemporaneous and lagged *income per capita*, *population*, *house price index*, and the *Herfindahl index* of mortgage origination. The sample includes urban counties in one of 36 MSAs crossed by a state border for which mortgage data is available during 1994-2005. Standard errors are clustered by state. "Test" denotes p values related to the hypothesis that the coefficients in panel A are zero and equal to those in panel B. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 5: Estimation Results Specification (2) for Different Banking Roles

	number of mortgages	*volume of mortgages*	*number of denials*	*mortgage to income ratio*	*number sold*	*number of local branches*
Panel A. Out-of-state banks : local branches						
Deregulation	0.161**	0.167***	0.069	0.165***	0.055	0.077**
	(0.060)	(0.061)	(0.059)	(0.061)	(0.082)	(0.030)
Observations	4,514	4,514	4,108	4,513	3,356	4,783
Number of counties	767	767	738	767	700	790
Number of states	49	49	49	49	47	49
R^2 within	0.159	0.145	0.221	0.140	0.258	0.108
Panel B. Out-of-state banks: no branches						
Deregulation	0.016	0.015	0.012	0.014	0.010	-
	(0.011)	(0.011)	(0.024)	(0.012)	(0.014)	-
Test	[0.012]	[0.017]	[0.429]	[0.018]	[0.673]	-
Observations	9,988	9,988	9,926	9,987	9,771	-
Number of counties	1,018	1,018	1,018	1,018	1,017	-
Number of states	50	50	50	50	50	-
R^2 within	0.160	0.122	0.475	0.112	0.188	-
Panel C. In-state banks						
Deregulation	0.003	-0.003	0.005	-0.003	-0.025	0.001
	(0.010)	(0.011)	(0.015)	(0.011)	(0.019)	(0.007)
Test	[0.016]	[0.024]	[0.431]	[0.024]	[0.400]	[0.032]
Observations	9,841	9,841	9,339	9,840	9,175	9,019
Number of counties	1,017	1,017	1,005	1,017	1,006	978
Number of states	50	50	50	50	50	50
R^2 within	0.025	0.391	0.067	0.042	0.097	0.047

Notes: Dependent variables are the *number of mortgages*, *volume of mortgages*, *number of denials*, *mortgage to income ratio*, *number sold*, and *number of local branches*. The treatment variable is the Rice & Strahan (2010) index of interstate branching deregulation. Control variables include a lagged dependent variable, the contemporaneous and lagged *income per capita*, *population*, *house price index*, and the *Herfindahl index* of mortgage origination. The sample includes urban counties in one of 36 MSAs crossed by a state border for which mortgage data is available during 1994-2005. Panel A shows estimation results for out-of state banks with local branches-, panel B for out-of-state banks with no local branches, and panel C for in-state banks. Standard errors are clustered by state. "Test" denotes p values related to the hypothesis that the coefficients in panel A are zero and equal to those in panel B. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

4.1.3 Reduced Sample of Counties for which Fair Market Rent Data is Available

Table 6 provides estimates of specification (2) for the sample of counties for which FMR data is available. The results are surprising because the significant effects of deregulation on mortgages supply that were present in the previous two samples have now vanished. Only the variable *number of mortgages* is significant at the 10% level.

Before starting the analysis described in the following section, we assumed that the significance of the estimates would hold in the reduced sample of counties for which FMR data was available. We only learned that this was not the case after encountering problems relating to weak instruments. This explains why the variables *volume of mortgages* and *mortgage to income ratio* are used as instruments in the subsequent analyses even though they are not significantly affected by deregulation in the reduced sample.

Table 6: Estimation Results Specification (2) for the Sample of Counties for which FMR Data is Available

	number of mortgages	*volume of mortgages*	*number of denials*	*mortgage to income ratio*	*number sold*	*denial rate*
Deregulation	0.018*	0.016	0.021	0.015	-0.004	-0.002
	(0.011)	(0.011)	(0.018)	(0.012)	(0.014)	(0.013)
Observations	5537	5537	5502	5537	5355	2377
Number of counties	562	562	562	562	561	266
Number of clusters	50	50	50	50	50	50
R^2-within	0.186	0.170	0.417	0.155	0.114	0.458

Notes: Dependent variables are the *number of mortgages*, *volume of mortgages*, *number of denials*, *mortgage to income ratio*, *number sold*, and *denial rate*. The treatment variable is the Rice & Strahan (2010) index of interstate branching deregulation. Control variables include a lagged dependent variable, the contemporaneous and lagged *income per capita*, *population*, *house price index*, and the *Herfindahl index* of mortgage origination. The reduced sample includes counties for which FMR data is available during the period 1995-2005. "Test" denotes p values related to the hypothesis that the coefficients in panel A are zero and equal to those in panel B. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

4.2 Effect of Mortgage Supply on Rents

Table 7 provides estimates of specification (4) for FMRs of houses with one to four bedrooms. From the section on 2SLS inference, we know that the t-test is not the preferred statistic to use, even when instruments are relatively strong. We are more interested in the Kleibergen & Paap (2006) *rk Wald F statistic*, which all show values below the 5.53 critical value indicating that a size distortion of at least 20% is present in a t-test. We thus conclude that the instruments are weak in this context.

Estimation results of β^i_{rents} in specification(5) for $i \in 0, 1, 2, 3, 4$ alongside robust AR statistics for the null hypothesis that $\beta^i_{rents} = 0$. Furthermore, confidence intervals are shown in Table 8 based on a 100-point grid search for a wide range of possible β^i_{rents}. The exact range that the grid points cover differs per specification and can be found in the estimation output of the replication package. It sometimes appears as though the confidence interval and the P-value disagree when the P-value is below 0.05, and the CI has as "entire grid" as its value. However, this is not the case, as zero is not always included as a grid point. All confidence intervals are open-ended, meaning that the parameter β^i_{rents} is unidentified. The for this is that the weak instruments we use do not cause enough variation in the endogenous variable that can be separated from the effect of other variables. This means we can not draw a conclusion on the effect of mortgages supply on rents because the sample we used did not experience a strong exogenous shock to the supply of mortgages.

Table 7: Estimation Results for Specification (4)

	1 bedroom FMR	*1 bedroom FMR*	*1 bedroom FMR*	*2 bedrooms FMR*	*2 bedrooms FMR*	*2 bedrooms FMR*
Instr. *number of mortgages*	0.140			0.175		
	(0.104)			(0.130)		
Instr. *volume of mortgages*		0.191			0.240	
		(0.161)			(0.205)	
Instr. *mortgage to income ratio*			0.161			0.201
			(0.135)			(0.170)
lagged FMR	-0.077**	-0.071*	-0.063	-0.054	-0.050	-0.034
	(0.035)	(0.042)	(0.041)	(0.046)	(0.058)	(0.059)
Income per capita	-0.099	-0.176	-0.093	-0.142	-0.240	-0.134
	(0.098)	(0.179)	(0.111)	(0.123)	(0.228)	(0.142)
lagged income per capita	0.027	0.016	0.094	0.028	0.015	0.112
	(0.050)	(0.059)	(0.094)	(0.060)	(0.072)	(0.118)
Population	-0.189	-0.244	0.124	-0.299	-0.369	0.094
	(0.291)	(0.372)	(0.304)	(0.339)	(0.450)	(0.359)
lagged population	-0.386**	-0.531	-0.571	-0.312	-0.493	-0.543
	(0.205)	(0.348)	(0.477)	(0.235)	(0.420)	(0.582)
house price index	0.082**	0.017	-0.020	0.029	-0.054	-0.100
	(0.040)	(0.088)	(0.114)	(0.044)	(0.106)	(0.137)
lagged house price index	0.079	0.047	0.080	0.098	0.059	0.100
	(0.052)	(0.052)	(0.071)	(0.061)	(0.058)	(0.086)
Herfindahl index	0.019	0.022	0.017	0.025	0.030	0.023
	(0.017)	(0.022)	(0.018)	(0.021)	(0.028)	(0.022)
lagged Herfindahl index	0.014	0.021	0.018	0.020	0.029	0.025
	(0.015)	(0.022)	(0.019)	(0.018)	(0.028)	(0.023)
Kleibergen & Paap (2006) *rk Wald F statistic*	4.601	2.356	2.458	4.847	2.317	2.458
Obs	5603	5603	5603	5603	5603	5603
N-Counties	562	562	562	562	562	562
R^2	-0.747	-1.651	-1.885	-1.351	-2.949	-3.318
	3 bedrooms FMR	*3 bedrooms FMR*	*3 bedrooms FMR*	*4 bedrooms FMR*	*4 bedrooms FMR*	*4 bedrooms FMR*
Instr. *number of mortgages*	0.104			-0.023		
	(0.106)			(0.141)		
Instr. *volume of mortgages*		0.144			-0.031	
		(0.157)			(0.194)	
Instr. *mortgage to income ratio*			0.120			-0.027
			(0.132)			(0.164)
lagged FMR	-0.060*	-0.060	-0.053	-0.021	-0.022	-0.023
	(0.036)	(0.041)	(0.041)	(0.031)	(0.028)	(0.023)
Income per capita	-0.089	-0.148	-0.085	-0.002	0.011	-0.003
	(0.092)	(0.164)	(0.099)	(0.124)	(0.200)	(0.120)
lagged income per capita	0.007	-0.0004	0.058	0.039	0.028	0.028
	(0.050)	(0.051)	(0.094)	(0.063)	(0.121)	(0.121)
Population	-0.166	-0.209	0.067	0.451	0.460	0.400**
	(0.263)	(0.330)	(0.242)	(0.295)	(0.344)	(0.197)
lagged population	-0.222	-0.331	-0.360	-0.148	-0.117	-0.117
	(0.187)	(0.310)	(0.408)	(0.248)	(0.410)	(0.410)
house price index	0.081**	0.031	0.004	0.040	0.050	0.057
	(0.039)	(0.078)	(0.103)	(0.046)	(0.080)	(0.114)
lagged house price index	0.075	0.052	0.077	0.081	0.080	0.080
	(0.059)	(0.050)	(0.071)	(0.067)	(0.070)	(0.070)
Herfindahl index	0.014	0.017	0.013	-0.006	-0.006	-0.005
	(0.018)	(0.021)	(0.018)	(0.023)	(0.027)	(0.022)
lagged Herfindahl index	0.009	0.014	0.012	-0.004	-0.005	-0.005
	(0.015)	(0.022)	(0.019)	(0.020)	(0.027)	(0.023)
Kleibergen & Paap (2006) *rk Wald F statistic*	4.754	2.358	2.458	4.824	2.317	2.458
Obs	5603	5603	5603	5603	5603	5603
N-Counties	562	562	562	562	562	562
R2	-0.386	-0.880	-1.007	-0.019	-0.044	-0.045

Notes: Dependent variables are the log change in the FMR. The treatment variables are the instrumented *number of mortgages*, *volume of mortgages*, and *mortgage to income ratio* by commercial banks. Control variables include a lagged dependent variable, the contemporaneous and lagged *income per capita*, *population*, *house price index*, and the *Herfindahl index* of mortgage origination. The Kleibergen & Paap (2006) *rk Wald F statistic* denotes the test statistic for the test that instruments in the first-stage regression are weak. The sample includes counties for which FMR data and data on the independent variables is available during the period 1995-2005. County and year-fixed effects are accounted for but not shown in the table. Standard errors are robust to heteroskedasticity and autocorrelation. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 8: Estimates of β^i_{rents} in Specification (5) Alongside AR Statistics, Corresponding p-Values, and Confidence Intervals

	β^0_{rents}	β^1_{rents}	β^2_{rents}	β^3_{rents}	β^4_{rents}
1 bedroom FMR data					
Instr. *number of mortgages*	0.14	0.18	0.25	0.12	-0.01
AR statistic	3.16	5.27	3.96	2.08	0.05
P-value	0.07	0.02	0.04	0.14	0.81
95% confidence interval	[-0.01, . . .]	[0.02, . . .]	$[\ldots, -0.55] \cup [0.01, \ldots]$	[-0.03, . . .]	[. . . , 0.18]
Instr. *volume of mortgages*	0.19	0.25	0.33	0.16	-0.01
AR statistic	3.16	5.27	3.96	2.08	0.05
P-value	0.07	0.02	0.04	0.14	0.81
95% confidence interval	[-0.01, . . .]	$[\ldots, -0.48] \cup [0.03, \ldots]$	$[\ldots, -0.32] \cup [0.01, \ldots]$	$[\ldots, -0.24] \cup [-0.04, \ldots]$	entire grid
Instr. *mortgage to income ratio*	0.16	0.20	0.21	0.11	-0.01
AR statistic	3.16	5.27	3.96	2.08	0.05
P-value	0.07	0.02	0.04	0.14	0.81
95% confidence interval	[-0.01, . . .]	$[\ldots, -0.49] \cup [0.02, \ldots]$	$[\ldots, -0.41] \cup [0.01, \ldots]$	[-0.02, . . .]	entire grid
2 bedrooms FMR data					
Instr. number of mortgages	0.17	0.26	0.37	0.16	-0.06
AR statistic	3.70	6.80	5.54	1.92	1.71
P-value	0.05	0.00	0.01	0.16	0.19
95% AR confidence interval	[0.00, . . .]	[0.05, . . .]	$[\ldots, -0.82] \cup [0.06, \ldots]$	[-0.03, . . .]	[. . . , 0.03]
Instr. volume of mortgages	0.23	0.36	0.50	0.21	-0.08
AR statistic	3.70	6.80	5.54	1.92	1.71
P-value	0.05	0.00	0.01	0.16	0.19
95% AR confidence interval	[0.00, . . .]	$[\ldots, -0.71] \cup [0.05, \ldots]$	$[\ldots, -0.53] \cup [0.08, \ldots]$	$[-0.37, \ldots] \cup [-0.05, \ldots]$	[. . . , 0.05]
Instr. *mortgage to income ratio*	0.20	0.28	0.31	0.14	-0.05
AR statistic	3.70	6.80	5.54	1.92	1.71
P-value	0.05	0.00	0.01	0.16	0.19
95% AR confidence interval	[0.00, . . .]	$[\ldots, -0.69] \cup [0.06, \ldots]$	$[\ldots, -0.62] \cup [0.05, \ldots]$	[-0.04, . . .]	[. . . , 0.04]
3 bedrooms FMR data					
Instr. number of mortgages	0.10	0.20	0.28	0.08	-0.16
AR statistic	1.25	3.08	2.35	0.29	7.38
P-value	0.26	0.07	0.12	0.58	0.00
95% AR confidence interval	[-0.09, . . .]	[-0.01, . . .]	[. . . , -0.63] U [-0.02, . . .]	[. . . , -0.60] U [-0.22, . . .]	[. . . , -0.04]
Instr. volume of mortgages	0.14	0.28	0.38	0.11	-0.20
AR statistic	1.25	3.08	2.35	0.29	7.38
P-value	0.26	0.07	0.12	0.58	0.00
95% AR confidence interval	[entire grid]	$[\ldots, -0.47] \cup [-0.01, \ldots]$	$[\ldots, -0.36] \cup [-0.02, \ldots]$	[entire grid]	[. . . , -0.05]
Instr. *mortgage to income ratio*	0.12	0.22	0.24	0.07	-0.14
AR statistic	1.25	3.08	2.35	0.29	7.38
P-value	0.26	0.07	0.12	0.58	0.00
95% AR confidence interval	[entire grid]	[. . . , -0.48] U [-0.01, . . .]	$[\ldots, -0.45] \cup [-0.03, \ldots]$	[entire grid]	[. . . , -0.03]
4 bedrooms FMR data					
Instr. number of mortgages	-0.02	0.08	0.10	0.28	-0.04
AR statistic	0.03	0.33	0.24	2.04	0.27
P-value	0.87	0.56	0.62	0.15	0.60
95% AR confidence interval	[-0.51, . . .]	[-0.21, . . .]	[. . . , -0.63]	[. . . , -0.07]	[. . . , 0.19]
Instr. volume of mortgages	-0.03	0.11	0.14	0.36	-0.05
AR statistic	0.03	0.33	0.24	2.04	0.27
P-value	0.87	0.56	0.62	0.15	0.60
95% AR confidence interval	[entire grid]	[. . . , -0.86]	$[\ldots, -0.58] \cup [-0.07, \ldots]$	[. . . , -0.05]	[. . . , 0.15]
Instr. *mortgage to income ratio*	-0.02	0.09	0.09	0.24	-0.03
AR statistic	0.03	0.33	0.24	2.04	0.27
P-value	0.87	0.56	0.62	0.15	0.60
95% AR confidence interval	[entire grid]	[. . . , -0.66]	[. . . , -0.80]	[. . . , -0.05]	[. . . , -0.19]

Notes: The table contains estimates of β^i_{rents} for the variables *number of mortgages*, *volume of mortgages*, and *mortgage to income ratio*. AR statistics are shown with corresponding p-values for the hypothesis that $\beta^i = 0$. All values are rounded to two decimals. The 95% confidence interval is based on a grid-search of 100 points. "Entire grid" means the null can not be rejected for all points in the grid search.

5 Conclusion

In this paper, we investigated whether the IBBEA caused an exogenous shock to the supply of mortgages and its subsequent effect on rent growth from 1995 to 2005. To achieve this, we first estimated a specification where the treatment variable was a deregulation index and the dependent variable was one of six different measures of mortgage supply. We subsequently utilized instrumental variable estimation to research whether a mortgage supply shock caused a reaction to rent growth.

We found that some measures of mortgage supply were significantly affected by the IBBEA in the total sample and the sample of contiguous counties traversed by a state border. However, in the sample of counties for which we had rent data available, this significance disappeared for the most part. The absence of a mortgage supply shock in this sample left us unable to find out how a mortgage supply shock would have affected rents during this period.

For those interested in researching this topic further, we suggest looking into whether alternative rent data might be available for the sample of counties in this paper for which a mortgage supply shock was identified. Next, it is worth looking into some of the results of our reference paper by Favara & Imbs (2015), who investigated the role of mortgage supply on housing prices. They state that an exogenous shock to the supply of mortgages caused by the Riegle–Neal Interstate Banking and Branching Efficiency Act of 1994 caused a significant positive increase in house prices from 1995-2005. However, their results are based on a conventional t-test, which has inflated power to judge estimates in the direction of the OLS bias as significant. It would be interesting to see whether the significant results are still present when the weak-instrument robust Anderson-Rubin test is used.

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A Summary Statistics

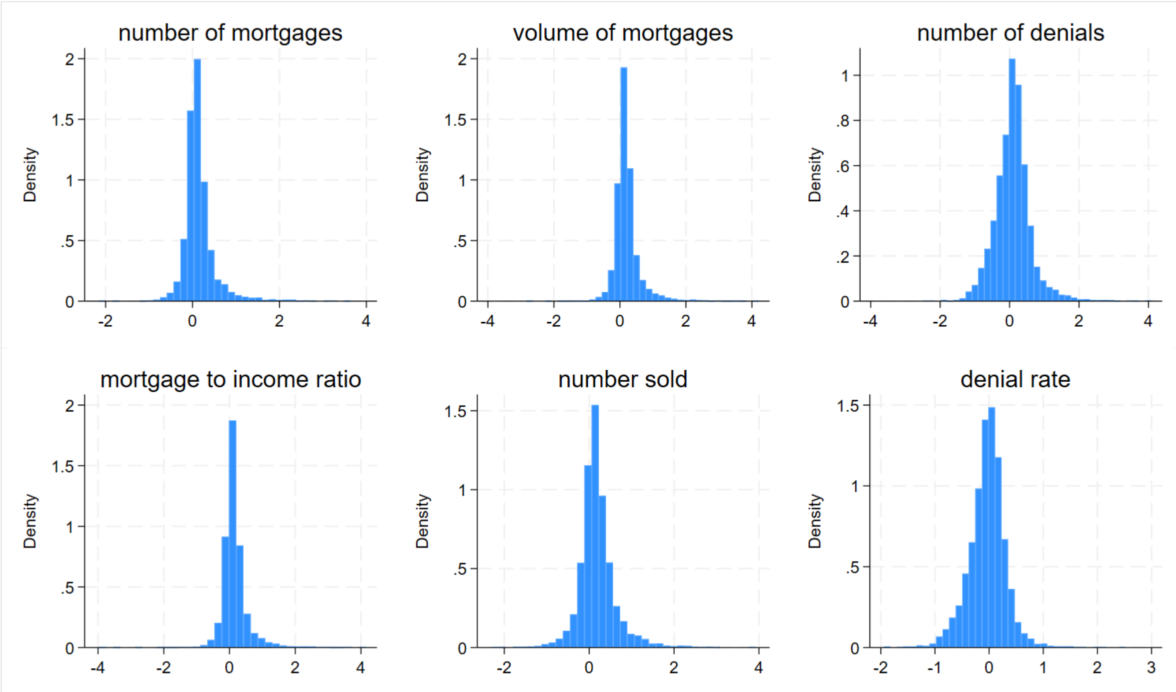
Table 9: Summary Statistics of Used Variables
Source: Favara & Imbs (2015) and the Office of Policy Development and Research

	Full Sample					Sample of Contiguous Counties				
	Mean	SD	10th pc	90th pc	Obs	Mean	SD	10th pc	90th pc	Obs
Commercial Banks										
number of mortgages	0.124	0.345	-0.135	0.364	10992	0.101	0.292	-0.130	0.320	2885
volume of mortgages	0.179	0.378	-0.100	0.436	10992	0.157	0.321	-0.092	0.386	2885
number of denials	0.090	0.468	-0.460	0.565	10948	0.087	0.412	-0.390	0.527	2877
mortgage to income ratio	0.131	0.385	-0.148	0.389	10992	0.110	0.323	-0.146	0.346	2885
number sold	0.173	0.393	-0.176	0.550	10859	0.156	0.363	-0.174	0.511	2861
denial rate	-0.042	0.307	-0.437	0.296	9047	-0.022	0.291	-0.388	0.309	2377
Mortgage Companies, Thrifts and mortgages Unions										
number of mortgages	0.071	0.312	-0.282	0.426	10741	0.064	0.280	-0.251	0.382	2829
volume of mortgages	0.121	0.319	-0.231	0.469	10741	0.112	0.302	-0.213	0.430	2829
number of denials	0.064	0.531	-0.527	0.666	10731	0.073	0.517	-0.497	0.607	2829
mortgage to income ratio	0.074	0.324	-0.280	0.418	10741	0.064	0.303	-0.256	0.392	2829
number sold	0.086	0.472	-0.369	0.539	10728	0.089	0.425	-0.336	0.525	2824
denial rate	-0.0251	0.268	-0.318	0.270	2853	-0.012	0.283	-0.328	0.296	819
Commercial Banks										
Out-of-State banks – local branches										
number of mortgages	0.242	0.917	-0.588	1.232	5407	0.196	0.982	-0.693	1.259	1612
volume of mortgages	0.324	1.075	-0.610	1.494	5407	0.277	1.130	-0.771	1.510	1612
number of denials	0.151	0.811	-0.693	1.099	5004	0.133	0.871	-0.847	1.131	1464
mortgage to income ratio	0.282	1.075	-0.655	1.450	5407	0.235	1.128	-0.824	1.460	1612
number sold	0.338	0.982	-0.693	1.609	4183	0.274	1.061	-0.760	1.639	1146
Out-of-State banks – no branches										
number of mortgages	0.195	0.414	-0.182	0.598	10917	0.176	0.370	-0.168	0.547	2872
volume of mortgages	0.243	0.450	-0.141	0.649	10917	0.224	0.391	-0.138	0.597	2872
number of denials	0.165	0.624	-0.619	0.854	10847	0.164	0.573	-0.528	0.804	2858
mortgage to income ratio	0.196	0.454	-0.186	0.598	10917	0.177	0.391	-0.183	0.548	2872
number sold	0.200	0.469	-0.248	0.693	10744	0.194	0.440	-0.211	0.657	2842
In-State Banks										
number of mortgages	0.026	0.466	-0.382	0.423	10806	-0.007	0.451	-0.419	0.354	2839
volume of mortgages	0.083	0.521	-0.375	0.525	10806	0.052	0.517	-0.413	0.461	2839
number of denials	-0.026	0.551	-0.613	0.550	10381	-0.041	0.541	-0.619	0.523	2747
mortgage to income ratio	0.035	0.527	-0.426	0.486	10806	0.004	0.521	-0.459	0.427	2839
number sold	0.082	0.646	-0.580	0.754	10244	0.043	0.648	-0.629	0.693	2635
All Lenders										
Herfindahl index of mortgage origination	-0.069	0.268	-0.369	0.203	10992	-0.053	0.270	-0.341	0.216	2885
house price index	0.052	0.045	0.005	0.103	10992	0.055	0.044	0.006	0.113	2885
income per capita	0.013	0.052	-0.017	0.045	10992	0.014	0.025	-0.014	0.044	2885
population	0.013	0.016	-0.003	0.033	10992	0.011	0.015	-0.004	0.029	2885
index of interstate branching deregulation	1.320	1.475	0.000	4.000	10992	1.315	1.524	0.000	4.000	2885
index of housing supply elasticity	2.528	1.316	1.120	3.993	9596	2.436	1.196	1.067	3.815	2751
1 bedroom FMR	0.0108	0.090	-0.105	0.070	5617	0.015	0.093	-0.104	0.093	1140
2 bedroom FMR	0.0022	0.010	-0.160	0.062	5617	0.008	0.101	-0.184	0.080	1140
3 bedroom FMR	0.016	0.067	-0.0616	0.063	5617	0.021	0.072	-0.065	0.077	1140
4 bedroom FMR	0.109	0.247	0	0.521	5617	0.113	0.241	0.001	0.501	1140

Notes: Summary statistics of county-year pooled data. Except for the Rice & Strahan (2010) deregulation index, all summary statistics are calculated for the log annual change. Full Sample contains all urban counties for which data was available from 1995-2005. Sample of Contiguous Counties contains all counties that lie in one of 36 MSAs traversed by a state border and for which data was available from 1995-2005.

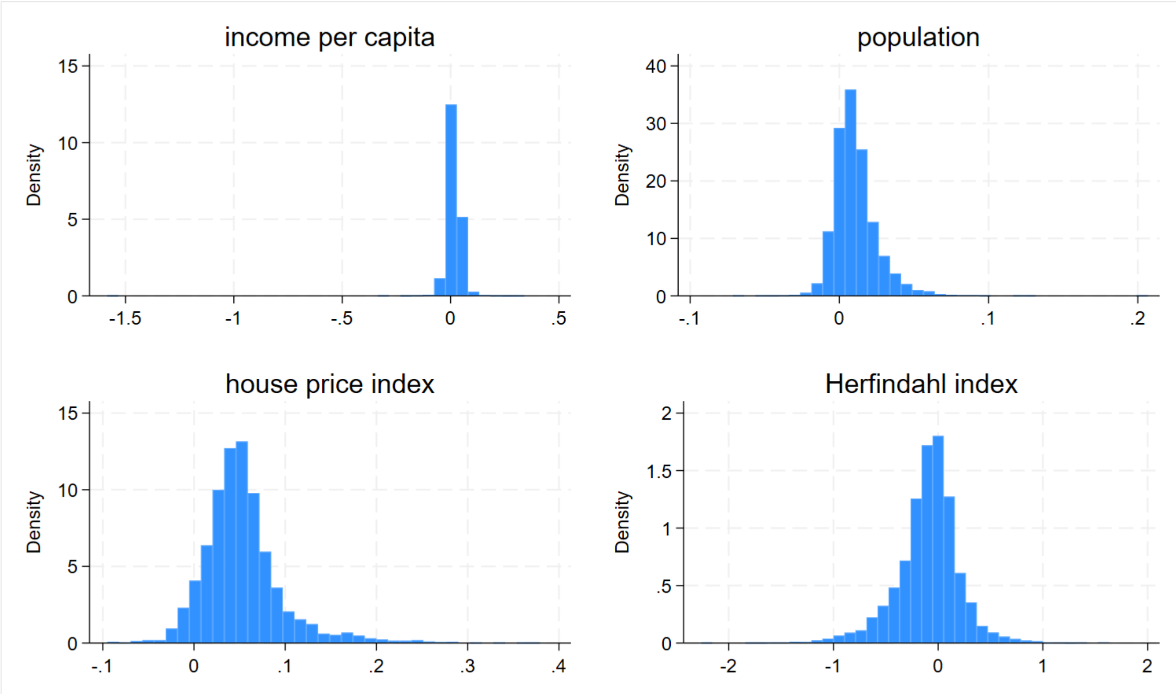
B Empirical Distributions

Figure 5: Empirical Distribution of Mortgage Supply Variables for Commercial Banks Across All Urban Counties



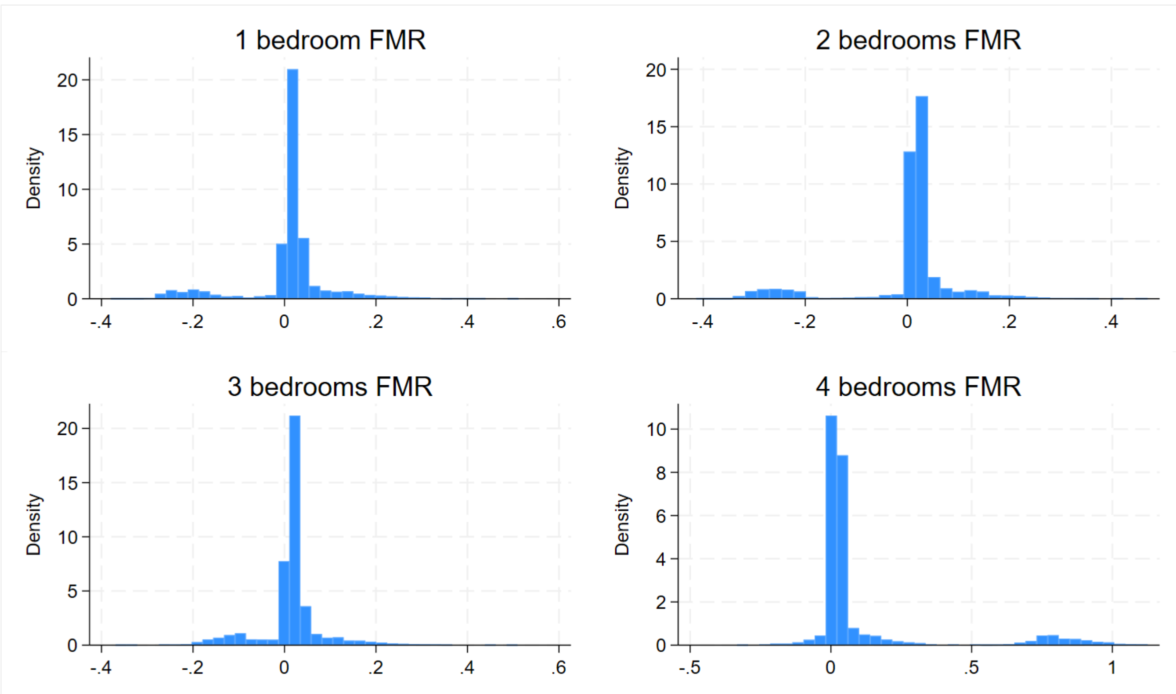
Notes: All variables are measured in log changes.

Figure 6: Empirical Distribution of Control Variables Across All Urban Counties



Notes: All variables are measured in log changes.

Figure 7: Empirical Distribution of FMR Data



Notes: All variables are measured in log changes.