US House Price Trends and Systemic Risk

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Abstract

My thesis examines how state heterogeneity and house price trends impact the housing cycle, with focus on the Great Recession. I construct multiple proxies for systemic risk using state-level house price trends including: cross-sectional variance, volatility, sensitivity to credit risk, correlation with other states, and dependence on national variables. Using FHFA and Freddie Mac Loan Level Data, I then analyze the marginal effects of these systemic risk proxies as well as traditional measures of credit risk like mortgage delinquency rates on mortgage spreads in a two-stage least squares framework to argue that credit markets were not accurately pricing systemic risk in the years leading into the Great Recession.

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Introduction

Housing in the United States is an essential component of the financial landscape; for most households, housing represents the most significant investment. From the 1970's onward, housing whas been an attractive sector due to the size of the market, low credit risk relative to returns, and the ability to diversify risk. Even in recessions, the national housing market still posted positive growth. Even though there were regional housing downturns, they were never severe enough to dampen the national housing market growth (Figure 1). Bona fide economic recessions seemed unable to produce negative house price growth. If the impressive performance of the housing sector wasn't attractive enough, Mortgage Backed Securities (MBS) offered an effective method to hedge against idiosyncratic risk in local markets by pooling geographical diverse assets. However, it appears in the lead up to the Great Recession, there was a disconnect from the housing finance market and the underlying housing market. With the benefit of hindsight, it is clear to see that the house price trends had introduced significant systemic risk to the housing finance system.

Measuring systemic risk is a tricky business. To assess how house price trends contributed to systemic risk, I construct proxies for systemic risk - dispersion, volatility, correlation, and dependence on national variables. Dispersion refers to cross-sectional variance and captures the benefits to diversification. Given that the U.S. housing finance system is dominated by MBS issuance, estimating the true value of diversification is critical to understanding the systemic risk in the housing market. Volatility in house price trends is another meaningful proxy for systemic risk due to the fact that dramatic drops in home values almost always lead to massive amount of mortgage defaults as borrowers suddenly find themselves with negative equity in their homes. Correlation too, captures the ability to diversify risk as well as well the likelihood for nation-wide house price swings as opposed to the regional-only house price swings that were typical of the 1980s and 1990s.

Dependence of state level house prices on national factors measures the ability for shocks to national factors that are common to all states to affect house price trends. Different from dispersion and correlation, dependence on nation factors measures how fragile state-level house prices are to changes in the national macro-economy. Although there is significant overlap between these proxies for systemic risk, having a broad set of proxies will allow for greater robustness. After constructing these proxies for systemic risk, I address the whether credit markets were appropriately taking into account systemic risk in the years leading up to the Great Recession when issuing mortgages and whether credit markets behaved better in some time periods relative to others.

Literature Review

My thesis lies at the intersection of many established, narrower avenues of analysis; while not focusing exclusively on heterogeneity in housing markets, dependence on national variables, transmission of shocks, or credit risk, I draw upon theory and methodology from these sub fields to present a broad analysis of the housing finance market. In this spirit, I attempt to unify many branches of existing literature into a coherent view of systemic risk leading up to the Great Recession.

Heterogeneity in Housing Markets

It is well known that housing markets are intensely local with wide variation even with MSAs. As Malone (2017) notes, "the severity and timing of the housing cycle vary greatly across cities." Housing

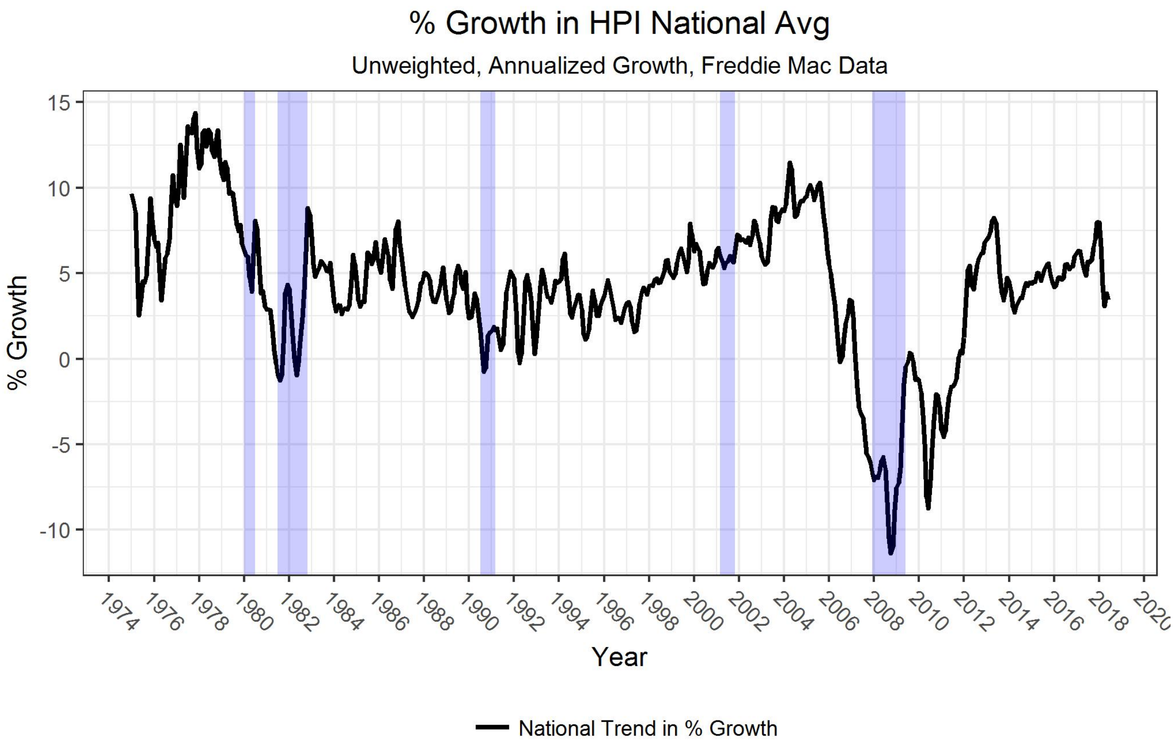

Figure 1: National House Price Growth

exhibits even greater heterogeneity than many other economic variables, due in large part to the unique nature of housing as an investment asset as well a necessity for living. Compared to other investment assets, housing is typically a larger and longer term investment, and housing is usually an indivisible asset (except for the case of Real Estate Investment Trusts - REITS - which allow investors to purchase a diversified portfolio of real estate). Housing is also extremely dependent on local economic conditions as house prices are given by the equilibrium of housing demand and supply which are constantly shifting, and house prices are often out of equilibrium due to length of time needed to construct new housing.

Defusco et al. (2013) examine the heterogeneity in the timing of housing booms and busts at the metropolitan level. In the paper, a boom is defined as the first structural break in the house price time series for the MSA in question. The data shows that the booms started as early as 1997 in a few highly concentrated and inelastic MSAs in California and New England. By the early 2000s there were housing booms across the country although many MSAs never exhibited a significant housing boom. The dramatic dispersion of house price trends suggests that there is still a high level of heterogeneity in housing markets, even if the level of heterogeneity is not at the shocking levels of the pre-1990 era. There is also mixed evidence of heterogeneity in the the bust; some MSAs experience a bust (the authors define a bust by the quarter in which nominal house prices peaked) as soon as mid 2005. The temporal dispersion of the busts were much smaller (only 2.5 years) when compared the 7-8 years for booms.

Cotter and Roll (2015) show how a decrease in regional heterogeneity can actually reduce the benefits of diversification through Mortgage Backed Securities (MBS). The paper rigorously shows that in the years preceding the housing bust, regional integration was on the rise. Integration is here defined as the proportion of housing market returns that can be explained by an identical set of factors. For example, two localities are perfectly integrated if the same national factors fully explain housing market return in both areas. The results have direct implications; many GSEs explicitly construct their mortgage pools to be geographically diverse, so the increase in regional integration increases the riskiness of "safe" assets. The paper examines a set of national factors including average LTV ratios, private residential mortgage backed security issuance, SP500, industrial production, Federal Funds rate, and single-family building permits and concludes that private MBS issuance and LTV ratios were the key drivers of integration. Clark and Coggin (2009) find similar but less conclusive results when examining the nine Census regions as opposed the MSA level analysis in Cotter and Roll (2015). My analysis in the paper largely adopts many of the conventions of Clark and Coggin (2009) and Cotter and Roll (2015) when selecting national variables and credit characteristics for controls.

Beraja et al. (2018) relates heterogeneity in house prices to heterogeneity is equity trends. The regional distribution of housing equity influences the effect of monetary policy through the refinancing channel. The paper finds that monetary policy was most effective in areas with higher home equity. Since most lenders require a certain amount of home equity (even if the refinancing is not cash-out), areas with low average home equity were not able to realize the full benefits of lower rates due to monetary policy.

Berger and Vavra (2018) examine sources of dispersion of endogenous economic variables. The paper argues that there are two mechanisms that drive time-varying dispersion. First, the dispersion could be a result of greater volatility of shocks. The alternative explanation is greater responsiveness to the shocks; agents are changing their behavior in responding to the exogenous shocks. Although the paper focuses on import prices instead of housing, the results and arguments still apply to the regional heterogeneity observed in housing markets.

Importance of National Factors

Another important aspect of regional heterogeneity is understanding the decomposition of house price trends. The conventional economic theory states that house price trends are a stochastic function of state-level fundamentals (per capita income, housing demand, residential investment etc.) as well as national factors (inflation, real interest rates, etc.). Similar to an ANOVA exercise Del Negro and Otrok (2007) use a factor model to identify a national trend (i.e. increase in house prices that is common to all states) from the idiosyncratic component. They conclude that historically house price trends are dominated by state-specific and regional shocks, but in the years before the housing crisis (specifically 2001-2004), the national factors played a larger role than in the period 1985-2000. In some states, the national factors explained upwards of 90% of the total variance in house prices. In their analysis, Del Negro and Otrok note that even during 2001-2004 which featured high overall variance in house prices, the variance in local factors remained fairly constant. This phenomena supports the view that national factors played a larger role in determining house price trends in the years leading up to the housing crisis. My analysis further confirms the results of Del Negro and Otrok (2007) albeit with a slightly different model; my model includes state-varying responsiveness to national factors as opposed to uniform responsiveness when estimating dependence on national variables.

Del Negro and Otrok note that their concept of national trend obscures the fact that states have different exposures to the common national cycle. For example, highly inelastic states like coastal states, especially the Northeast are strongly affected while more elastic states in the Midwest are less affected. They find that the about two thirds of cross-state heterogeneity is due to the differences in responsiveness to the national factors.

Del Negro and Otrok also compare heterogeneity of house price growth and real per capita income growth which is often taken to be a proxy for the local business cycle. The authors find that the real income growth rates are substantially less volatile than local housing prices, and that real income growth at the state level is more closely tied to national factors.

Vansteenkiste (2007), Del Negro and Otrok (2007), Gottlieb et al. (2013) all estimate the effects of monetary policy on house prices across the United States. Vansteenkiste (2007) uses a Global Vector Auto-Regression model to assess the effects of a monetary policy shock while Del Negro and Otrok (2007) and Gottlieb et al. (2013) both rely on more standard regression analysis. The findings are all relative similar - monetary policy significantly effects house prices but only explains a portion of the housing bubble (Vansteenkiste and Gottlieb et al. place the effect at 30-45 %).

Transmission of Shocks

The prevailing theory suggests that a shock in one region should be transmitted through migration and trade. Ferreira et al. (2010) examines the “lock-in effect” whereby the mobility of homeowners is reduced by falling home prices or rising interest rates. For neighboring real estate markets to be in equilibrium, there must be significant migration between localities to spread out the impact of any shocks. Negative equity is associated with 5.6 % reduction in the two year mobility rate, so during the crisis, when negative equity became more frequent, one of the main mechanisms to transmit shocks was weakening. The trade relationship between localities is reflected in the local income per capita and unemployment figures which is why most of the studies in the literature control for changes in local income and unemployment. Keys (2018) show how job loss can permanently alter one’s consumption path for housing, thereby reducing demand for housing.

Defusco et al. (2013) contributes evidence to the contrary. Their paper studies the relationship between the house prices of neighboring metropolitan statistical areas (MSAs), and they find that there is no significant change in the fundamentals of one MSA even as its neighboring MSA experiences a housing boom. Specifically, the paper examines local income, migration flows, and lending behavior, so the authors conclude that there must be some other mechanism beyond these chosen indicators to explain the price contagion effect. In line with Schiller (2000), the authors conclude that the positive price contagion is mainly driven by irrational exuberance or perhaps unobserved fundamentals. The paper makes no conclusion about the mechanisms of transmission for negative price contagion. DeFusco et al. (2018) further corroborates these findings, emphasizing the role of non-rational forces at play in the house price cycle.

Contagion and Interdependence

The literature presents many definitions for contagion, interdependence, and convergence. The most commonly used definition is presented in Defusco et al. (2013) which defines contagion as the “price correlation across space between two different housing markets following a shock to one market is that is above and beyond that which can be justified by common aggregate trends.” Importantly, this definition of contagion applies equally to positive and negative shocks and is defined on the timing of the shock. An alternative definition for contagion is presented by Forbes and Rigobon (2002); they define contagion as“a significant increase in the cross-market correlation during a period of turmoil”. Here the definition applies only to negative shocks and is defined by the time of the downturn (i.e. the realization of the shock). In addition, the paper defines an interdependence as “continued high level of market co-movement.”

Defusco et al. (2013) presents strong evidence that contagion played a significant role in the housing boom and mixed evidence that contagion played a significant role in the bust. The authors estimate that up to one third of the average increase in price growth at the start of a boom is due to contagion from a MSA's nearest neighbor. Furthermore, Defusco et al. (2013) find that the spillover effects are almost entirely driven by a MSA's nearest neighbor and that a positive effect is only significant when the neighboring MSA has a significant boom (i.e. small steady increases in house prices are not transmitted in any significant way). The effects of contagion are larger when examining the transmission of shocks from large MSAs to small MSAs. The evidence for contagion during the bust is much weaker. At the beginning of the bust, the cross-MSA house price elasticities are nearly zero and only increase slightly over the duration of the bust. The fact that most of the MSAs experienced busts within the same 18 month window make identifying contagion difficult.

Forbes and Rigobon (2002) explores the theoretical underpinnings of contagion; contagion can be broadly linked to one of three propagation mechanisms: aggregate shocks which affect the economic fundamentals of more than one state (alternatively, region or MSA), shocks to local fundamentals that then influence the fundamentals of another state, and shocks that are not explained by fundamentals or aggregate variables, termed pure contagion. Aggregate shocks might include shocks to monetary policy, inflation, oil prices, etc. Shocks to local fundamentals may include changes in legislation, industry growth, or a change in migratory trends. Housing in nearby cities are often close substitutes so the effects of the shocks are transmitted to the neighboring localities as the system tends toward equilibrium.

Forbes and Rigobon (2002) also addresses the issue of bias in the correlation coefficient. The common tests for contagion use regression analysis to examine if cross-state correlations increase after a shock. During economic downturns (which usually lead to increased volatility) the correlation coefficient is biased upwards. The bias can easily be large enough to falsely conclude that contagion was present, and the paper presents a straightforward method for consistently estimating the cross-state correlations. After correcting for the bias, the authors find no contagion in the 1997 East Asia crises, 1994 Mexican peso crisis, and 1987 U.S. stock market crash, all of which are typically presented as the textbook cases of contagion. Far from dismissing the literature on contagion, the authors suggest that future study ought to examine the linkages between markets themselves instead of the changes in linkages.

Credit Markets

Gottlieb et al. (2013) examines the role of credit markets in determining house prices. Specifically, the paper estimates the elasticities of long term real interest rates, approval rates, and down payment requirements with respect to house prices. The authors introduce a user cost model which allows the case where private discount rates differ from market interest rates – the link between interest rates and house prices is weaker when the two rates are disconnected due to the credit constraints of the borrowers. Overall, the paper finds, in line with results from Himmelberg et al. (2005), that the decline of long term real interest rates explains a significant portion of the housing bubble and that the elasticities of interest rates with respect to housing prices is greatest at how interest rates. Gottlieb et al. (2013) find that the interest rates can account for no more than 45% of the increase in house prices from 2000-2005 and that the relationship breaks down from 2006-2008 at the start of the housing crisis. The paper also discusses how interest rate expectations, instead of interest rates themselves might be the driving force that explains the link between real long term interest rates and house prices. In addition to concluding that the decline in real long term interest rates do not fully explain the housing bubble, the authors find no significant link between approval rates or down payments and house prices, although the authors note that the changing nature of the marginal borrower (see Bhutta (2015) for more details) may obscure the relationship.

The size and quality of the mortgage debt market is not constant over time. Bhutta (2015) documents the dynamics of mortgage debt inflows and outflows as well as the changing characteristics of borrowers leading up to the crisis. Although interest rates and therefore house prices (through the established links) depend on credit risk (likelihood of mortgage default), they also depend heavily on mortgage demand. The paper uses detailed panel data to show that the contraction in new credit was far greater than the increase of defaults. By overemphasizing defaults, the existing literature missed the role that the size and health of credit markets played in determining house prices. None of the papers previously cited in the literature review have controlled for the size of the mortgage market or mortgage inflows/outflows. The paper continues by documenting how the characteristics of the marginal borrower deteriorated over time. From 1999-2011, the rate of first-time borrowing among high credit score individuals declines as the rate of real estate investment was increasing, so even if the default rate was relatively constant, the risk profile of the mortgage market was increasing. Also, during the boom, there was a marked increase in lending towards historically minority areas, possibly due to the increase in sub-prime lending.

Description of Data

Table 1 shows the source, frequency, and starting data of the individual time series that I utilize for the following empirical work. The time series themselves are split into *state fundamentals* and *national controls*. Although most of the data exists in daily or monthly time intervals, a few key variables exist only at quarterly frequencies. I have converted these quarterly time series into monthly time series via linear interpolation. Due to the obvious autocorrelation concerns, all standard errors presented in the paper are heteroskedastic robust. [2]

Variables	**Source**	**Frequency**	**Start Date**
State Variables			
1. HPI Growth	Freddie Mac HPI	Monthly	1978
2. Unemployment Rate	Census Bureau	Monthly	1976
3. State GDP Growth	BEA	Quarterly	1998
4. Mortgage Delinquency Rate (MDF)	CFPB	Monthly	2008
5. Building Permits	Census Bureau	Monthly	1995
National Variables			
1. Mortgage - Treasury Sprd	FRED/FHFA	Weekly	1971
2. Mortgage Debt Outstanding (MDO)	FRED	Quarterly	1949
3. S&P 500	Yahoo Finance	Daily	1950
4. National Mortgage Delinquency Rate (MDF)	FRED	Quarterly	1991
5. Inflation (CPI measure)	FRED	Monthly	1947
6. Federal Funds Rate (FFR)	FRED	Monthly	1954
7. Treasury 10 - 2 Spread (TSPRD)	FRED	Daily	1976
8. Treasury 10 Year	FRED	Daily	1962
9. GDP Growth	FRED	Quarterly	1947

Table 1: Data Summary Table

[2] Computed in R with the 'sandwich' package, type = 'HC0')

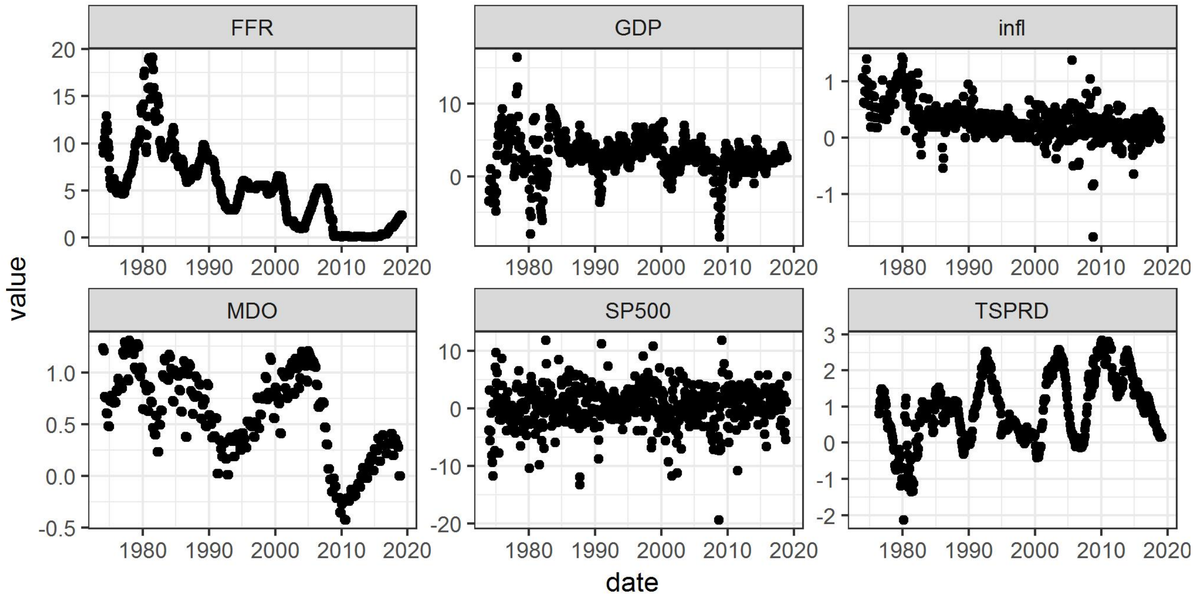

Figure 2: Summary of National Variables over Time

Although one could make the case for many other national controls (productivity growth, residential fixed investment, etc.), the national variables in this analysis are similar to those found in the previous literature. Beyond the typical controls for inflation, Federal Funds Rate and GDP growth, the Mortgage Debt Outstanding (MDO) is to measure the depth of the mortgage market, the S&P 500 is to control for private wealth, and the Treasury 10 - 2 spread (TSPRD) is to control for future expectation. If investors have expectations of future growth, the yield curve will be steep and therefore the Treasury 10 - 2 spread will increase – thus the Treasury 10 - 2 is an imperfect but still necessary control for investor expectations in the medium term. Note that the variables GDP, inflation, S&P 500 and Mortgage Debt Outstanding are calculated as percentage change from month to month.

The CFPB data comes from the National Mortgage Database (NMDB), a nationally representative sample of residential mortgages. Although the CFPB publishes data on delinquencies 30-89 days and delinquencies > 90 days separately, I combine these figures here to match the methodology of the figures published by the Board of Governors/FRED [3] which "represents the proportion of loans from the 100 largest U.S. banks that are more than 30 days past due" Zimmerman (2018). The differences between these measures is examined more thoroughly later in the paper.

Other Data Sets

In addition to the variables defined above, I also rely on the FHFA Monthly Interest Rate Survey (MIRS). Each month, FHFA samples savings institutions, commercial banks, and mortgage loan companies, and asks them to report the terms and conditions on all single-family, fully amortized, purchase-money, nonfarm loans that they close during the last five business days of the month. The survey excludes FHFA-insured and VA-guaranteed loans, multifamily loans, mobile home loans, and loans created by refinancing another mortgage. Specifically, I use Datasets 15 and 17 in this table. [4] The FHFA datasets contain information on contract interest rates, fees and charges associated with

[3] The National Mortgage delinquency rate from FRED (original source is the Board of Governors)
[4] FHFA 15: By State, Annual (1978 - 2018) and FHFA 17: All Homes, Monthly (1973 - 2018)

mortgage, effective interest rates, term, mortgage loan amount, purchase price, LTV, and percentage of mortgages that are adjustable rate.

The final major data source I use is the Freddie Mac Loan Level data set. I rely on the sample data sets provided by Freddie which contain 50,000 loans randomly sampled from the overall balance sheet (roughly 1,000,000 per year) although my analysis could be easily adapted to the full data set with more computing power. The Freddie Mac data comes into two components; the origination files and performance files. The origination files contain detailed borrower characteristics for all loans originated during the specific time period (for example, the 2003 origination file will contain loans issued in 2003 even if Freddie Mac waited until 2005 to purchase the loan). Thus, these data sets are not static and will change over time, especially for the most recent years. The performance files track the payment history of each mortgage in panel data format which allows us to track delinquency status of each mortgage.

Dispersion

Figure 3 shows how the **dispersion**, or cross-sectional variance, of HPI growth across all 50 states and District of Columbia. Dispersion is a relevant measure since the U.S. housing finance system is dominated by MBS which offer hedging against idiosyncratic, geographic risk. A decrease in dispersion, if not properly accounted for, will leave investors vulnerable to dramatic swings in the housing market. The pattern helps explain why the US never experienced a national housing crisis from the Great Depression until the most recent housing cycle, even during the 4 mild recessions from 1980 - 2002 (Figure 1. In fact, the conventional wisdom preceding the 2008 housing crisis was the US housing markets were segmented enough to prevent a true national housing crisis. During the prolonged housing boom (positive national house price growth from 1991 - 2005, although some authors rely on a different definition of housing boom), dispersion lessened. The potential causes of the decrease in dispersion include: convergence of state-level fundamentals or a decreased impact of the state-level fundamentals on housing prices. The drop in dispersion is most likely due to banking deregulation in the 1980s and advances in technology that reduced the segmentation in local housing markets although one could speculate any number of causes for the decline in dispersion. Furthermore, Figure 3 shows that most of the dispersion in house prices truly idiosyncratic since the variance between regions is smaller than variance within region throughout the sample. [5]

Volatility

Figure 4 presents a more traditional measure of systemic risk, **volatility**, here defined to be the variance of a state's monthly HPI growth over the previous 24 months. Thus, each data point should be interpreted as the variance in house price growth for the previous 24 months. Volatility in the housing market is an important factor of systemic risk due to its affect on default risk on mortgages. Similar to dispersion, the volatility is highest at the beginning of the sample and declines until immediately before the housing boom. Formally if $\Sigma_{t-24:t}$ is the variance-covariance matrix of state HPI growth of the previous 24 months, then the volatility of state i for the time t is the i^{th} diagonal element of $\Sigma_{t-24:t}$. The quintiles reported in figure 4 show how volatility was declining until the years immediately preceding the housing bust. The volatility of other state level fundamentals is included in the appendix (figure 12). The proxy used later in the paper to capture volatility is the *median* volatility so as to avoid the influence of outlier states.

[5] The regions used for the dispersion decomposition were the 9 Sub-regions defined by the Census Bureau

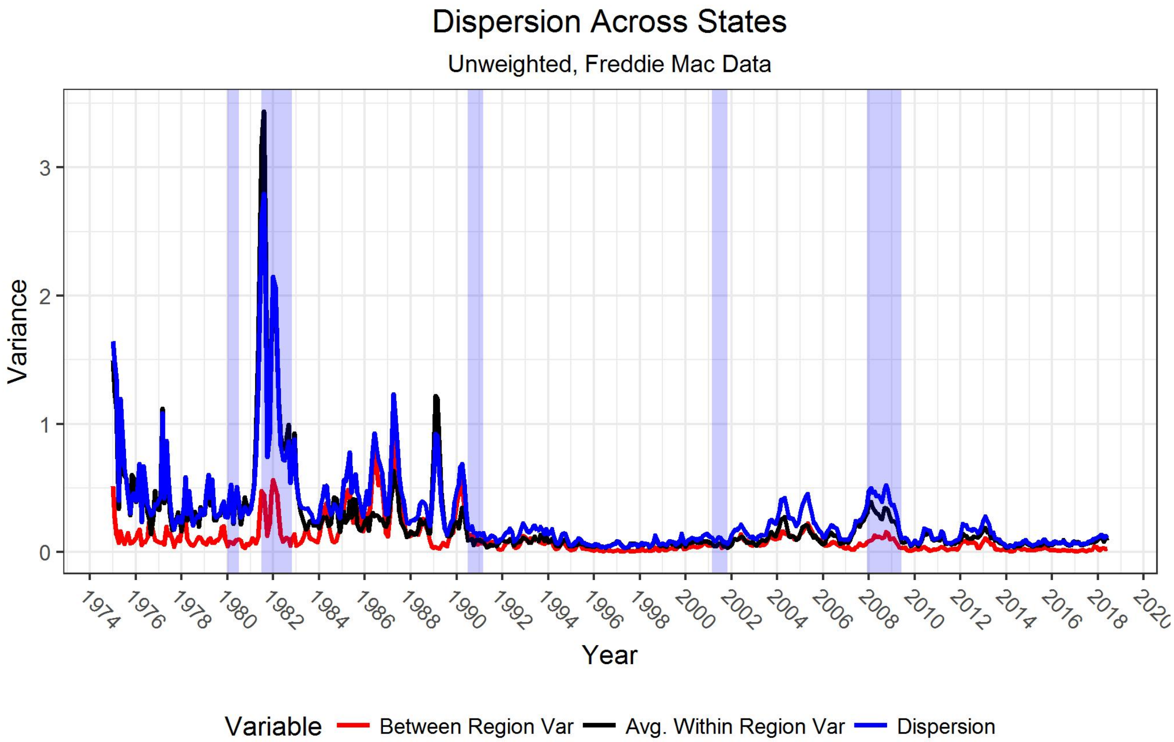

Figure 3: Dispersion of HPI Growth

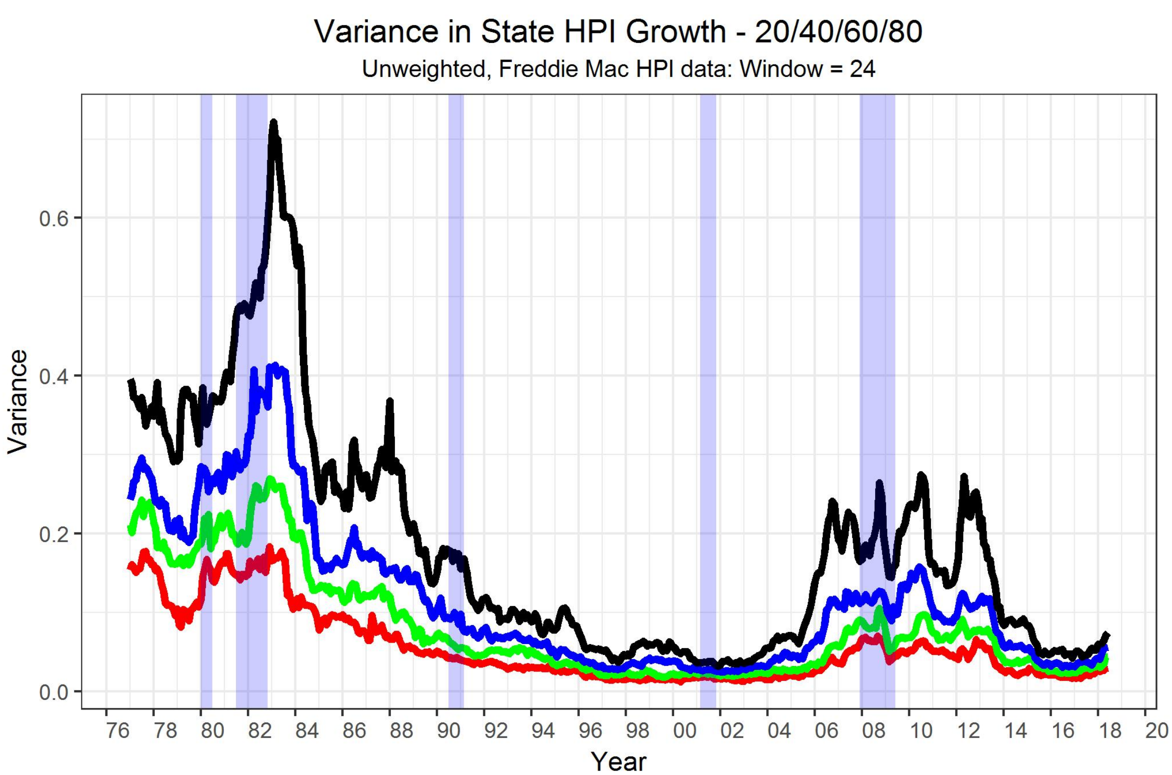

Figure 4: Volatility of HPI Growth

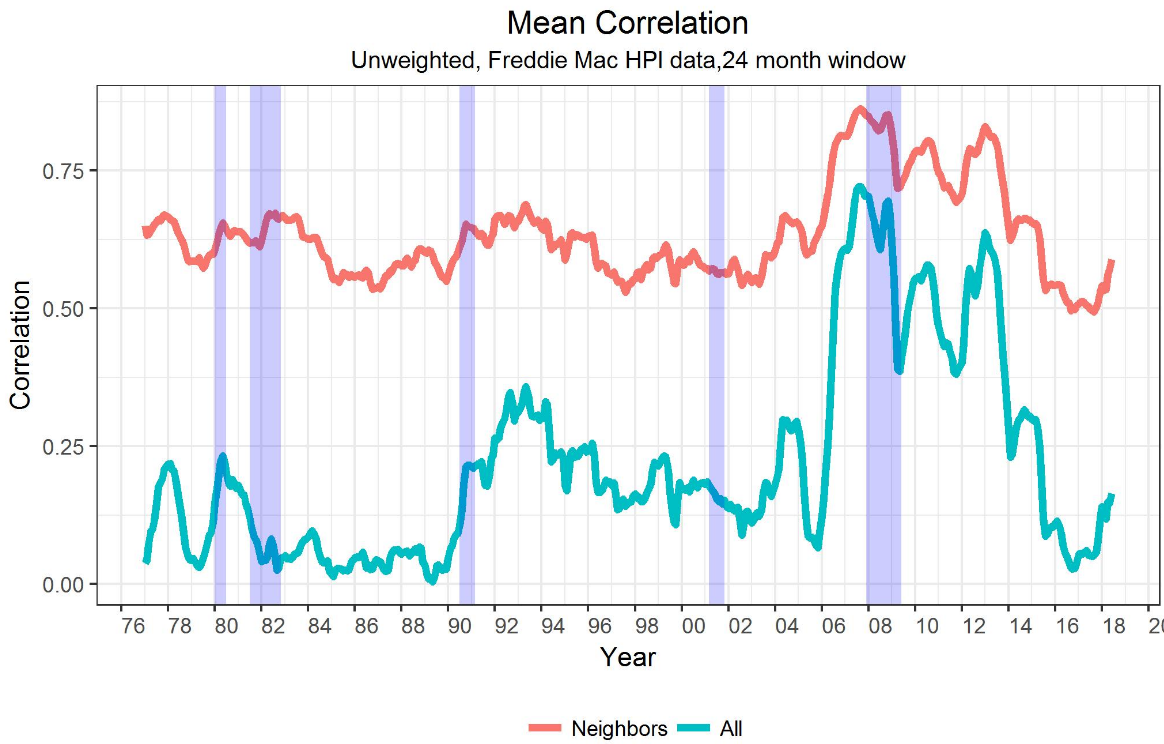

Figure 5: Correlation of HPI Growth

Correlation

Similar to variances, correlations between state HPI growth are measured in 24 month windows.[6] The red line plotted in Figure 5 shows the average correlation between states and their closest 5 neighbors. [7] The blue line shows the average correlation between states and all other states. Correlation between states and their closest neighbors remains constant from 1976-2002 even though total correlation increases around 1990-2002 (the beginning of the housing boom). During the bust, correlation between states and their neighbors increases but not as much total correlation increases. The fact that the increase in correlation comes from non-neighboring states suggests that the US housing market is less segmented than it was before the 1990-2010 housing cycle. Similar to dispersion and volatility, pinpointing a singular cause for the increase of correlation is difficult; however, one might suspect that a housing market primarily fueled by investor expectations instead of state fundamentals played a role in increasing correlation between previously weakly correlated states.

Correlation of returns is a major factor when analyzing systemic risk. As documented by Zimmer (2018) the Gaussian copula models widely used to assess systemic risk perform poorly with highly correlated assets. Given the historical lack of high correlation between disparate states, one might suspect that investors grossly underestimated the overall risk in the housing market.

[6] Similar to variances, the choice for a 24 month rolling window is somewhat arbitrary although it seems to be the smallest window that clearly presents the trend.

[7] Closest neighbors here refers to the states with the highest five correlations over the previous 24 months, not physical distance although in many cases these are the same.

Dependence on National Factors

Another measure of systemic risk is how closely the state house price trends are tied to national trends. If the house price trends of individual states are all highly tied to national variables then small shocks to at the national level have the potential to send the broader housing market into disarray. Following the spirit of Del Negro and Otrok (2007), I utilize an F-test method to assess the level of dependence of house price growth on national variables. The F-test method presents an easily understood and interpretable result. First I examine the following regression:

$$\tilde{h}_{it} = \Lambda_0 + \Lambda t + \Lambda t^2 + \alpha_i + \beta_i X_{it} + \gamma Y_t + \epsilon_{it} \tag{1}$$

- $\tilde{h}_{it}$ is real house prices (in percentage points)
- X is a vector of state-level fundamentals: In the complete sample (i.e. 1976 - present) x = {Unemployment Rate} and in the reduced sample (1998 - present) x = {Building Permits, Unemployment Rate, State Income Growth}
- Y is vector of national variables: { Federal Funds Rate, growth in Mortgage Debt Outstanding, SP500 growth, Treasury 10-2 Spread, Mortgage Default Rate (%) } Mortgage Default Rate begins in 1991 so is excluded in the 1976-present sample. [8]
- α_i state fixed effects to control for unobserved effects.
- Model includes polynomial time trend
- "National" regression in Table 2 refers to the regression below where the state-level variables are omitted. "Full" refers to the model with no omissions except for those that do not exist (i.e. State Income and Building Permits omitted from the '76 models)

$$\tilde{h}_{it} = \Lambda_0 + \Lambda t + \Lambda t^2 + \alpha_i + \gamma y_t + \epsilon_{it} \tag{2}$$

From Table 2, we can see that the national variables are all significant and fairly consistent between samples except for $TSPRD$ which switches signs. The inconsistency in $TSPRD$ suggests that there is significant collinearity between $TSPRD$ and the state fundamentals. In fact from 1998 - present the correlation between $TSPRD$ and UR is .76.

We need to address the serious problem of serial and spatial correlation, especially since next additions to the model involve rolling window analysis. Even with serial correlation, the estimators are consistent, but the standard errors might be very misleading. The autocorrelation for $\bar{\epsilon}_t$,which is the average of all residuals in the cross section (i.e. average of all residuals at time t across all 50 states), is presented in Figure 13. The spike around 10-12 months shows that there is a slight annual pattern. There is far less autocorrelation than one might initially suspect and thus we can be more confident in the rolling window analysis presented next although all of the results should be interpreted cautiously. Furthermore, I regress the residuals from the full model ('76 - present, including all variables) on a categorical variable and Census regions (one model with the 9 sub-regions, one with the 4 regions) in Table 9 in the appendix. Overall there is absolutely no evidence of spatial correlation. The next model includes state interactions

[8] Inflation is not included as a right hand side variable since the dependent variable is real house price growth and therefore inflation is implicitly already on the left hand side.

Table 2: Comparing Models Without State Interactions

	Dependent variable:			
	Real HPI Growth		Real HPI Growth	
	76 Full	76 National	98 Full	98 National
	(1)	(2)	(3)	(4)
State Income			0.01^{***}	
			(0.001)	
Building Permits			0.0000^{***}	
			(0.0000)	
Unemployment Rate	-0.08^{***}		-0.09^{***}	
	(0.004)		(0.01)	
Fed Funds Rate	-0.06^{***}	-0.08^{***}	-0.16^{***}	-0.12^{***}
	(0.004)	(0.003)	(0.01)	(0.01)
Mortgage Debt Out	0.43^{***}	0.52^{***}	1.01^{***}	1.07^{***}
	(0.01)	(0.01)	(0.04)	(0.04)
SP500	0.02^{***}	0.01^{***}	0.01^{***}	0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Treasury Spread	0.07^{***}	-0.04^{***}	-0.12^{***}	-0.11^{***}
	(0.01)	(0.01)	(0.02)	(0.02)
Mortgage Delinq.			0.10^{***}	0.07^{***}
			(0.005)	(0.005)
Observations	25,449	25,449	12,087	12,087
R^2	0.18	0.16	0.36	0.33
Note:		*p<0.1; **p<0.05; ***p<0.01		

on national variables to capture differences in response to national shocks. Allowing the differential responses to national factors allows us to more accurately capture the degree to which housing markets are vulnerable to national shocks.

In rolling windows of width 48 months:

$$\tilde{h}_{it} = \Lambda_0 + \Lambda t + \Lambda t^2 + \alpha_i + \beta_i x_{it} + \gamma_i y_t * state + \epsilon_{it} \tag{3}$$

- Compute $F.National$ which is the F-statistic on the null hypothesis that $\gamma_i = 0 \ \forall i$. The F statistic has (250, 2197) degrees of freedom and 99% rejection cutoff represented by the dashed red line in 6 and 7

- Compute $F.State$ which is the F-statistic on the null hypothesis that $\beta_i = 0 \ \forall i$. The F statistic has (50, 2397) degrees of freedom in '76 model and (150,2297) in the '98 model. The rejection cutoff is not presented on the graph.

- Compute Ratio of the two variables $Ratio = \frac{F.National}{F.State}$

Although one might have endogeneity concerns from all of the contemporaneous variables on the right hand side of the regression models 1 and 3, the notion of dependence on national variables relies on purely on strength of association. The primary contribution of the model is not consistent or efficient estimation of parameters but analyzing the explanatory power of national factors. Due to the rolling window analysis, each data point should be interpreted as the dependence on national variables for the previous 48 months. From Figures 6 and 7, one can see the dramatic rise in dependence on national variables in the years building up to the crisis. It is worth noting that the sample from 1998 - 2017 is likely more accurate due to the inclusion of more state and national variables. In the 1976 - 2017 sample, the only state variable available is unemployment which is volatile and closely associated to trends in the business cycle. Even the ratio which is more robust to economic turmoil between the two F-statistics is increasing from 2003-2008 which is not the case for all of the previous recessions in the sample period. The results in this section indicate that in the years leading up to the Great Recession dependence on national variables and dependence on national variables relative to dependence of state-level variables was increasing in a dramatic fashion. Both F.National and the Ratio will be examined as measures of systemic risk in the next section since they both speak to the ability of unrelated housing markets to be shaken by shocks to national variables.

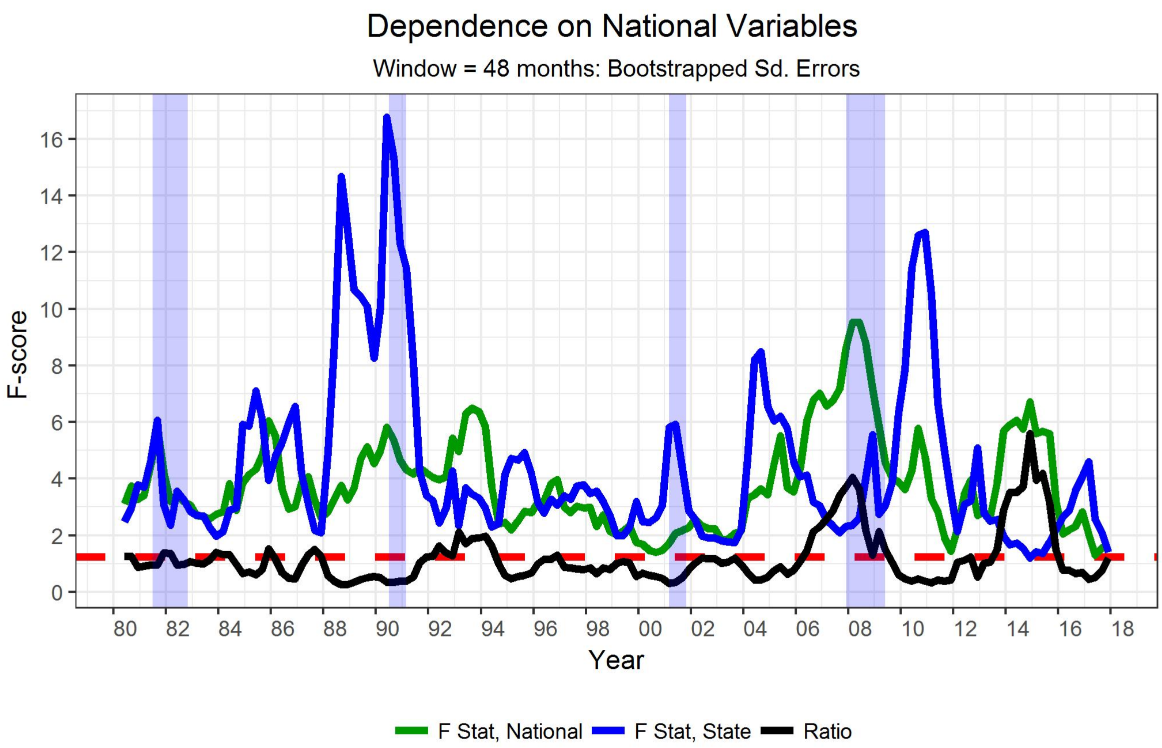

Figure 6: Dependence '76 Model

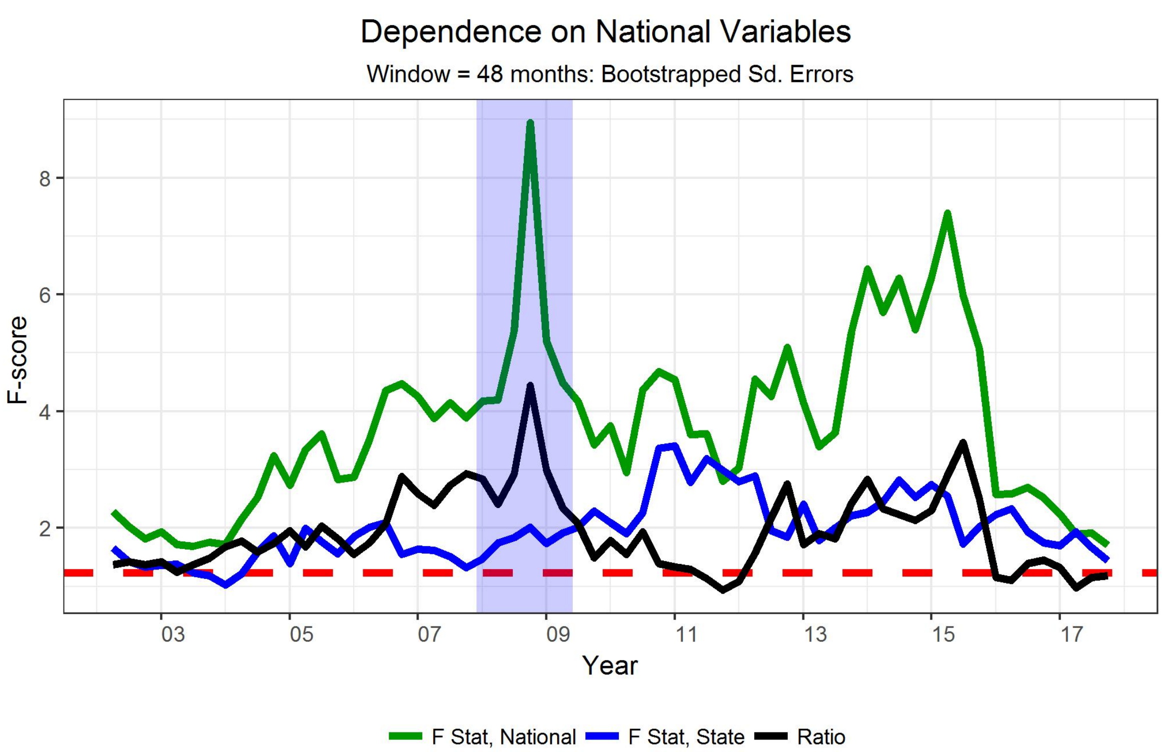

Figure 7: Dependence '98 Model

Sensitivity

The previous sections have developed proxies for systemic risk due to the house price trends. The next logical question is whether credit markets were appropriately taking into account systemic risk when financing mortgage loans. For the sake of clarity, I define **sensitivity** as the marginal effect of "risk" on mortgage spread. For mortgage spread, I benchmark the effective mortgage rate to the 10 year Treasury yield as is typical in the literature. In the following analysis, credit sensitivity to the proxies for systemic risk - dispersion, median volatility, correlation, and dependence - are compared to the more traditional measures of credit risk like mortgage delinquency rates.

The fact that borrowers endogenously choose the terms of their loan - the size of the loan, size of down payment, etc. - are determined by the mortgage spread at the time of origination introduces a difficulty in estimating the marginal effect of risk. In order to combat the likely endogeneity on borrower characteristics, I implement the a simple two stage least squares regression design. Using UPB_{t-2} and $TSPRD_{t-2}$ as instruments for UPB_{t-1}, I establish the Model 4. The table comparing OLS and IV coefficient estimates is included in the appendix (Table 10). Although one could reasonably argue for the endogeneity of many variables in this regression, there are only so many valid instruments, so the reader ought to interpret the conclusions drawn in this section cautiously.

$$sprd_t = \beta_0 + \Lambda_0 t + \Lambda_1 t^2 + \gamma_0 risk_{t-1} + \Phi Y_{t-1} + \beta_1 U\hat{P}B_{t-1} + \epsilon_{it} \quad (4)$$

- $sprd_t$ is measured in basis points is the mortgage spread by month
- Y is vector of controls that includes lagged values for average Term (from FHFA), average LTV , Fed Funds Rate, GDP growth (annualized), Mortgage Debt Outstanding in 1999 dollars, SP500, Treasury 10-2 Spread and two lags of home price growth
- $U\hat{P}B_{t-1}$ are the predicted values from the first stage regression. UPB is the average loan amount in 1999 dollars.
- Note that all right hand side variables are lagged in an attempt to reduce simultaneity concerns .

By examining this model and slight variations presented later in this section, we can determine whether the credit market was accurately pricing each measure of risk. The later models presented here will involve various interactions to examine whether sensitivity to risk changed over time. Ex ante, all the measures of risk should have positive coefficients since high risk should lead to a higher spreads. Indeed, Table 3 shows that all of the measures of risk have positive coefficients. Many of the measures have no significance or low significance, especially the systemic measures of risk. The measures of dependence and correlation which are especially important for investors looking for geographic diversification in their assets are not significantly correlated with mortgage spreads. However, the traditional measure of credit risk, mortgage delinquency rates, are significantly correlated with mortgage spreads.

The sign and significance of the variables show that credit markets were doing a very poor job of sensibly pricing risk. The coefficient on *ltv* and *upb* are both negative and significant in multiple models which would suggest that as borrowers were rewarding for taking out larger and riskier loans with lower rates.

In general, all of the conclusions from this class of regression models ought to be taken with a grain of salt. Investment in mortgage markets is usually a long term investment and thus is necessarily connected to both investors' and borrowers' long term beliefs about the market which are difficult to model. Furthermore, this model suffers from multicollinearity, especially in the model which includes both mortgage delinquency rate and mortgage debt outstanding due to the fact that defaulted mortgages are necessarily subtracted from the mortgage debt outstanding. However, despite the problems, the model paints a clear picture that mortgage markets were not pricing credit risk and systemic risk appropriately.

Model 5 measures whether the sensitivity to risk changes by time period. By interacting the mortgage delinquency rate with time periods carefully chosen to match the early boom ('91 -'97), boom ('98 - 05') , bust ('06 - '11), and recovery ('12 - 17), we can see that sensitivity to the mortgage delinquency rate was highest during the early boom and boom and then decreased dramatically during the bust and recovery.

$$sprd_t = \beta_0 + \Lambda period + \Lambda_1 t^2 + \gamma_0 risk_{t-1} + \Phi Y_{t-1} + \beta_1 U\hat{P}B_{t-1}\epsilon_{it}\epsilon_{it} \tag{5}$$

The coefficients on the national controls provide insight into the market dynamics over the time period. The coefficients on GDP, Treasury Spread, inflation, and lagged house prices are the sign that traditional theory would suggest. An increase in economic growth, positive medium run expectations, and price growth should all cheapen the cost of mortgage financing. However some of the coefficients are a bit puzzling. The negative coefficients on the Federal Funds Rate suggests that monetary policy effects the mortgage market on a lag greater than one month, which is a reasonable assumption. The FOMC likely *responds* to a overly loose credit market by raising rates, which takes more than one month to effect the mortgage market; thus a rate hike is correlated with a loose credit conditions and therefore lower mortgage spreads. The positive coefficient on S&P500 suggests that that investment and equities are acting as substitutes and therefore a growth in the S&P500 reduces investment in the mortgage market.

Following a slight modification to regression 5, we can examine the sensitivity to mortgage delinquencies by year.[9] Figure 8 shows the coefficients and their robust confidence intervals. We can note the dramatic decrease in sensitivity to mortgage delinquency over time, especially in the years immediately proceeding the recession. Although it this model doesn't speak to causes of the decline in sensitivity, one could speculate that the rise of private label securities with low grade debt and the rise of global saving reduced investors aversion to risk.

$$sprd_t = \beta_0 + \Lambda_0 t + \Lambda_1 t^2 + \gamma_0 risk_{t-1} * year + \Phi Y_{t-1} + \beta_1 U\hat{P}B_{t-1} + \epsilon_{it} \tag{6}$$

Freddie Mac Loan Level Data Set

The results presented in the previous section provide key insights into the behavior of the credit markets, however the completeness of the data leaves much to be desired. In the time period 1991 - 2018 there were dramatic changes in the mortgage market include shifting borrower characteristics and increased popularity of Adjustable Rate Mortgages to name a few. In order to corroborate the previous findings I construct a similar analysis on the Freddie Mac Loan Level Data. Although the data covers a shorter time period (1999 - 2018) and only covers 30 year fixed rate mortgages, the data set presents an opportunity to further analyze borrower characteristics and well as how the general market affected the agency loans.

[9]The decision to use a polynomial time trend instead of year dummies was to reduce the number of variables for estimation. Both produce similar results.

Table 3: Sensitivity for Various Risk Measures

	Dependent variable: Mortgage Spread						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lag(F.National76)	2.58						
	(1.83)						
lag(Ratio)		3.06					
		(2.50)					
lag(disper)			6.82				
			(13.40)				
lag(cor.neighbors)				147.65***			
				(36.84)			
lag(cor.all)					54.91***		
					(19.24)		
lag(Volatility)						457.46***	
						(82.68)	
lag(MDF)							2.86*
							(1.60)
lag(ltv)	−1.02***	−0.93***	−0.92***	−1.03***	−0.93***	−0.72***	−0.08
	(0.24)	(0.23)	(0.21)	(0.21)	(0.20)	(0.20)	(0.16)
lag(upb)	−42.11***	−42.68***	−18.13***	−26.18***	−24.39***	−16.47***	−26.87*
	(9.05)	(9.05)	(5.61)	(6.49)	(6.48)	(5.11)	(13.77)
lag(FFR)	−8.73***	−8.77***	−13.08***	−14.13***	−13.41***	−15.45***	3.51
	(3.28)	(3.31)	(3.37)	(3.17)	(3.11)	(3.20)	(3.37)
lag(GDP)	−9.91***	−10.22***	−10.13***	−10.22***	−10.15***	−10.59***	−5.21***
	(1.36)	(1.39)	(1.39)	(1.34)	(1.32)	(1.37)	(1.01)
lag(MDO)	54.98***	54.88***	51.34***	62.20***	61.40***	42.82***	53.50***
	(12.17)	(12.22)	(11.82)	(12.12)	(12.57)	(11.16)	(15.01)
lag(SP500)	2.03***	2.07***	2.49***	2.37***	2.42***	2.50***	−0.49
	(0.75)	(0.75)	(0.77)	(0.76)	(0.77)	(0.76)	(0.52)
lag(TSPRD)	−38.41***	−38.19***	−36.79***	−42.76***	−39.97***	−43.05***	−8.87*
	(7.25)	(7.29)	(7.73)	(7.76)	(7.55)	(7.54)	(5.36)
lag(infl)	−20.59**	−19.92**	−22.42**	−21.85**	−22.67**	−17.23*	−15.76**
	(9.88)	(9.90)	(9.81)	(9.56)	(9.77)	(9.22)	(6.26)
lag(hpi)	53.60	48.48	32.87	47.32	42.85	44.03	50.82*
	(41.31)	(40.77)	(36.34)	(36.01)	(36.56)	(32.98)	(27.00)
lag(hpi, 2)	−74.75*	−75.28*	−60.54*	−61.80*	−62.95*	−46.39	−90.30***
	(40.65)	(40.82)	(36.39)	(35.52)	(36.36)	(33.17)	(27.10)
Poly. Time Trend	Y	Y	Y	Y	Y	Y	Y
Years	’80-17	’80-’17	’77-’17	’77-’17	’77-’17	’77-’17	’91-’17
R^2	0.320	0.324	0.318	0.321	0.315	0.392	0.541
Adjusted R^2	0.266	0.270	0.302	0.305	0.299	0.378	0.525

*p<0.1; **p<0.05; ***p<0.01

Table 4: Sensitivity by Period, FHFA Data

	Dependent variable:
	sprd
lag(MDF)	60.676***
	(12.077)
('98 - '05)	89.569**
	(39.151)
('06 - '11)	123.061***
	(29.331)
('12 - '17)	84.554**
	(41.628)
lag(ltv)	0.248
	(0.154)
lag(upb)	−39.939***
	(11.333)
lag(FFR)	−5.327*
	(3.209)
lag(GDP)	−2.826***
	(0.836)
lag(MDO)	18.539
	(11.346)
lag(SP500)	0.050
	(0.474)
lag(TSPRD)	−28.970***
	(5.572)
lag(infl)	−13.236***
	(5.025)
lag(hpigrowth)	−0.009
	(22.143)
lag(hpigrowth, 2)	−82.550***
	(21.462)
lag(MDF):('98 - '05)	−9.250
	(16.522)
lag(MDF):('06 - '11)	−61.865***
	(11.911)
lag(MDF):('12 - '17)	−56.378***
	(11.897)
Constant	514.092***
	(127.338)
Years Covered	1991 - 2017 Observations
323	
R^2	0.699
Adjusted R^2	0.682
Note:	*p<0.1; **p<0.05; ***p<0.01

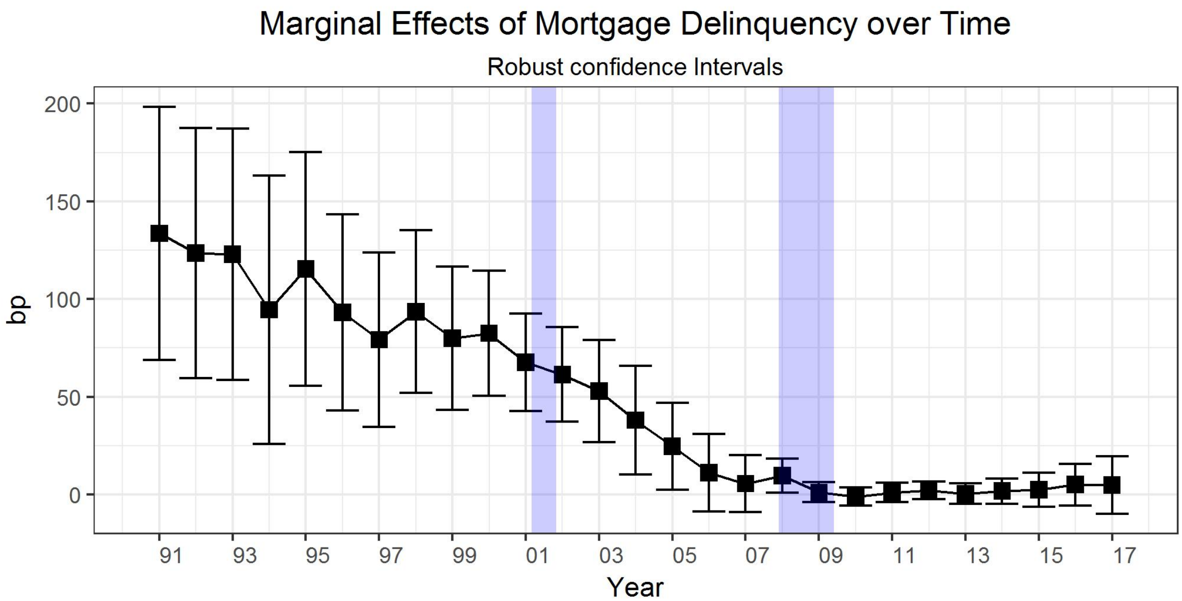

Figure 8: Marginal Effect of Mortgage Delinquency

Variable	Units	Description
Spread	Basis Points	Mean Spread (Interest Rate - 10 yr Treasury)
Median FICO Score	-	Median FICO score loans in sample
High LTV	%	Percentage of Loans with LTV > 70
High DTI	%	Percentage of Loans with DTI > 40
Percent Refi	%	Percentage of Loans that refinancing a previous loan (includes both cash out and non-cash out)
Median Unpaid Principal Balance	$	Median Loan Amount Adjusted for inflation (in 1999 dollars)
Mortgage Delinquency Rate	%	Mortgages that became more than 90 days delinquent within less than 3 years**

Table 5: Variables From Freddie Mac Loan Level Data

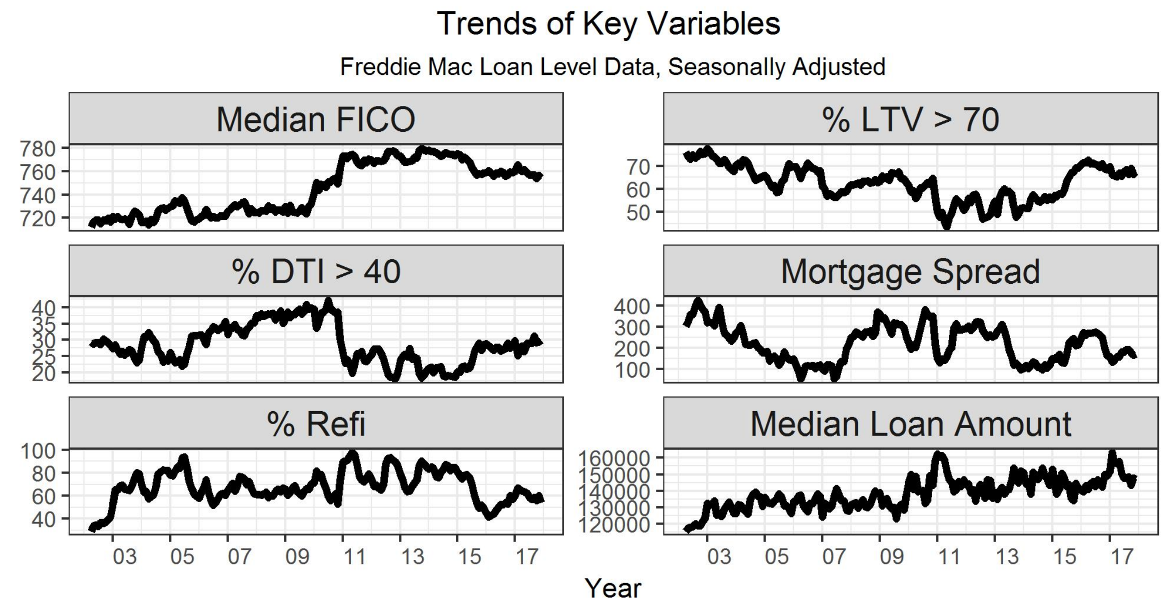

Figure 9: Summary of Freddie Mac Loan Level Variables

There are many qualities of the Freddie Mac data that make it an attractive robustness check. First, Freddie Mac and its agency peers had a large share of the mortgage securities market. Even at its lowest point, in the years leading up to the 2008 Housing Crisis, Freddie Mac and its agency peers made up almost half of the mortgage backed securities market (see figure 10). Even in the time periods where agency loans were not completely representative of the market, they still present a chance to observe how credit risk was being priced throughout the time sample. Second, the data offers accurate and detailed information on borrower characteristics, which is difficult to come by when analyzing the broader mortgage market. Third, the mortgage product stays constant throughout the data (30 Year Fixed Rate) and covers mortgages all over the country.

There are some serious concerns with the Freddie Mac Loan Level Data Set with regards to selection bias, both ex-ante and ex-post. First, not all mortgages are eligible for purchase. Freddie Mac only purchases "conforming" loans, so the loans in the data set are not even close to representative of the entire mortgage market. Specifically, the data set will miss high values homes, adjustable rate mortgages, and borrowers with inferior credit characteristics[10]. Furthermore, the loan level data set is not even a representative sample of Freddie Mac's entire balance sheet. Freddie Mac was actually involved in riskier products than show up in the data set, a maneuver justified by the fact that the data set is meant to be reflective of its post-crisis underwriting standards. However, despite the concerns with the data set, the data set will allow us to see if the same patterns in sensitivity for the general market carry over into the market for agency securities.

One pressing problem in the model is deciding which measure of mortgage delinquency to use. Figure 11 shows the comparison between the three competing measures of mortgage delinquency and default. For the first half of the time period, the mortgage delinquency rate is an extremely good proxy for the national mortgage delinquency rate from the Board Governors. Furthermore, even in the second half of the time period the mortgage default rate proxy from Freddie Mac data matches the decline seen in the

[10]The conforming loan limit in 2018 was $453,100 – with slight adjustments for high price areas

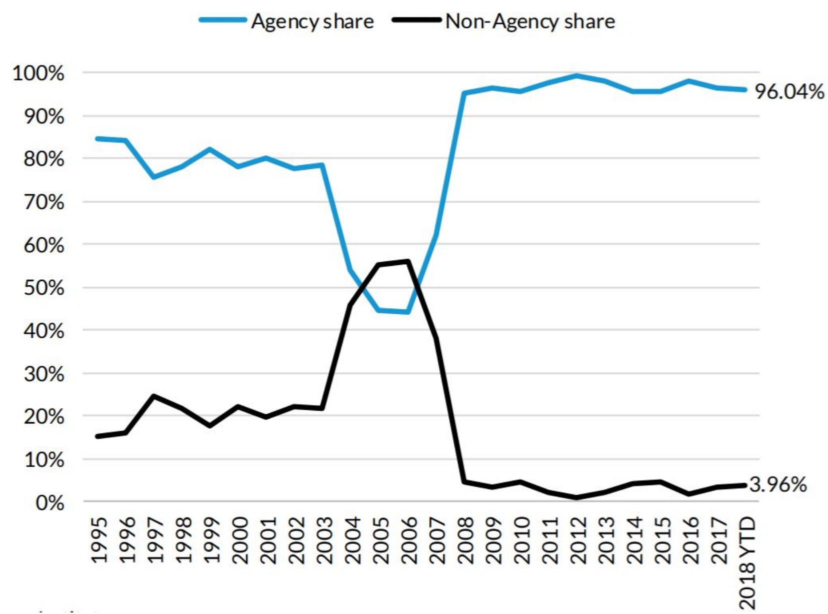

Figure 10: Agency Share from 1995 - 2018,Source: Urban Institute

Board of Governors and CFPB data after considering the endogenous change in purchasing decisions (see 9). In the following analysis, both the National Delinquency Rate and the delinquency rate from within Freddie Mac Loan Level Data is used as a measure of credit risk.

I restrict my analysis to loans with "full information," so I remove all loans with a missing FICO score, non-primary residences, missing LTV or DTI, and multiple unit loans. After removing these loans, there are still 45,000 - 47,000 loans in each year which translates into roughly 37,500 observations per month which is plenty for identification. Between the origination and performance files, I construct the variables presented in table 5:

Table 6 reports the results of a similar two stage least squares regression to 4. Again, the model uses UPB_{t-2} and $TSPRD_{t-2}$ as instruments for UPB_{t-1}. I report the OLS coefficients in the appendix (Table 10); overall, the IV estimates are generally lower than the OLS coefficients. Now, with the more detailed data on borrower characteristics, Y has expanded to include median FICO, % high LTV borrowers, % high DTI borrowers, and % refinance.

$$sprd_t = \beta_0 + \gamma_0 risk_{t-1} + \Phi Y_{t-1} + \beta_1 U\hat{P}B_{t-1} + \epsilon_{it}$$

Table 6 matches the key findings of Table 3. Most of the measures are not significant and the measure for dependence on national factors is significantly negative which implies that credit markets were less sensitive to increasing systemic risk even as the risk was growing, especially in the years leading up to the crisis. One interesting observation is that the coefficient on the national mortgage delinquency rate is higher (and significant) than the coefficient on the delinquency rate on mortgages within the Freddie Mac Loans which suggests that Freddie Mac, despite its large market share, was most responsive to broader credit market conditions.

Table 7 matches the trends presented in Table 4 where sensitivity is high in the build up to the crisis, decreases during the bust, and then increases slightly again during the recovery.

Table 6: Freddie Mac Loan Level: Measures of Risk

	Dependent variable: Spread (bp)						
	Years Covered 2002 - 2017						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lag(F.National)	-34.44^{***}						
	(5.15)						
lag(disper)		31.64					
		(43.46)					
lag(cor.neighbors)			11.89				
			(77.93)				
lag(cor.all)				47.79			
				(36.04)			
lag(Volatility)					$1,489.69^{***}$		
					(296.30)		
lag(Freddie Mac MDF)						3.60	
						(2.25)	
lag(National MDF)							12.16^{***}
							(3.41)
lag(medfico)	5.04^{**}	-0.32	-0.46	-0.83	-1.72	-0.45	-1.32
	(2.25)	(1.70)	(1.86)	(1.79)	(1.51)	(1.67)	(1.64)
lag(highltv)	4.80	-2.35	-2.63	-2.55	-0.94	-2.67	-1.31
	(3.35)	(2.89)	(2.94)	(2.91)	(2.56)	(2.91)	(2.75)
lag(highdti)	4.92^{*}	0.16	0.20	-0.59	-4.47^{**}	-1.49	-2.48
	(2.81)	(2.31)	(2.55)	(2.41)	(2.20)	(2.29)	(2.30)
lag(medupb)	-0.01^{***}	-0.01^{***}	-0.01^{**}	-0.01^{**}	-0.004^{*}	-0.01^{***}	-0.005^{**}
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
lag(perc_refi)	2.42	-2.07	-2.08	-2.38^{*}	-2.97^{**}	-2.32^{*}	-2.52^{**}
	(1.65)	(1.31)	(1.44)	(1.36)	(1.18)	(1.26)	(1.20)
lag(MDO)	85.70^{**}	38.74	44.44	49.55^{*}	63.71^{***}	43.25	80.28^{***}
	(34.93)	(30.31)	(28.46)	(27.80)	(23.99)	(28.17)	(27.44)
lag(infl)	-20.48	2.94	3.09	4.92	11.68	2.16	6.55
	(12.74)	(11.56)	(11.36)	(11.24)	(10.76)	(11.30)	(10.58)
lag(SP500)	-1.28	-0.30	-0.36	-0.33	-0.27	-0.42	-0.56
	(1.00)	(1.06)	(1.04)	(1.04)	(1.01)	(1.04)	(0.98)
lag(FFR)	-37.24^{***}	-49.10^{***}	-51.00^{***}	-54.85^{***}	-58.87^{***}	-49.14^{***}	-45.12^{***}
	(8.03)	(7.11)	(8.77)	(8.62)	(7.44)	(7.28)	(7.15)
lag(GDP)	-8.95^{***}	0.18	-0.38	0.13	0.95	-1.48	-0.99
	(2.68)	(2.49)	(2.37)	(2.28)	(1.96)	(2.32)	(2.06)
lag(TSPRD)	-6.28	-12.66	-14.40	-18.06	-19.93^{**}	-18.19^{*}	-19.66^{*}
	(10.71)	(10.38)	(11.27)	(11.24)	(9.67)	(10.58)	(10.16)
Observations	187	187	187	187	187	187	187
Adjusted R^2	0.574	0.562	0.707	0.703	0.714	0.760	0.703
Note:							$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7: Sensitivity by Period, Freddie Mac Data

	Dependent variable: Spread (BP)
lag(medfico)	1.605
	(1.866)
lag(highltv)	1.294
	(3.388)
lag(highdti)	3.591
	(2.928)
lag(medupb)	-0.007^{***}
	(0.003)
lag(perc_refi)	-0.451
	(1.590)
lag(mdf)	44.811^{**}
	(17.704)
('06 - '11)	-46.296
	(41.226)
('12 - '17)	-34.573
	(46.134)
lag(MDO)	-48.911
	(35.523)
lag(infl)	-2.485
	(10.125)
lag(SP500)	-0.553
	(1.011)
lag(FFR)	-39.168^{***}
	(8.547)
lag(GDP)	-0.353
	(2.083)
lag(TSPRD)	-43.201^{***}
	(12.228)
lag(hpi)	84.510
	(51.569)
lag(hpi, 2)	-171.602^{***}
	(52.842)
lag(mdf):('06 - '11)	-45.422^{**}
	(18.293)
lag(mdf):('12 - '17)	-36.274^{*}
	(19.348)
Constant	2.543
	(1,434.296)
Observations	187
Years	2002 - 2017
R^2	0.762
Adjusted R^2	0.739
Note:	*p<0.1; **p<0.05; ***p<0.01

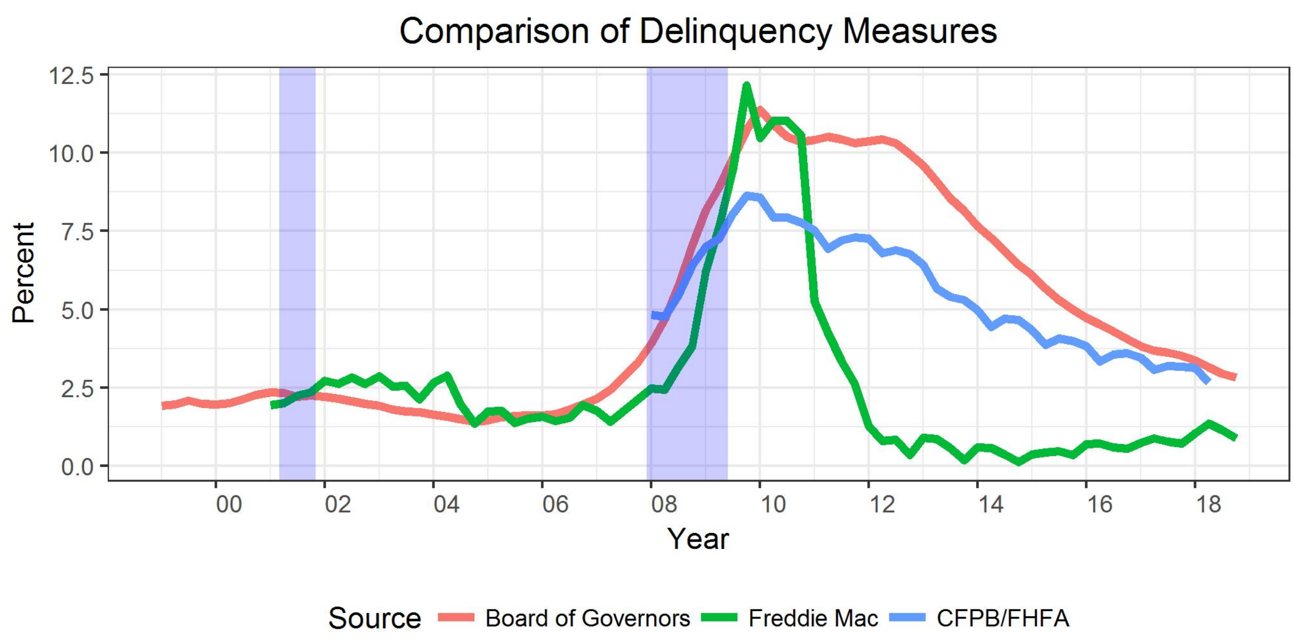

Figure 11: Comparison of Mortgage Delinquency Measures

Conclusion

The main findings of the paper show how credit markets mispriced risk, especially systemic risk in the years leading into the Great Recession. A summary of the proxies for systemic risk in found in Table which shows how sensitivity to systemic risk had an inverse relationship with the amount of systemic risk present in the credit market. After first constructing proxies for systemic risk, I analyze the marginal effect of these proxies as well as traditional measures of risk like mortgage delinquency in a two-stage least squares framework to correct for endogenous borrower decisions. The initial findings of mispriced risk using the FHFA data are further corroborated using the Freddie Mac Loan Level Data Set.

Years	Dispersion	Volatility	Correlation	Defaults	Sensitivity	Dependence
'74 - '90	High	High	Low	-		-
'91 - '97	Low	Low	Low	Low	High	-
'98 - '02	Low	Very Low	Moderate	Low	High	Low
'03 - '05	Low	Low	Moderate	Low	Moderate	High
'06 - '11	Moderate	Moderate	High	High	Low	High
'12 - '18	Low	Low	Low	Moderate	Low	Low

Table 8: Summary Table

The findings presented in this paper have broad implications for policy makers. Systemic risk is an unfortunate externality in the housing finance market. When times are good, investors are the main benefactors, and when times are bad, the public is the biggest loses. As the housing market collapsed in the Great Recession, the public was forced to bail out the investors in the credit markets as well suffer the effects of high employment, stagnant growth, etc. If investors do not accurately price systemic risk in their lending strategies as this paper suggests, this story will likely repeat itself. Either policy makers must force mortgage lenders to explicitly incorporate systemic risk into their lending strategies via regulation or stress tests, or lenders must also be responsible for the negative externalities inflicted upon the public. One could imagine a social insurance systemic similar to the FDIC where mortgage lenders are required to make contributions to a fund so that during crisis years the fund would be able to make payments to at risk borrowers. While the regulation path is more practical and politically feasible, strict regulations are likely to unintentionally reduce credit to marginal borrowers with mediocre credit (i.e. borrowers who barely qualifies for loans without regulations and do not qualify at all with the regulations). On the other hand, a social insurance scheme is more economically appealing but politically unattainable. The policy prescriptions to prevent the next housing crisis are as relevant as ever and deserve our thorough attention. Future work in this field will examine the ways in which policy can force credit markets to accurately price systemic risk into their lending policies.

Appendix: Tables and Figures

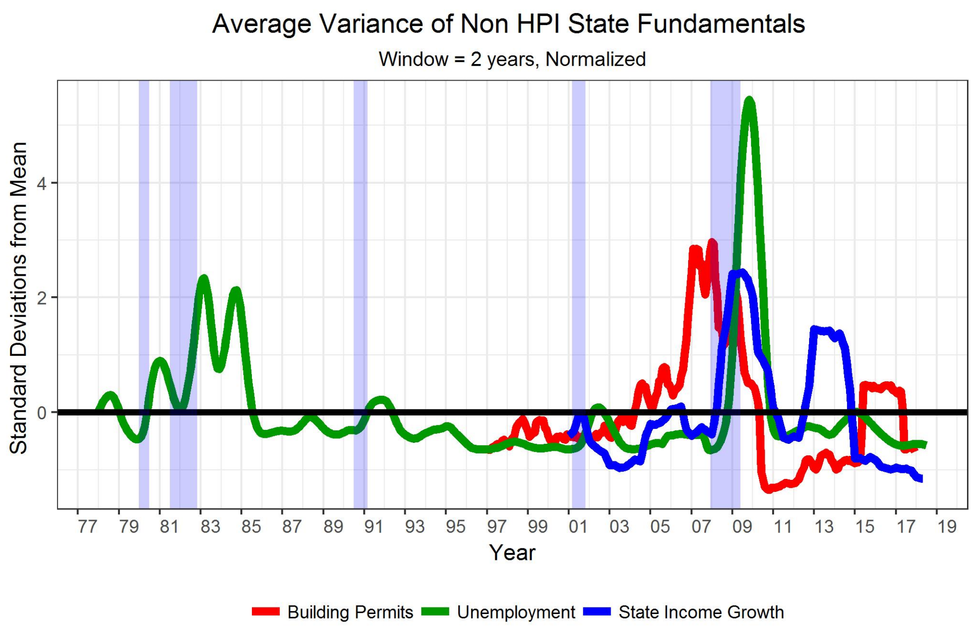

Figure 12: Non HPI Growth State Fundamentals

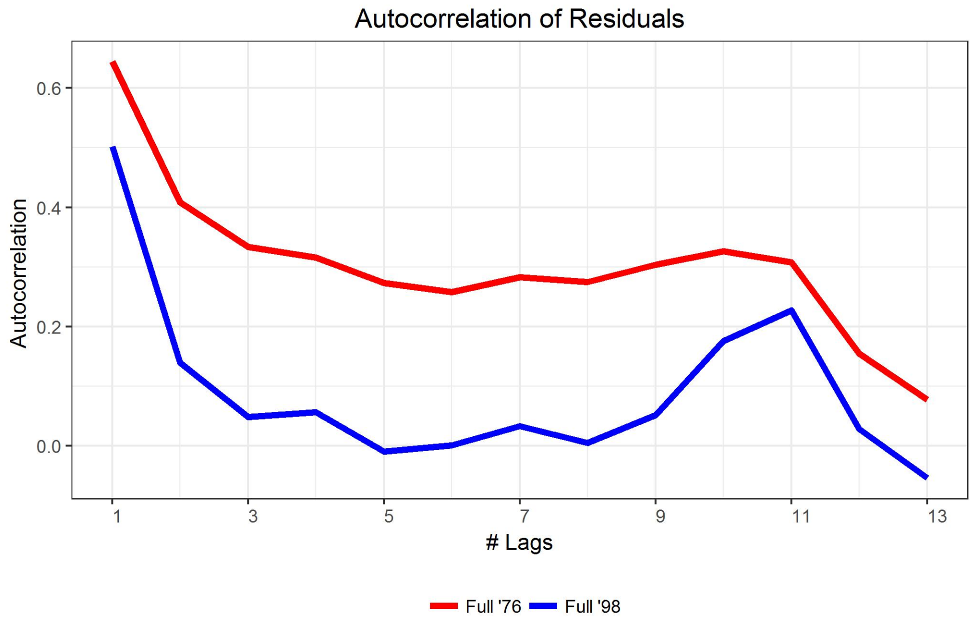

Figure 13: Auto Correlation of Residuals

Table 9: Spatial Correlation of Residuals

	Dependent variable:		
	Residuals		
	Time	Time + Subregion	Time + Region
	(1)	(2)	(3)
subregionESCentral		−0.000	
		(0.015)	
subregionMidAtlantic		−0.000	
		(0.016)	
subregionMountain		−0.000	
		(0.013)	
subregionNewEngland		0.000	
		(0.014)	
subregionPacific		−0.000	
		(0.014)	
subregionSouthAtlantic		0.000	
		(0.013)	
subregionWNCentral		0.000	
		(0.013)	
subregionWSCentral		0.000	
		(0.015)	
regionNortheast			−0.000
			(0.010)
regionSouth			−0.000
			(0.009)
regionWest			−0.000
			(0.009)
Observations	25,449	25,449	25,449
R^2	0.306	0.306	0.306
Note:			*p<0.1; **p<0.05; ***p<0.01

Data Set	FHFA Data		Freddie Mac Data	
Variable	OLS Coef	IV Coef	OLS Coef	IV Coef
F.National	3.10	2.58	-24.34^{***}	-34.44^{**}
F.Ratio	3.52	3.06	-34.01^{***}	-49.29^{***}
Dispersion	7.61	6.82	51.57	31.64
Correlation (Neighbors)	137.4^{***}	147.65^{***}	61.71	11.89
Correlation (All)	48.66^{*}	54.91^{***}	59.70^{*}	47.49
Volatility	459.2^{***}	457.4^{***}	1452^{***}	1489
Mortgage Default (Freddie)	-	-	3.41	3.60
Mortgage Default (Total)	2.81^{*}	2.86^{*}	9.71^{**}	12.16^{***}

Table 10: OLS vs. IV

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