ADJUSTABLE-RATE MORTGAGES, SYSTEMATIC MONETARY POLICY, AND THE ROOT CAUSE OF THE FINANCIAL CRISIS

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Adjustable-Rate Mortgages, Systematic Monetary Policy, and the Root Cause of the Financial Crisis*

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Abstract

Motivated by the theoretical prediction that the indexation mechanism underlying adjustable rate mortgages (ARMs) can serve as a significant shock-absorber for mortgage default rates, this paper highlights a novel mechanism based on the initial share of prime ARMs as a potential root cause of the recent financial crisis. Using U.S. state-level data in a panel fixed-effects Bayesian local projections framework, I find that the joint existence of the favorable credit supply shock realizations and high prime ARM prevalence of the mid-2000s boom period significantly raised mortgage default rates in the period leading up to the onset of financial crisis, thus setting the stage for its materialization.

JEL classification: E32, E52, E58

Key words: Prime adjustable rate mortgages; Mortgage default rates; Systematic monetary policy; Bayesian local projections

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1 Introduction

The role of systematic monetary policy in macroeconomic stabilization has long occupied the minds of policymakers and researchers alike. The ability of monetary policy to stabilize the economy in response to demand shocks, at least to some extent, is largely undisputed among macroeconomists and is strongly rooted in economic theory (see, e.g., Clarida et al. (1999), Woodford (2003), and Galí (2015)). The main transmission channel by which monetary policy is thought to moderate the effects of demand shocks is the conventional real interest rate channel, although the firm balance sheet channel pioneered in Bernanke et al. (1999) has also received significant attention, especially in recent years (see, e.g., Christiano et al. (2014)).

The recent financial crisis has brought to center stage an alternative monetary policy transmission channel that is based on the link between monetary policy and adjustable rate mortgage (ARM) contracts. This ARM channel speaks to the potential real effects that policy-induced interest rate changes can exert by altering payments owed by ARM borrowers. As such, this channel can be thought of as a possibly important driver of the recent mortgage default crisis, whose outset can be traced back to late 2006 (following the significant interest rate increases on the part of the Fed in 2004-2006). Specifically, one arguably reasonable narrative of the root cause of the financial crisis is that favorable credit supply shocks were realized in the mid-2000s boom period, pushing the Fed to raise rates which in turn induced a rise in default rates that set the stage for the subsequent financial crisis. The basis for the focus of this narrative on credit supply shocks is the common notion that credit supply shocks, in addition to playing an important role in the crisis itself, also appear to have played a substantial role in the preceding boom period (see, e.g., Di Maggio and Kermani (2017) and Justiniano et al. (2018)).

The objective of this paper is to thoroughly examine the aforementioned ARM-based narrative. Toward this end, the paper unfolds in three parts. The first part presents theoretical motivation for studying this narrative. The second part provides evidence from aggregate data consistent with a potentially important role for a *prime* ARM channel in setting the stage for the crisis. And the third part conducts a thorough empirical investigation into this role by exploiting cross-sectional variation in prime ARM prevalence across U.S. states.

Theoretical Motivation. In this part I lay out a simple mortgage debt contract problem capable of isolating the role of an ARM indexation mechanism in increasing mortgage default rates in the presence of positive risk-free rate changes. The problem assumes lenders and borrowers engage in a mortgage debt contract subject to the costly state verification (CSV) framework from Townsend (1979) as used in Bernanke et al. (1999) (BGG) in the context of borrowing entrepreneurs, with a simplifying modification relating to the assumption that contractual mortgage rate is the only choice variable underlying the optimal debt contract. This assumption facilitates the making of an *existing* ARM contract that can only adjust along its contractual rate dimension and not its housing stock dimension, which accords with both realism as well as my objective of isolating the role of the ARM indexation mechanism in producing a positive relation between the risk-free rate and default rates.

I use this framework to demonstrate two results. First, changes in the risk-free rate translate into nearly one-for-one changes in the contractual mortgage interest rate in this CSV setting, thus making it virtually observationally equivalent to a framework which explicitly models a full ARM indexation mechanism. Second, to isolate the shock-absorbing role of the ARM indexation mechanism for the dynamics of default rates, I compute the impulse responses of the default rate to a 50 basis point shock to the risk-free rate. The results from this experiment indicate that an increase in the risk-free rate produces higher mortgage default rates owing to the higher mortgage payments induced by the ARM indexation mechanism. This finding serves as theoretical motivation for studying the potential role of the ARM indexation mechanism in overturning the initially good effects of the mid-2000s favorable credit supply shocks on mortgage default rates.

Aggregate Evidence. Figures 1 and 2 can be helpful in underscoring the empirical motivation for this paper's narrative while simultaneously stressing a potentially important distinction between prime and subprime mortgages in the context of this narrative. Figure 1 shows the default rates on prime and subprime ARMs and fixed-rate mortgages (FRMs), measured by the number of mortgages whose payments are overdue by at least 90 days or in the process of foreclosure as a percentage of the corresponding number of total outstanding mortgages, while Figure 2 shows the shares of prime and subprime ARMs and FRMs of total outstanding mortgages in the entire mortgage market. Two notable facts stand out from these two figures, as they pertain to the above-mentioned narrative and the distinction between prime and subprime mortgages: *i*) the default rate on prime ARMs increased by a substantially higher rate than that on prime FRMs from the trough of the ending of the mid-2000s credit boom period onwards, and this relative rate of increase is much higher than the corresponding difference between the increase rates for subprime ARM and FRM default rates (e.g., from 2006:Q2 to 2008:Q3, right before the beginning of the materialization of the Lehman shock's effects, the default rate on prime ARMs grew by 742% compared to 154% for the prime FRM default rate, while the subprime ARM default rate grew by 342% compared to a growth rate of 99% for subprime FRMs); and *ii*) shares of prime and subprime ARMs both increased considerably during the credit boom period, with roughly similar increases in absolute terms (the two share increased by 5.4 and 5 percentage points over the period 2000:Q4-2006:Q4, respectively, reaching 13.9% and 6.6% shares in 2006:Q4), thus keeping the gap between the two shares roughly constant at about 7 percentage points.

These two facts join time series econometric analysis of the responses of default rates by borrower and product type in suggesting a limited role for the *subprime* ARM channel in accounting for the root cause of the financial crisis while implying a meaningful role for the *prime* ARM channel. Specifically, I demonstrate that favorable credit supply shocks do not induce differential effects on subprime ARM and FRM default rates while prime ARM default rates increase by much more than prime FRM default rates in response to these shocks. These results prompted me to focus on the prime ARM channel when resorting to a panel fixed-effects U.S. states based analysis, which I now turn to discuss.

U.S. State-Level Evidence. The main contribution of this paper lies in conducting an empirical investigation into the suitability of the above-mentioned prime ARM based narrative for correctly depicting the root cause of the financial crisis. Toward this end, I utilize the state-of-theart measure of credit supply shocks from Gilchrist and Zakrajek (2012) along with U.S. state-level data on mortgage default rates and prime ARM shares of total mortgages outstanding to estimate the ARM-share-dependent effects of favorable credit supply shocks on mortgage default rates. My results can be summarized as follows. First, the negative effect of favorable credit supply shocks on mortgage default rates is significantly dampened when the initial level of prime ARM share is higher.[1,2] Second, the results show that this prime-ARM-based mechanism is sufficient for completely reversing the decline in default rates that a favorable credit supply shock would have under a low prime ARM share state, as after 3 years mortgage default rates begin to significantly increase following the shock in the high prime ARM share state. Third, I also show that favorable credit supply shocks lead to a significantly stronger relative fall in house prices when prime ARM prevalence is high, with a similar reversal in responses as the one observed for default rates.

Lastly, to facilitate the interpretation of my results as being informative about the root cause of the financial crisis, I compute an historical decomposition that shows that, conditioned on being in a high prime ARM share state, credit supply shocks increased the overall mortgage default rate by more than 44% from the ending of the boom period to the pre-Lehman shock period, accounting for 58% of the actual average rise in mortgage default rates across U.S. states. This evidence provides support for the plausibility of the narrative that a prime ARM channel played a meaningful role in setting the stage for the financial crisis by significantly raising mortgage default

[1] The results from doing the panel fixed-effects econometric analysis with subprime ARM share data instead of prime ARM share data broadly accord with the above-mentioned aggregate evidence in indicating a much lesser role of the subprime ARM channel in setting the stage for the recent financial crisis. Specifically, while differential responses of default rates across the high and low subprime ARM share states are significantly positive for a total of 11 horizons, credit supply shocks' effects in the former state are significantly positive for only 3 horizons and imply a contribution of only 22.7% of the total rise in default rates from the ending of the boom period to the pre-Lehman shock period compared to corresponding numbers of 14 horizons and 58% contribution share for the baseline prime ARM share state specification. Moreover, in contrast to the prime ARM share case, the baseline results for the subprime ARM share state specification do not appear sufficiently robust to the various sensitivity checks considered in Section 4. (E.g., when using 6 lags instead of 8 lags, the responses in the high subprime ARM share state are never significantly positive.) Taken together with the aggregate results, these findings further reinforce my focus on the prime (rather than subprime) ARM channel in this paper.

[2] This result for prime ARM shares is shown to be consistent with the favorable credit supply shock's positive effect on 1-year treasury rates, a commonly used ARM index, which is the first result I present in the empirical analysis given that it serves as a basic litmus test for the validity of a meaningful ARM channel.

rates in the period leading up to its focal point.

Put together, the results of this paper tell an interesting tale of the root cause of the financial crisis. In response to favorable credit supply shocks in the mid-2000s boom period the Fed aggressively raised rates. This in turn induced an increase in mortgage default rates owing to the relatively high prime ARM prevalence in this period, concurrently also lowering house prices, and effectively setting the stage for the subsequent financial crisis. Notably, I do not claim this story to be the sole narrative for the root cause of the financial crisis; rather, my aim is to advance it as a reasonable and likely important driver of the crisis which can still coexist with other reasonable explanations such as poor credit quality or magnified presence of real estate investors in the boom period. (A more detailed discussion on competing explanations appears below on Page 7.)

Literature Review. This paper is related to the emerging new literature studying the link between monetary policy and mortgage contracts. Calza et al. (2013), estimating country-specific VARs, show that consumption and residential investment respond more strongly in economies in which ARM contacts are more prevalent; they further demonstrate that a two-sector DSGE model with price stickiness and collateral constraints is capable of producing results that accord well with their empirical counterparts. Villar Burke (2015) delivers empirical evidence that mortgage lending rates in European economies that rely more on ARM contracts respond much more strongly to monetary policy shocks. A recent paper by Garriga et al. (2017) provides a theoretical general-equilibrium framework with both ARM and FRM mortgage contracts in which larger responses of the economy to monetary policy shocks are generated under ARM than FRM contracts.

There has also been micro-data based work that focused on the effects of monetary policy shocks on consumption and default risk, distinguishing between adjustable and fixed-rate contracts. Flodén et al. (2016) study the consumption response of Swedish households to monetary policy shocks while distinguishing between both ARM and FRM contracts as well as high and low debt levels; their conclusion supports a cash-flow channel of monetary policy in that changes in interest rates affect highly indebted households tied to ARM contracts much more strongly than households with little debt or FRM contracts. Di Maggio et al. (2017) show that the consumption response to the 2008 interest rate reduction is stronger in U.S. counties where the share of ARM contracts is greater. Focusing on default risk, Foote et al. (2008), Gerardi et al. (2008), Mayer et al. (2009), Demyanyk and Van Hemert (2009), and Foote et al. (2012) provide micro-data based evidence that the positive rate resets of the mid-2000s played a minor role in driving the increase in subprime mortgages' default rates; and Tracy and Wright (2016) and Fuster and Willen (2017) show that mortgage defaults significantly drop in response to downward adjustment in mortgage interest rates for prime and nonprime (Alt-A) ARM borrowers, respectively. Lastly, focusing on the effects of within-month variation in mortgage payments resulting from ARM index choice (Treasury versus Libor rates) and different lookback periods on defaults of nonprime and Jumbo-prime borrowers as well as their neighbors, Gupta (2018) finds a significant relation between higher mortgage payments and foreclosure probability as well as significant evidence for foreclosure contagion.[3]

This paper contributes to the above literature by looking into the specific role the prime ARM channel of monetary policy possibly played in laying down the roots of the financial crisis. The literature above either mostly takes a look at the general relation between monetary policy effects and ARM prevalence or focuses specifically on the implications of the post-2007 rate reductions for this relation. While Flodén et al. (2016) do study the implications of interest rate increases, their focus is on consumption behavior (imputed from income and financial flows) and in the context of Sweden; by contrast, my focus is on mortgage default behavior as it is arguably the defining characteristic of the financial crisis and the events leading up to it. Moreover, the results from Foote et al. (2008), Gerardi et al. (2008), Mayer et al. (2009), Demyanyk and Van Hemert (2009), and Foote et al. (2012) relate to the *subprime* ARM channel whereas my focus is on the *prime* ARM channel and thus constitutes a different lens through which to tell the narrative about the root

[3] Using a conceptually similar identification framework to study the correlation between mortgage leverage and default, Gupta and Hansman (2019) exploit ARM payment shocks to show that moral hazard is responsible for 60%-70% of this correlation, while adverse selection explains 30%-40%.

cause of the financial crisis.[4]

Lastly, Gupta (2018) obtains his results by exploiting within-month variation in interest rates coming mainly from the financial crisis period itself, thus somewhat limiting the *direct* relevance of his results for this paper's narrative, i.e., that the systematic contractionary monetary policy of the mid-2000s played a decisive role in driving up mortgage default rates and therefore setting the stage for the financial crisis. That said, as also discussed in Gupta (2018)'s Conclusion Section, his results are consistent with my proposed narrative in suggesting that the joint prevalence of ARM upward resets and lower house prices (with the latter making it hard to refinance) prior to the crisis led to increased ARM defaults which arguably induced price drops and falls in refinancing activity among neighboring homes and thus caused a cascading wave of additional defaults and further price drops in surrounding areas. This chain of events is a potentially important amplification mechanism in driving the financial crisis and is broadly in line with the evidence put forward in this paper.

Importantly, my paper is also related to the literature that tries to uncover the root cause of the financial crisis. While this literature and the one discussed above naturally overlap, there is still enough of a distinction between them to warrant a separate discussion on the former. As pointed out by Ferreira and Gyourko (2015), about three-quarters of this literature use data only from the subprime sector and typically include outcomes from no later than 2008 (Table 1 in their appendix non-exhaustively lists the papers belonging to this literature), with most emphasis being placed on poor credit quality as the root cause of the crisis.[5] A notable example is Mian and Sufi (2009), who find that moral hazard on behalf of originators selling subprime mortgages is a main culprit for the U.S. mortgage default crisis.

Utilizing new panel micro data on the ownership sequences of all types of borrowers from 1997-2012, Ferreira and Gyourko (2015) provide evidence that leads to a reinterpretation of the

[4]While nearly all of the analysis in Foote et al. (2012) focuses on the subprime segment of the mortgage market, they do present in the upper panel of their Table 1 evidence that, at face value, appears to undermine the narrative advanced in this paper in showing that payment increases preceded initial delinquency for only 12 percent of mortgage foreclosures in 2007-2010. In Section 5 I discuss the reasons for why the validity of this paper's narrative is robust to the result from Foote et al. (2012).

[5]Also see Foote and Willen (2018) for a brief survey of this literature.

U.S. foreclosure crisis as being driven more by prime borrowers than by subprime borrowers. In line with this evidence, Adelino et al. (2016, 2017) stress that mortgage expansion during the boom period was shared across the entire income distribution and that prime default rates were a major driver of the overall rise in defaults. This prime-borrowers-based narrative is also supported by evidence from Foote et al. (2016) and Albanesi et al. (2017), both stressing the important role of prime borrowers in driving the mid-2000s credit boom. The latter paper, beyond showing that the rise in mortgage defaults during the crisis was concentrated in the middle of the credit score distribution, underscores the fact that this rise is mostly attributable to real estate investors. I contribute to the literature on the root cause of the financial crisis by shifting focus to an ARM based narrative from a credit quality based one, and in doing so I provide evidence which complements that from Ferreira and Gyourko (2015), Adelino et al. (2016, 2017), Foote et al. (2016), and Albanesi et al. (2017) by adding on top of it the special role that ARMs played for prime borrowers' default rates.

Outline. The remainder of the paper is organized as follows. The next section presents theoretical motivation for this paper's focus on the ARM indexation channel as a potential driver of the financial crisis. Section 3 begins with a brief description of the data, after which it presents the methodology and main empirical evidence of this paper. Section 4 examines the robustness of the baseline results. Section 5 discusses the results of this paper in the context of earlier work on ARM upward resets' effects. The final section concludes.

2 Theoretical Motivation

In what follows, I sketch out a simple mortgage debt contract that demonstrates the effects of ARM indexation on the mortgage default rate. The debt contract embodies an agency problem between borrowers and lenders á la the costly state verification (CSV) problem from Townsend (1979). I apply the CSV setting to my debt contract along the lines of how Bernanke et al. (1999) (BGG) applied it to borrowing entrepreneurs, with a simplification manifested through the assumption that the only choice variable underlying the debt contract is the contractual mortgage rate while housing stock is assumed to be constant.[6]

The assumption that only the contractual mortgage rate is state-contingent facilitates the replication of an experiment where only the contractual mortgage rate is free adjust in response to a risk-free rate change and thus reasonably replicates the effect of such a change on an ARM for which the loan-to-value ratio is pre-determined and thus can not adjust. Such an experiment is both a realistic depiction of how an *existing* ARM contract practically adjusts in response to a risk-free rate change as well as a means by which to demonstrate the positive relation between the risk-free rate and the default rate. As I explain below, the considered setting, although not explicitly modeling an ARM debt contract, effectively admits observational equivalence with respect to such a contract and is therefore appealing for my purposes of showing the positive effects of risk-free rate changes on ARM default rates in the simplest possible setting.[7]

[6] I set its value as equal to a steady state value which is consistent with an optimal debt contract that allows for state-contingency also for this variable. More generally, the formulation of my debt contract only materially deviates from that of BGG in the dynamic sense, as I compute the steady state of the housing stock based on the assumption that the optimal debt contract holds in the steady state. Out of steady state, however, I only allow the contractual rate to adjust to capture the essence of an *existing* ARM contract.

[7] Granted, from a structural standpoint, it would be preferable to explicitly model such a contract along the lines of other papers such as Rubio (2011), Campbell and Cocco (2015), and Garriga et al. (2017). Campbell and Cocco (2015) solve an elaborate dynamic model of a household who finances the purchase of a house with a mortgage (either FRM or ARM) and decides in each period how much to consume and whether to default on the loan, showing that higher interest rates are expectedly more detrimental for ARMs in terms of default. Rubio (2011) and Garriga et al. (2017) abstracted from default, which is the focal point of this paper's narrative. All in all, given my goal of producing theoretical motivation for my narrative with the simplest possible setting capable of embedding an ARM indexation mechanism and endogenous mortgage default, I have opted to use the BGG-type setting described in the next section.

2.1 ARM Indexation and Default Rate

2.1.1 Homeowners.

There is a continuum of identical, finitely-lived, and risk-neutral homeowners. The i-th homeowner produces good $Y_{i,t}$ using the following technology:

$$Y_{i,t} = \omega_{i,t} K_{i,t}^{\alpha}, \tag{1}$$

where $\omega_{i,t}$ is a random idiosyncratic productivity shock which is assumed to be log-normally distributed $ln\omega_{i,t} \sim N(\frac{-\sigma^2}{2}, \sigma^2)$ so that $\mathbb{E}(\omega_{i,t}) = 1$; and $K_{i,t}$ is the housing stock of the i-th homeowner. The assumption that housing stock serves as a factor input in the production function of homeowners follows Iacoviello (2005).

Homeowners purchase houses from housing producers in the beginning of period t at price Q_{t-1}, which they then operate in period t and resell it at the end of the period at price Q_t. As part of my intention to isolate the role of the ARM indexation mechanism, I refrain from modeling housing producers and assume $Q_t = Q_{t-1} = 1$ for all t. The operation of the housing stock on the part of homeowners can be considered as their utilization of their real estate to produce good $Y_{i,t}$, which is not modeled here explicitly due to the partial equilibrium formulation of the model.[8] An example of one such unmodeled activity can be rental services provided by homeowners to other households.[9] The gross real rate of return on housing stock for the i-th homeowner, denoted by $R_{i,t}^{k}$, is the sum of the marginal profitability of housing, e.g., the marginal profit from renting it,

[8] Iacoviello (2005), e.g., considers these homeowners as entrepreneurs using their real estate (along with endogenous labor) to produce an intermediate good which is then sold to retailers.

[9] Albanesi et al. (2017) stress that prime real estate investors played a central role in both the boom period leading to the financial crisis as well as in the bust period. Unfortunately, my data only allows identification of mortgage types in the product space and not in the borrower space, thus not enabling me to distinguish between owner-occupied mortgages and non-owner-occupied ones. Nevertheless, both the theoretical motivation part of my paper as well as its empirical results can be viewed as being consistent with the findings from Albanesi et al. (2017), only emphasizing the role of the ARM indexation channel (which is unstudied in their analysis) in contributing to the crisis.

and the capital gain:

$$R_{i,t}^{k} = \frac{\alpha \frac{Y_{i,t}}{K_{i,t}} + (1-\delta) Q_t}{Q_{t-1}}, \tag{2}$$

where δ is the rate of housing stock depreciation. Homeowners' housing purchases are financed partly internally and partly by borrowing from risk-neutral financial intermediaries within a CSV framework á la Bernanke et al. (1999), such that the assets of the i-th homeowner $Q_{t-1}K_{i,t}$ are the sum of her debt $B_{i,t}$ and net worth $N_{i,t}$:

$$Q_{t-1}K_{i,t} = B_{i,t} + N_{i,t}. \tag{3}$$

Owing to constant returns to scale in production, law of large numbers, and the fact that $\mathbb{E}(\omega_{i,t}) = 1$, we can express the gross real rate of return on housing for the i-th homeowner as $R_{i,t}^{k} = \omega_{i,t} R_t^k$, where R_t^k is the average, or aggregate, gross real rate of return on housing in the economy. Hence, the gross proceeds from homeowner i's production activity in period t are $\omega_{i,t} R_t^k Q_{t-1} K_{i,t}$.

The focal assumption underlying the agency problem between the borrower and lender is that the realization of $\omega_{i,t}$ is private information of the homeowner and that in order to observe it the lender has to pay a monitoring cost of $\mu \omega_{i,t} R_t^k Q_{t-1} K_{i,t}$, where $0 < \mu < 1$ is the monitoring cost parameter. The optimal debt contract between the homeowner and the lender specifies that, in the case of no default, the former pays the lender $Z_{i,t} B_{i,t}$, where $Z_{i,t}$ is the no-default contractual interest rate; that is, if $\omega_{i,t} R_t^k Q_{t-1} K_{i,t} \geq Z_{i,t} B_{i,t}$, the homeowner will pay the debt and retain any residual profit. In the case of default, i.e., $\omega_{i,t} R_t^k Q_{t-1} K_{i,t} < Z_{i,t} B_{i,t}$, the lender will pay the monitoring cost and obtain $(1-\mu)\omega_{i,t} R_t^k Q_{t-1} K_{i,t}$. Moreover, it is straightforward to define the default threshold value of $\omega_{i,t}$, $\bar{\omega}_{i,t}$, as $\bar{\omega}_{i,t} = \frac{Z_{i,t} B_{i,t}}{R_t^k Q_{t-1} K_{i,t}}$.

I now turn to the maximization problem that characterizes the optimal mortgage contract. To facilitate the mimicking of an *existing* ARM contract that can only adjust to a risk-free rate change along the contractual rate (Z_t) dimension, I assume that Z_t is the only choice variable underlying the optimal contract with the housing stock $K_{i,t}$ being constant at a value which is consistent with the steady state value it would obtain if it were also a choice variable. Assuming that financial intermediaries operate in a perfectly competitive environment in which they earn, in expectation, the gross risk-free return R_t, the optimal contract problem that maximizes the homeowner's expected profit subject to the lenders' zero-profit condition is[10]

$$\begin{aligned} &\max_{\bar{\omega}_{i,t}} \int_{\bar{\omega}_{i,t}}^{\infty} \left[\omega_{i,t} R_t^k Q_{t-1} K_{i,t} - Z_{i,t} B_{i,t}\right] dF(\omega_{i,t}) = [1 - \Gamma(\bar{\omega}_{i,t})] R_t^k Q_{t-1} K_{i,t} \\ &s.t \;\; R_t(Q_{t-1}K_{i,t} - N_{i,t}) = [\Gamma(\bar{\omega}_{i,t}) - \mu G(\bar{\omega}_{i,t})] R_t^k Q_{t-1} K_{i,t}, \end{aligned} \tag{4}$$

where $F(\omega_{i,t})$ is the CDF; $\Gamma(\bar{\omega}_{i,t}) \equiv \int\limits_0^{\bar{\omega}_{i,t}} \omega_{i,t} dF(\omega_{i,t}) + \bar{\omega}_{i,t} \int\limits_{\bar{\omega}_{i,t}}^{\infty} dF(\omega_{i,t})$; and $G(\bar{\omega}_{i,t}) \equiv \int\limits_0^{\bar{\omega}_{i,t}} \omega_{i,t} dF(\omega_{i,t})$. The first component of $\Gamma(\overline{\omega}_{i,t})$ (which is also equal to $G(\bar{\omega}_{i,t})$) gives the homeowner's expected return in case of a default, whereas the second one gives the expected return in case of solvency; hence, the optimization constraint dictates that the expected returns of the lenders on a risky loan net of monitoring costs, given by the RHS of the constraint, be equal to the risk-free return given by the LHS of the constraint.

Effective ARM Indexation. We are now in position to see why the optimal debt contract implies practical observational equivalence between my considered setting and one where full ARM indexation applies. The crux of this rough equivalence lies in the behavior of the constraint from Problem (4) following a change in the risk-free rate. Since the only other non-constant variable in this constraint is $\bar{\omega}_{i,t}$, it is clear that $\Gamma(\bar{\omega}_{i,t}) - \mu G(\bar{\omega}_{i,t})$ changes one-for-one in percentage terms with a change in the risk-free rate. Moreover, the log-normal distribution assumption turns out to imply that the elasticity of $\Gamma(\bar{\omega}_{i,t}) - \mu G(\bar{\omega}_{i,t})$ with respect to $\bar{\omega}_{i,t}$ is very close to one.[11] These two facts, along with the definition of the contractual mortgage rate as $Z_{i,t} = \frac{R_t^k Q_{t-1} K_{i,t}}{\bar{\omega}_{i,t} B_{i,t}}$, imply a nearly one-for-one relationship between the risk-free rate and the contractual mortgage rate.

[10]The optimal contract specifies $\bar{\omega}_{i,t}$ as the choice variable, which is equivalent to specifying $Z_{i,t}$ as the choice variable due to the relation $\bar{\omega}_{i,t} = \frac{Z_{i,t} B_{i,t}}{R_t^k Q_{t-1} K_{i,t}}$.

[11]This statement is true for various reasonable calibrations, including the one considered in my simulations where this elasticity is 0.97.

Stochastic Process for the Risk-Free Rate. As explained on 9, I consider an experiment corresponding to the risk-free rate intended to isolate the role of the ARM indexation mechanism by looking at the effects of risk-free rate changes. To accommodate shocks to the risk-free rate, denoted by $r_t = R_t - 1$, I assume r_t follows the $AR(1)$ process

$$r_t = (1-\rho)\bar{r} + \rho r_{t-1} + \epsilon_t, \tag{5}$$

where ρ governs the persistence of the process; $\bar{r}$ is the steady state level of r_t; and ϵ_t is a white noise shock. In Section 2.1.3 I present the impulse responses of the economy to risk-free rate shocks.

Net Worth Dynamics. The last piece of modelling related to homeowners is to lay out the dynamics of their aggregate net worth.[12] Toward this end, I make the standard assumption that homeowners "die" with a constant exogenous probability in each period, $1-v$, in which case they simply consume their entire net worth and are replaced within the period by new homeowners.[13] This setting implies the following law of motion for aggregate homeowners' net worth:

$$N_{t+1} = v[1-\Gamma(\bar{\omega}_t)]R_t^k Q_{t-1} K_t, \tag{6}$$

where $[1-\Gamma(\bar{\omega}_t)]R_t^k Q_{t-1} K_t$ is the aggregate profit of all homeowners in period t, which also corresponds to the objective function in Problem (4). Notably, in line with my aim to isolate the role of the ARM indexation mechanism in altering the default rate on an *existing* ARM, I set N_t at its steady state value so as to shut down any leverage effects; in accordance with the reasoning underlying the constancy of the housing stock, these leverage effects are irrelevant given my postulation of an existing ARM for which leverage is not free to adjust.

[12] BGG show that the chosen optimal level of $\bar{\omega}_{i,t}$ is identical across borrowers. This result is important as it facilitates aggregation of net worth in the economy.

[13] This assumption guarantees that homeowners will never accumulate enough net worth so as to avoid borrowing to finance their operations.

2.1.2 Calibration

I solve the model by taking a first-order approximation of its system of equilibrium equations about the steady state values of the variables. Table 1 presents the calibration used for the model's parameters. The calibration for the parameters that are unrelated to the financial accelerator side of the model (α, δ, and $\bar{r}$) follows BGG. Although the housing stock share in the production function and housing stock depreciation rate in my model do not pertain to firm capital stock as in BGG, the calibration used in BGG (0.35 and 0.025) is quite similar to that used in Iacoviello (2005) (0.36 and 0.03), who also directly models housing stock in the production function. Hence, I simply follow BGG also for these two parameters.

The parameters related to the debt contract and homeowners' net worth are the following: the monitoring cost, μ; the standard deviation of the idiosyncratic productivity shock, σ; and homeowners' death rate, v. While my baseline results are robust to a wide range of parameterizations of these parameters, the baseline calibration I have opted for is aimed to reasonably capture some basic features of the prime ARM market. Specifically, I calibrate these parameters to $\mu = 0.08$, $v = 0.969$, and $\sigma = 0.13$ so as to match a steady state annual contractual mortgage rate spread $(\left(\frac{\bar{Z}}{\bar{R}}\right)^4 - 1)$ of 0.6%, the approximate guarantee fee charged by Fannie Mae and Freddie Mac on prime ARMs;[14,15] a steady state housing stock to net worth $(\frac{\bar{K}}{\bar{N}})$ of 3.9, roughly corresponding to the inverse of the loan-to-value ratio for prime ARMs (Jarsulic (2010)); and an annual steady state mortgage default rate of 5.4%, which corresponds to the average share of prime ARMs that are either late on payments by at least 90 days or in the process of foreclosure. Lastly, the persistence parameter for the risk-free rate shock is set to $\rho = 0.8$.

[14] https://www.fhfa.gov/AboutUs/Reports/ReportDocuments/GFee-Report_12-10-18.pdf.

[15] This fee is the amount paid (in basis points) to Fannie Mae and Freddie Mac by financial institutions (who purchase from them mortgage backed securities) in return for the guarantee that principal and interest payments are made even if borrowers default. As such, this fee can be viewed as the compensation for default risk, which is also what is structurally captured by the contractual mortgage rate spread in the model.

2.1.3 The Effects of Risk-Free Rate Shocks

Figure 3 shows the response of the risk-free rate, contractual mortgage rate, and mortgage default rate ($\int_0^{\bar{\omega}_{i,t}} \omega_{i,t} dF(\omega_{i,t})$) to a 50 basis-point risk-free rate shock. The impulse responses demonstrate two particularly important results in the context of the channel this paper is trying to highlight. The first is that the contractual mortgage rate (Z_t) effectively rises one-for-one with the change in the risk-free rate. This result implies that the CSV debt contract considered here, albeit not explicitly modeling an ARM indexation mechanism, in practice produces one. This observational equivalence between the setting considered here and full indexation of the contractual mortgage rate to the risk-free rate conditional on the latter moving facilitates an examination of the role of the ARM indexation mechanism in producing a positive relation between the risk-free rate and mortgage default rates.

The second finding, whose structural informativeness regarding the shock-absorbing role of the ARM indexation mechanism stems from the first finding, is the meaningful rise in mortgage default rates which embody the exacerbation of the agency problem between lenders and homeowners induced by higher interest payments. In sum, the structural setting used in this section has shown that the ARM indexation mechanism has the potential to overturn the response of mortgage default rates to favorable shocks which cause the risk-free rate to rise. This result serves as theoretical motivation for studying the role of the joint occurrence of the favorable credit supply shocks and high ARM prevalence of the mid-2000s in setting the stage for the financial crisis, which is what I turn to study next.

3 Empirical Analysis

3.1 Data

In this section I discuss both the aggregate data I use in my initial analysis as well as the U.S. state-level data I use in the more comprehensive panel, fixed-effects regression analysis subsequently.

Aggregate Data. The variable I use to measure credit supply shocks is the excess bond premium (EBP) series from Gilchrist and Zakrajek (2012), who use micro-level data to construct a credit spread index computed from the spreads between non-financial firms' bond yields and U.S. government bond yields of comparable maturities. They then decompose this credit spread series into a component that captures firm-specific information on expected defaults and a residual component that they term as the excess bond premium (EBP). Hence, EBP is arguably a reliable proxy for exogenous credit supply shocks. The most updated series of EBP, available from Favara et al. (2016),[16] is my measure of credit supply shocks in this paper. It is in quarterly frequency where quarterly values are averages of corresponding raw monthly values.

To establish the necessary condition for the existence of the prime ARM channel of monetary policy, I examine the effects of credit supply shocks on the 1-year treasury rate, a commonly used ARM interest rate index. The latter is downloaded from FRED, which converts it into quarterly frequency from daily frequency by averaging over corresponding raw daily values.

I also use aggregate mortgage default rates by borrower and product type to shed light on the macroeconomic relevance of the prime ARM channel of monetary policy relative to the subprime one in possibly being the root cause of the financial crisis. Toward this end, I use data from the National Delinquency Survey (NDS) conducted by the Mortgage Bankers Association (MBA). The NDS is a voluntary survey of over 120 mortgage lenders, including mortgage banks, commercial banks, thrifts, savings and loan associations, subservicers, and life insurance companies; it covers roughly 85%-88% of all first lien mortgages outstanding in the U.S. mortgage market for one- to four-unit residential properties and provides data by both borrower type (prime, subprime,

[16] The permanent link for this updated excess bond premium series is https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv.

Federal Housing Administration (FHA)) and product type (FRMs and ARMs).[17,18] The mortgage default rate for each mortgage type is measured as the percentage of all mortgages serviced for that specific mortgage type that are either late on their payments by at least 90 days or in the process of foreclosure. This default measure is termed by the MBA (as well as other mortgage market information providers such as CoreLogic) the 'seriously delinquent' rate and is a common formal measure of mortgage distress.[19] The data cover 1998:Q1-2016:Q4 and are available in seasonally adjusted form from the MBA except for the foreclosure inventory data which I seasonally adjusted using ARIMA X12. All mortgage default rate variables are log-transformed.

U.S. State-Level Data. Data are quarterly and cover the 51 U.S. states with samples that span 1998:Q1-2016:Q4. The prime ARM share data is based on state-level data from the NDS. I compute U.S. state-level prime ARM shares by dividing the number of outstanding mortgages for prime ARMs by the total number outstanding mortgages in each U.S. state. The main outcome variable I consider is the mortgage default rate, measured in accordance with the aggregate measure discussed above as the 'seriously delinquent' rate for each U.S. state, i.e., the percentage of all mortgages serviced that are either late on their payments by at least 90 days or in the process of foreclosure.

To gain an understanding of the potential role of both borrower and mortgage types in driving both the absolute overall default rate as well as its differential behavior as a function of prime ARM shares, I also look at ARM- and FRM-specific default rates for prime and subprime mortgages for each U.S. state. Lastly, I also examine the response of U.S. state-level house prices, as measured

[17] An FHA loan is a mortgage that is insured by the Federal Housing Administration (FHA). I exclude this mortgage category from my analysis given the generally null attention it has received from the literature as a potential root cause of the financial crisis.

[18] Mortagage credit quality is usually divided into three categories: prime (high quality), Alt-A (intermediate quality), and subprime (low quality). While the NDS does not identify or track Alt-A mortgages explicitly, it reports having conversations with survey participants that have established that Alt-A loans are divided between the prime and subprime groups. Thus, Alt-A mortgage performance is captured in the delinquency and foreclosure rates estimated in the NDS.

[19] I have confirmed the baseline results of this paper are robust to using the 60-day delinquency rate instead of the 90-day one when constructing my default measure as well as to separately considering the 60- or 90- day delinquency rate and the foreclosure rate as the measure of mortgage default.

by the Federal Housing Finance Agency (FHFA) 'expanded-data' house price index, which is a weighted, repeat-sales index that supplements the already-existing suite of FHFA indexes in using not only data on Fannie Mae and Freddie Mac financed mortgages but also sales price data from county recorder offices and FHA-endorsed loans.[20] All variables are seasonally adjusted using ARIMA X12 and log-transformed.

3.2 Methodology

I follow the econometric framework employed in Auerbach and Gorodnichenko (2012), Owyang et al. (2013), Tenreyro and Thwaites (2016), and Ramey and Zubairy (2018) who use the local projection method developed in Jorda (2005) to estimate impulse responses. This method allows for state-dependent effects in a straightforward manner while involving estimation by simple regression techniques. Moreover, it is more robust to misspecification than a non-linear VAR.

I make use of the Jorda (2005) local projections method within a fixed-effects panel model, where a Bayesian estimation and inference procedure is performed by assuming a diffuse normal-inverse Wishart prior distribution for the local projection regressions' coefficients and residual variance. To account for correlations of the error term across U.S. states and time, I apply a correction to the standard errors within my Bayesian estimation procedure, based on Driscoll and Kraay (1998) and following Auerbach and Gorodnichenko (2012)'s use of this correction in a classical setting, which accounts for arbitrary spatial and temporal correlations of the error term. In doing so I accord with the reasoning from Miranda-Agrippino and Ricco (2017), who estimate a hybrid VAR-local-projections model and follow the suggestion from Müller (2013) to increase estimation precision in the presence of a misspecified likelihood function (as in mine and their setting) by replacing the original posterior's covariance matrix with an appropriately modified one. I discuss my Bayesian estimation and inference approach in more detail below and Appendix A provides

[20]Specifically, this expanded price index extends the sample of mortgages financed by Fannie Mae and Freddie Mac which underlies existing FHFA prices indexes by also including transactions for homes financed with nonconforming mortgages which include 'jumbo' loans as well as homes purchased with cash. To the extent that home price trends for those types of properties differ from those for Enterprise-financed homes, the standard FHFA price index does not reflect those price patterns.

full technical details of my estimation procedure.[21]

My initial set of results is based on aggregate data where I simply run rolling regressions of an aggregate variable of interest on its own lags and current and lagged values of Gilchrist and Zakrajek (2012)'s EBP variable. After the aggregate analysis I turn to what much of the analysis in this paper centers on, which is exploiting cross-sectional variation in U.S. states' prime ARM shares within a panel fixed-effects regression framework. In particular, I estimate the impulse responses to the credit supply shock by projecting a variable of interest on its own lags and current and lagged values of Gilchrist and Zakrajek (2012)'s EBP variable, while allowing the estimates to vary according to being in a high, intermediate, and low prime ARM share state in a particular U.S. state and time.[22]

Econometric Specification: Aggregate Framework. For example, when I use the log of the aggregate, U.S. prime ARM default rate (y_t) as the dependent variable, the response of the default rate at horizon h is estimated from the following regression:[23]

$$y_{t+h} - y_{t-1} = \alpha_h + \Xi_h EBP_t + \Omega_h(L) EBP_{t-1} + \Gamma_h(L)\Delta y_{t-1} + v_{t+h}, \tag{7}$$

where t indexes time; α_h is the intercept; $\Omega(L)$ and $\Gamma(L)$ are lag polynomials; Ξ_h gives the response of the outcome variable at horizon h to a credit supply shock at time t, and therefore constitutes the coefficient of interest; and v_{t+h} is the residual.

Econometric Specification: U.S. States' Panel Fixed-Effects Framework. For example, when I use the log of U.S. state-level mortgage default rate ($z_{i,t}$) as the dependent variable, which is

[21] While classical estimation produced similar results to those from the baseline Bayesian procedure, I opted to use the latter as it facilitates inference when conducting an historical decomposition based on the estimated regressions in a much cleaner, more natural way.

[22] Since 'state' here constitutes an homonym, I will write 'U.S. state' when wanting to use it in its regional context while simply writing 'state' when using it in its conditional sense.

[23] All outcome variables are entered in cumulative differences and first-differences in the left- and right-hand sides of Equation (7) (as well as in Equation (8) that follows), respectively. This differencing procedure is important in removing any potential stochastic trends and making the data stationary, which is necessary for validating the local projections estimation and inference approach undertaken in this paper.

the main variable of interest in this paper, the response of the default rate at horizon h is estimated from the following non-linear fixed-effects panel regression:

$$\begin{aligned} z_{i,t+h} - z_{i,t-1} = I^{A}_{i,t-1}[\alpha_{A,i,h} + \Xi_{A,h} EBP_t + \Omega_{A,h}(L) EBP_{t-1} + \Gamma_{A,h}(L)\Delta y_{i,t-1}] + \\ + I^{B}_{i,t-1}[\alpha_{B,i,h} + \Xi_{B,h} EBP_t + \Omega_{B,h}(L) EBP_{t-1} + \Gamma_{B,h}(L)\Delta y_{i,t-1}] + \\ + I^{C}_{i,t-1}[\alpha_{C,i,h} + \Xi_{C,h} EBP_t + \Omega_{C,h}(L) EBP_{t-1} + \Gamma_{C,h}(L)\Delta y_{i,t-1}] + u_{i,t+h}, \end{aligned} \tag{8}$$

where i and t index U.S. states and time; $\alpha_{i,h}$ is the U.S. state fixed effect; $\Omega(L)$ and $\Gamma(L)$ are lag polynomials; Ξ_h gives the response of the outcome variable at horizon h to a credit supply shock at time t; $u_{i,t+h}$ is the residual; and, importantly, all the coefficients vary according to whether we are in state "A", i.e., corresponding to an observation that jointly belongs to an intermediate prime share state and to a high prime ARM share state; or state "B", i.e., corresponding to observations jointly belonging to an intermediate prime share state and an intermediate prime ARM share state; or state "C", i.e., corresponding to an observation that jointly belongs to an intermediate prime share state and to a low prime ARM share state.

Specifically, $I^{A}_{i,t}$ is a dummy variable that takes the value of one when its corresponding observation possess two properties: *i*) belonging to the interquartile range of the 51 U.S. states' prime share distribution (i.e., being above and below the 25th and 75th percentiles of this distribution, respectively, where prime share is the ratio of the number of prime mortgages outstanding to the total number of mortgages outstanding); and *ii*) having an ARM share (number of prime ARMs outstanding divided by the total number of mortgages outstanding) which is *at or above* the 75th percentile of the ARM share distribution of the 51 U.S. states, where the latter percentile choice is meant to embody a reasonably high threshold that facilitates identification. Correspondingly, $I^{B}_{i,t}$ is a dummy variable that takes the value of one when its corresponding observation belongs to the interquartile ranges of the prime share and prime ARM share distributions, while $I^{C}_{i,t}$ obtains one when its corresponding observation belongs to the interquartile range of the prime share distribution and has an ARM share which is *at or below* the 25th percentile of the ARM share distribution.[24] A total of 481, 1102, and 355 observations correspond to $I^A_{i,t}$, $I^B_{i,t}$, and $I^C_{i,t}$.

An important point to stress with regard to these state dummies is that, by only considering them in the context of being in an intermediate prime share state, I alleviate the concern that my results may pick up the credit quality channel emphasized by the literature in place of the prime ARM channel. Specifically, since I am looking for variation in ARM shares, I am bound to mechanically also pick up in the process variation in prime shares, which can be thought of as a reasonable proxy for credit quality. The correlation between prime shares and prime ARM shares is over 50%. This means that U.S. states with more prime ARM exposure are naturally also prone to having higher mortgage credit quality which in turn can bias my results. E.g., following a favorable credit supply shock, U.S. states with a lesser prime share and thus worse credit quality can suffer from higher default rates owing to the mere materialization of the aforementioned lower credit quality; but since these U.S. states are also likely to have a lower prime ARM share, their higher mortgage default rate can lead to inference that understates the role of the prime ARM channel. My effective removal of extreme observations corresponding to very high and low prime shares ensures that my identification is unlikely to be biased by the credit quality channel as I am comparing between U.S. states that are roughly similar along their credit quality dimension.

Identification. Lags of the outcome variable and EBP are included in the regressions to remove any predictable movements in EBP. This facilitates the identification of the unanticipated shock to EBP, which is what is sought after. I assign the value of the order of lag polynomials $\Omega(L)$ and $\Gamma(L)$ to 8, i.e., I allow for 8 lags of log-first-differences of the outcome variable and EBP in the regressions. My choice of specifying this somewhat large number of lags in the regressions is a conservative one and is rooted mainly in my desire to purge my state dummies of any endogenous variation resulting from past credit supply shocks or state-specific factors that go beyond the usual one year lag normally controlled for in empirical macro work. In Section 4 I examine the

[24]This way of constructing these dummy variables guarantees that they are perfectly complementary and thus estimation of the coefficients from Regression (8) is equivalent to separately estimating three regressions with each one only including observations that correspond to either $I^A_{i,t}$, $I^B_{i,t}$, or $I^C_{i,t}$.

robustness of the results to using different lag specifications.

The impulse responses to the credit supply shock for the three states at horizon h are simply $\Xi_{A,h}$, $\Xi_{B,h}$, and $\Xi_{C,h}$, respectively. (And Ξ_h from Equation (7) represents the impulse response in the aggregate, time series regression framework.) Note that a separate regression is estimated for each horizon. I will estimate a total of 20 regressions and collect the impulse responses from each estimated regression, allowing for an examination of the effects of credit supply shocks for the 5 years following the shock. I now turn to a discussion on the estimation and inference procedure used in this paper, with a focus on the panel setting from Equation (8); a similar discussion applies to the somewhat simpler time series setting from Equation (7), whose estimation can be viewed as a special case of that of Equation (8). (For the full technical details of this paper's estimation procedure the reader is referred to Appendix A).

The first element worth discussing in the context of inference is how the credit supply shock itself is identified. This is important because a central empirical object I look at within the panel analysis is historical decomposition, i.e., how did credit supply realizations occurring in the pre-crisis period contribute to the pre-crisis rise in mortgage default rates. To properly estimate this contribution I need to identify the associated credit supply shock realizations. Toward this end, I assume a simple AR specification for the EBP process, depicted by the following equation:

$$EBP_t = B_1 EBP_{t-1} + B_2 EBP_{t-2} + ... + B_p EBP_{t-p} + B_c + \epsilon_t, \tag{9}$$

where B_i are scalar coefficients; p denotes the number of lags, which I set to 8 in accordance with the lag specification choice from Equation (8); B_c is a constant; and $\epsilon_t \sim i.i.d.\ N(\mathbf{0}, \sigma_{cs}^2)$ is the credit supply shock where σ_{cs} is its standard deviation. For future reference, let the stacked $(p+1)$x1 $B = [B_1, ..., B_p, B_c]'$ matrix represent the coefficient matrix from Equation (9) such that B and σ_{cs} correspond to the parameters to be estimated from this equation.

I estimate Equation (9) jointly with Equation (8) by applying the Bayesian estimation algorithm for strong block-recursive structure put forward by Zha (1999) in the context of block-recursive VARs, where the likelihood function is broken into the different recursive blocks. In my case, I only have two blocks, where the first consists of Equation (9) and the second contains Equation (8). As shown in Zha (1999), this kind of block separation along with the standard assumption of a normal-inverse Wishart conjugate prior structure leads to a normal-inverse Wishart posterior distribution for the block-recursive Equation parameters. Specifically, considering that the number of RHS variables is 2 and number of U.S. states is 51, let the stacked $(1 + 2 \times p + 51)$x1 $Q_h^j = [\Xi_{j,h}, \Omega_{j,h}, \Gamma_{j,h}, \alpha_{j,1,h}, ..., \alpha_{j,51,h}]'$ matrix represent the coefficient matrix corresponding to each state in Equation (8), where j represents the state, i.e., $j = A, B, C$. Now simply denote the stacked-by-state matrix by $Q_h = [Q_h^A, Q_h^B, Q_h^C]$. Moreover, let σ_h represent the standard deviation of the residual from Equation (8) at each horizon h. Hence, the parameters to be estimated from Equation (8) can be summarized by the coefficient matrix Q_h and residual variance σ_h^2.[25]

I assume a diffuse normal-inverse Wishart prior distribution for both $[B, \sigma_{cs}]$ and $[Q_h, \sigma_h]$; this conjugate prior structure coupled with the assumption of a Gaussian likelihood for the data sample imply a posterior density of these parameters that is also distributed as a normal-inverse Wishart. Following the suggestion from Müller (2013) to increase estimation precision in the presence of a misspecified likelihood function (as in my setting owing to the spatial and temporal correlation in $u_{i,t+h}$), I apply a correction to σ_h based on Driscoll and Kraay (1998) which accounts for arbitrary spatial and temporal correlations of the error term.

Operationally, for each posterior draw of σ_{cs}, I estimate the state-dependent response of the outcome variable at horizon h to a one standard deviation credit supply shocks by computing $\Xi_{j,h} \times \sigma_{cs}$ for $j = A, B, C$, where $\Xi_{j,h}$ is the posterior draw of the state-specific coefficient on EBP_t in Equation (8). I generate 500 such posterior draws from which I am then able to estimate the median state-dependent impulse responses to credit supply shocks along with their posterior confidence bands. Importantly, I can also collect the credit supply shock realizations from Equation (9) by using the estimated coefficients and the actual data on EBP, in turn facilitating the historical decomposition analysis (to be presented on Page 29).

[25]Given that all three states are prefect complements, I can treat the estimation of Equation (8) as if I were estimating three separate models, each corresponding to observations only belonging to state j. While this facilitates the estimation in terms of easing the computational burden, it has no bearing on the validity of the general exposition outlined above.

3.3 Results

This section presents the main results of the paper. All impulse response are computed in response to a negative, one standard deviation credit supply shock so as to facilitate an interpretation of responses to a favorable credit supply shock.

3.3.1 Aggregate Variables

Before turning to the panel fixed-effects estimation results, I present in this section results from estimating Equation (7) for various aggregate variables whose responses serve both as motivational information as well as basic litmus tests for the existence of an ARM channel of monetary policy.

1-Year Treasury Rate. The first subfigure of Figure 4 presents the median response of the 1-year treasury rate to a favorable credit supply shock along with 68% posterior confidence bands. The regression underlying this figure is Equation (7), i.e., I run a time series regression where impulse responses are estimated via local projections of the 1-year treasury rate onto own lags and current and lagged EBP values. I begin my analysis with this variable so as to confirm the necessary condition for the existence of an ARM channel of monetary policy, i.e., that a commonly used ARM index such as the 1-year treasury rate significantly rises in response to a favorable credit supply shock. Specifically, if an ARM channel is truly in place, then we should be observing monetary policymakers raising rates following a favorable credit supply shock which, in turn, should lead to a rise in interest rates to which ARMs are indexed such as the 1-year treasury rate. As is clear from Figure 4, the 1-year treasury rate significantly rises for effectively all horizons, with its response peaking at 96 basis points after 3 years.

The significant and persistent increase in the 1-year treasury rate signifies the passing of a basic litmus test of the ARM channel of monetary policy, i.e., that contractionary monetary policy does take effect in response to a favorable credit supply shock setting in motion a rise in interest rates to which ARMs are commonly indexed. I next turn to an examination of the potential implications of this channel for aggregate mortgage default rates, broken down by borrower and product type.

Default Rates by Borrower and Product Type. Sub-figures 2-5 of Figure 4 depict the responses of aggregate mortgage default rates by borrower and product type: prime ARM, prime FRM, subprime ARM, and subprime FRM. The next 4 sub-figures (6-9) show the response differences for the following mortgage pairs: prime ARM-prime FRM, subprime ARM-subprime FRM, prime ARM-subprime ARM, and prime FRM-subprime FRM, where inference for response differences accounts for arbitrary correlations of the regressions' residuals both temporally and spatially.[26]

The findings from these 8 sub-figures can be summarized as follows. First, default rates on prime ARMs never drop in a significant way, beginning to significantly rise from the 10th quarter onwards with a peak rise at the last considered 5-year horizon of 43%. No other mortgage default rate experiences such a strong and persistent increase although all other three variables do exhibit some level of an increase in default rates a few years after the realization of the favorable credit supply shock. Comparing prime ARM default rates' responses to the corresponding responses of prime FRMs, it is clear that the former exhibit a significantly stronger relative rise for all horizons with the response difference reaching its peak of 23.7 percentage points at the last considered 5-year horizon. Second, there are no significant differences between subprime ARM default rates' responses and those of subprime FRMs. Lastly, prime ARM default rates seem to rise significantly more at long horizons than subprime ARM default rates (subfigure 8) while subprime FRM default rates fare significantly worse than prime FRM ones for 8 of the first 11 quarters following the shock.

Taken together, these findings are consistent with a relatively weak role for the subprime ARM channel in setting the stage for the recent financial crisis and a potentially strong corresponding role for the prime ARM channel. (The former result is consistent with micro-data based evidence from Mayer et al. (2009) and Demyanyk and Van Hemert (2009) which stresses a limited role for

[26] To account for potential correlations between the residuals of the different outcome variables' regressions, I apply a correction to the standard errors that is based on the panel, fixed-effects correction from Driscoll and Kraay (1998), which accounts for arbitrary spatial and temporal correlations of the error terms. In doing this I effectively treat the various outcome variables as cross-sectional units with heterogenous intercepts and slope coefficients.

the positive rate resets of the mid-2000s in driving the spike in subprime mortgages' default rates in the period leading up to the financial crisis.) Moreover, they stress that looking at aggregate data does not imply a clear, dominant role for the credit quality channel relative to the prime ARM channel. That said, aggregate data alone is incapable of identifying the role of the latter channel because it lacks the variation in ARM prevalence that is needed for this identification. I therefore now turn to a panel fixed-effects setting that is more capable of doing that.

3.3.2 Panel Fixed-Effects Analysis

The results of this section are based on the estimation of Equation (8) for several U.S. state-level variables, the central of which is the overall mortgage default rate. The centrality of this variable stems from the focal role of mortgage defaults in setting the stage for the recent financial crisis. The above aggregate evidence indicates that the *prime* ARM channel is likely to have played a more considerable role as root cause of the crisis than the *subprime* ARM channel. Moreover, in accordance with this aggregate evidence (also see discussion in Footnote 1), I found that estimation of Equation (8) when conditioning on the subprime ARM share state yields insufficiently robust results whose main takeaway is that the subprime ARM channel, while seeming to exist in the data, does not seem to have played an important role in setting the stage for the financial crisis. Hence, I proceed by only considering the prime ARM share as my state variable which, as will be made clear below, yields strong and robust results.

Overall Mortgage Default Rate. The first set of results from my panel fixed-effects analysis, shown in Figure 5, depicts mortgage default rate responses to a favorable credit supply shock in the non-linear model described in Specification (8). Specifically, the first three sub-figures depict the median impulse responses along with 68% posterior confidence bands for the high prime ARM share state, intermediate prime ARM share state, and low prime ARM share state, respectively; and the last two sub-figures show the response differences for the high-intermediate prime ARM share states and the high-low prime ARM share states.

The results from Figure 5 clearly indicate that being in a state of high prime ARM share significantly reduces the effects of credit supply shocks on mortgage default rates. The reduction is both economically and statistically significant, ultimately completely overturning the initially favorable response of default rates. E.g., after 4 years, default rates in the high prime ARM share state are higher by 13.9% in absolute terms and by 14.9 and 20.5 percentage points in relative terms compared to the intermediate and low prime ARM share states, respectively. The mortgage default rate in the low prime ARM share state significantly falls for all horizons following the favorable credit supply shock, with the strongest decline during this stretch taking place in the 8th quarter reaching -10.2%. By contrast, default rates rise in the high prime ARM share state starting from the 10th horizon after the shock, and significantly so from the 11th horizon onwards where the peak rise takes place after 19 quarters reaching 18.1%. Accordingly, apart from the 2nd quarter, the default rate never differentially falls significantly in the high prime ARM share state relative to the low one, while beginning to exhibit a significant differential rise from the 7th quarter onwards, reaching a peak differential response of 22.8 percentage points after 19 quarters.

Overall, the results from Figure 5 imply that being in a high prime ARM share state significantly dampens the effects of credit supply shocks on mortgage default rates, to the point where mortgage default rates actually rise very strongly from the 11th-quarter mark onwards. This first piece of evidence stresses a likely dominant prime ARM channel of monetary policy and offers support for the notion that favorable credit supply shocks in the mid-2000s credit boom period in the U.S. economy ultimately led to rising mortgage default rates which in turn set the stage for the subsequent financial crisis.

Default Rates by Borrower and Product Type. The results shown in Figure 5 pertain to the overall mortgage default rate. I now dissect this variable into 4 underlying subcomponents: prime ARM, prime FRM, subprime ARM, and subprime FRM default rates, whose associated responses appear in Figures 6a-7b, respectively. Such a breakdown of the behavior of mortgage default rates can be informative for understanding the extent of pervasiveness of the prime ARM channel in terms of its implications for these various default rate types.

Specifically, the overall default rate for each U.S. state can be written as a weighted average of these underlying 4 default rates, where the weights are the respective shares of each mortgage type in the overall mortgage market in the corresponding U.S. state. At it most basic level, the prime ARM channel implies that higher mortgage payments will ultimately have bigger effects on overall default rates in U.S. states in which ARMs are more prevalent. From a mechanical standpoint, for this to take place it is not merely sufficient for the subcomponent default rates to respond the same across U.S. states as there can also be offsetting effects from the lower prevalence of the other mortgage types; a sufficiently large differential rise in defaults in the subcomponent variables needs to take place, most predominantly in the prime ARM segment owing to its relatively larger weight but not necessarily limited to this segment. Such an across-the-board differential rise can occur, e.g., due to a contagion effect where all segments in the mortgage market of U.S. states with higher ARM shares suffer relatively higher default rates.

As is apparent from Figures 6a-7b, all 4 types of default rates exhibit a much stronger relative increase in the high prime ARM share state versus the low one, with prime ARMs and FRMs and subprime FRMs experiencing quantitatively stronger relative increases than subprime ARMs. If no spillovers across these different mortgage types existed, then we would not expect to see such a wide-reaching stronger relative increase in default rates in the high prime ARM share state. But, clearly, such spillovers are borne out by the data as the results indicate that all mortgage types exhibit stronger relative increases in the high prime ARM share state, with the stronger relative increase in prime ARMs becoming continuously significant earlier than the corresponding relative increases in the other default rate types (from the 3rd horizon onwards for prime ARMs compared to after 10, 12, and 16 quarters for prime FRMs, subrime ARMS, and subprime FRMs, respectively). These timing differences are crucial for the argument that there is causal spillover from the prime ARM segment of the mortgage market to the other segments. Notably, these results are broadly consistent with recent evidence from Gupta (2018) on foreclosure contagion where increased foreclosure owing to increased mortgage payments has a significant positive effect on neighboring houses' foreclosures due to lower house prices, reduced credit supply, and peer effects relating to information on defaults costs obtained from observing local defaults.

House Prices. Figure 8 depicts the state-dependent responses of house prices.[27] In the low prime ARM share state, house prices exhibit a rather standard hump-shaped response to the favorable credit supply shock, peaking after 11 quarters at 0.68%. By contrast, in the high prime ARM share state, house prices significantly rise for only one year, after which they embark on a persistent and significant decline that culminates after 19 quarters at -1.95%. Accordingly, response differences across the high and low prime ARM share states are significantly negative for most horizons. (Similar results obtain when comparing the intermediate prime ARM share state to the high one albeit to a lesser extent quantitatively.)

The results from Figure 8 emphasize a potentially important role for house prices in driving the pervasive relative increase in default rates in the high prime ARM share state across the mortgage borrower and product space observed from Figures 6a-7b. In particular, taken together, the results so far seem to suggest that U.S. states where prime ARMs were more prevalent exhibited both higher default rates' and lower house price responses conditional on a favorable credit supply shock, which were likely reinforcing one another.

Establishing the Narrative: An Historical Decomposition Analysis. The main objective of this paper is to examine the importance of the prime ARM channel of monetary policy in setting the stage for the financial crisis. More specifically, I am interested in the relevance of the narrative that systematic contractionary monetary policy of the mid-2000s in response to the favorable credit supply shocks of this period caused higher mortgage default rates which in turn set the stage for the crisis. To provide direct evidence for this narrative, however, one needs to go beyond what I have done so far in taking the extra step of showing that the credit supply realizations of the boom period produced sizable increases in default rates conditional on being in a high prime ARM share state.

[27] In estimating the state-dependent responses of house prices, I add U.S. state-specific time trends to Equation (8) as U.S. states' house prices were found to posses rather significant log-quadratic trends.

Toward this end, I generate a posterior distribution of credit supply shock realizations from the estimation of Equation (9) which I then bring together with the posterior distribution of state-dependent impulse responses estimated from Equation (8) to compute the posterior distribution of the contribution of credit supply shock realizations to the pre-crisis rise in default rates. To get an idea of how the actual credit supply shock realizations look in the data, I show in Figure 9 the time series of the median realizations of the credit supply shock series as estimated from Equation (9). As is apparent from this figure, realizations of this series became favorable rather continuously from roughly 2002:Q4 through 2007:Q1, averaging -0.4 standard deviations.

In line with the timing of the trough of the average of mortgage default rates across U.S. states and the timing of the focal point of the crisis (the Lehman shock), I compute the aforementioned contribution for the period 2006:Q2-2008:Q3. By having available state-dependent impulse responses, I can compute the evolution of mortgage default rates for each of the three considered prime ARM share states (i.e., high, intermediate, and low prime ARM share states) conditional on actual shock realizations.[28]

The three rows of Table 2 present the median and 16th and 84th percentiles of the posterior distribution of absolute and relative contribution of credit supply shocks to the movement in mortgage default rates in the 2006:Q2-2008:Q3 period, respectively, where the relative contribution is computed in relation to the average growth rate in default rates across U.S. states over this period. In particular, the results from the second column of Table 2 show how much of the average movement in default rates in the 2006:Q2-2008:Q3 period is accounted for (in percentage terms) by credit supply shocks, with the first column containing the numerator of the share from the second

[28] In the historical decomposition I consider shock realizations that go back to 2003:Q3, in line with my estimating Equation (8) for rolling regressions up to $h = 20$.

column.[29,30]

It is clear from Table 2 that credit supply shocks account for a very significant share of the pre-Lehman-shock rise in default rates in the high prime ARM share state. The median share in the 2006:Q2-2008:Q3 period explained by the credit supply shock is 58%, with the absolute contribution being 44.7%. The 16th percentile share explained by the credit supply shock for this period is also large at 47.7%. While being in the intermediate prime ARM share state results also in a significant contribution share of 10.3%, the low prime ARM share state produces a significantly negative median contribution share of -11.4%. Overall, the results from Table 2 deliver a rather strong message that being in a high prime ARM share state generated a dominant role for credit supply shocks in driving the pre-Lehman-shock rise in mortgage default rates, which is in line with a narrative that places the prime ARM channel of monetary policy on center stage in terms of its potential role as root cause of the crisis.

4 Robustness Checks

This section examines the robustness of the baseline results along six dimensions: experimenting with different lag specifications in Equation (8); removing from the sample the so called 'sand states'; controlling for leverage; removing from the sample the 11 U.S. states where mortgages are nonrecourse, i.e., the lender can seize the collateral but has no recourse to any other of the borrower's assets in case of default; conditioning on a pre-2007 sample; and specifying alternative

[29] The relative contribution is computed as $\frac{contribution\ of\ shock}{average\ percentage\ change\ in\ default\ rates\ in\ deviation\ from\ steady\ state\ growth}$, where the annual steady state growth rate for default rates is assumed to be 3.4%, which is the average growth rate in the sample period (averaged across U.S. states). The average increase in default rates across U.S. states relative to its steady state growth was 77.2% in the 2006:Q2-2008:Q3 period.

[30] An alternative way to compute the relative contribution of credit supply shocks is to consider the state-specific movement in default rates for the calculation in each state instead of looking uniformly at the average movement across U.S. states. The problem with this approach is that no observation in the sample belonged to the low prime ARM share state for the period 2006:Q2, thus making the corresponding calculation for this state vacuous. Notwithstanding my effective removal of high- and low-prime-share observations (which prevents my state dummies from covering the entire sample), that the low prime ARM share state receives no representation for the period 2006:Q2 sits well with the narrative of this paper as it stresses that the U.S. economy was experiencing relatively high prime ARM shares during the mid-2000s boom period.

prime ARM and prime share percentile thresholds for the construction of the state dummies from Equation (8). The outcome variable I consider is the overall mortgage default rate given its focal role in establishing the narrative studied in this paper.

4.1 Alternative Lag Specifications

I have included the relatively large number of 8 lags of mortgage default rates' growth rates and EBP values in my baseline specification so as to ensure that my identification is not contaminated by unobserved macro shocks and/or U.S. state-specific shocks taking place with potentially distant lags. Nevertheless, it is worthwhile to examine the robustness of the results to having less than 8 lags in the regressions. And for completeness it is also of value to consider the sensitivity of the results to having even more than 8 lags in the regressions.

Figures 10a-11c present the results from the different lag specifications I consider: 4, 5, 6, 7, 9, and 10 lags. The expository structure of each figure corresponds to that of Figure 5. Clearly, the main results of this paper are not sensitive to the number of lags considered in the regressions. Specifically, all considered lag specifications yield significantly stronger increases in default rates in the high prime ARM share state than in the low one from roughly the 2-year mark onwards, similarly to the baseline case.[31]

4.2 Excluding the 'Sand States'

One may argue that the inclusion in my analysis of the so called 'sand states' (Arizona, California, Florida, and Nevada), for which the 2000s boom-bust pattern in the housing marker was by far

[31] It is noteworthy that what is especially crucial for validating the proposed narrative of this paper is the differential behavior of default rates at relatively longer horizons, rather than short ones, owing to the timing of the realization of favorable credit supply shocks in the mid-2000s period and the somewhat delayed timing of the onset of the crisis. It is therefore not worrisome that default rates briefly fall by more at short horizons in the high prime ARM share state; these short horizon response differences are very small relative to those at longer horizons, thus not bearing any meaningful implications for the validity of this paper's narrative. This point is best illustrated by the historical decomposition results from Table 2, which clearly delineate how these longer horizon effects dominate in terms of their contribution to establishing this paper's narrative.

the most pronounced relative to the other U.S. states, is driving my results. If this were true, I could not make the case for a prime ARM channel based narrative for the financial crisis as my results would merely be the outcome of the special characteristics of these four states which in turn induced their severe, outlier housing boom-bust cycle in the 2000s. (E.g., recent work by Choi et al. (2016) argues that the extreme housing cycle experienced by the four sand states can be explained by an abnormally low supply of publicly traded firms headquartered there relative to total income, which in turn leads households there to be more likely to purchase investment homes nearby rather than stocks.)

More specifically, with relation to the story I am trying to put forward, one may raise the concern that the severe house price boom in these states increased both their ARM prevalence as well as their propensity to suffer from a deeper bust, implying that in such a case my results can not be based on a prime ARM channel. And, indeed, three of the four sand states (Arizona, Florida, and Nevada) belong to the high prime ARM share state in the relevant boom-bust period, making it all the more important to address the aforementioned concern and the more general argument about the potential bias resulting from including the sand states in my analysis.[32]

Toward this end, I re-estimate Equation (8) on a sample that excludes the four sand states, leaving me with a sample of 47 U.S. states. The results from this exercise appear in Figure 12, whose expository structure corresponds to that of Figure 5. It is apparent that the baseline results of this paper are robust to excluding the four sand states as the significantly stronger rise in default rates in the high prime ARM share state continues to hold. We can therefore deduce that the results of this paper are unlikely to be driven by the outlier severity of the housing boom-bust cycle experienced by these states.

[32]California, although also having very high prime ARM shares (the highest throughout most of the sample), does not belong to the high prime ARM share state due to my restriction of only considering observations belonging to the interquartile range distribution of prime shares (see discussion on Page 20), which effectively removes California from the sample because of is very high prime share. However, as discussed on Page 37 and associated Footnote 36, alleviating and even removing altogether this restriction has no meaningful bearing on the results, implying also that excluding or including California in the analysis has no such bearing.

4.3 Controlling for Leverage

One potential propagation mechanism that may bias my interpretation of the results is that based on total household leverage. In particular, standard models with financial frictions (e.g., Bernanke et al. (1999)) emphasize borrowers' higher leverage as a shock amplifier. It is therefore of value to alleviate the concern that part of what I am attributing to a prime ARM channel is actually related to a leverage based mechanism.

To alleviate this concern, I proceed in two steps. First, constructing a U.S. state-level leverage variable defined as the ratio of U.S. state-level total household debt data (available from the New York Fed Consumer Credit Panel from 2003 onwards) to U.S. state-level personal income,[33] I compute the correlation between my high prime ARM share state dummy and a leverage-based dummy variable that obtains 1 when leverage is at or above the 75th percentile of U.S. states' leverage distribution. This correlation stands at a negligible -0.7%, suggesting an effectively null relation between having high leverage and being in a high prime ARM share state. The correlations between the high leverage dummy and the intermediate and low prime ARM share state dummies stand at -2.2% and -15.6%, respectively, indicating that only the impulse responses in the low prime ARM share state may be affected by a leverage-based propagation mechanism, albeit to a fairly limited extent that is very unlikely to undermine the interpretation of this paper's results.

Second, complementing the above unconditional evidence, I provide conditional evidence based on re-estimating Equation (8) while imposing on my 3 prime ARM share state dummies to obtain 0 if an observation does not belong to the interquartile range of U.S. states' leverage distribution.[34] This additional restriction imposed on these dummy state variables removes high- and

[33] Household debt data is annual whereas personal income data (downloaded from FRED) is in quarterly frequency. To obtain a quarterly frequency for the leverage variable, I assume identical debt values within the year and divide the resulting quarterly debt series by the personal income series.

[34] My assuming identical debt values within the year (see previous footnote) can potentially generate a bias-inducing correlation between the state dummies and the residual from Equation (8) or EBP_t itself. Any shock, be it an EBP shock or some unobserved shock contained in the latter residual, that potentially moves leverage from being in an intermediate state to some extreme (high or low) state has the capacity to also move the one-quarter-lagged state dummy given that this dummy is now based on the assumption of with-the-year identical leverage values. E.g., a value of 0 for this dummy in the first quarter of a particular year necessarily implies a 0 value for the end quarter of that year as well. To prevent this potential bias-inducing correlation, I insert the state dummies in Equation (8) with four lags instead of one lag.

low-leverage observations from the estimation, thus purging the results of any potential leverage based effects owing to only keeping observations with roughly similar leverage levels. The results from this exercise appear in Figure 13, whose expository structure corresponds to that of Figure 5. It is clear that the baseline results of this paper are robust to controlling for leverage in the estimation, as results are both quantitatively as well as qualitatively similar to the baseline case. We can therefore deduce that the results of this paper are unlikely to be driven by a leverage-based mechanism.

4.4 Considering Only Recourse U.S. States

One can reasonably argue that my not controlling for heterogeneity in U.S. states' recourse versus nonrecourse nature of mortgages may bias my results. E.g., if being in a high prime ARM share state is positively correlated with having nonrecourse mortgages, then my results could be partly picking up the stronger likelihood of borrowers of nonrecourse mortgages to default rather than a pure prime ARM channel.

In similar spirit to the previous section's approach, I proceed in two steps to alleviate this concern. First, building on the U.S. state recourse classification from Ghent and Kudlyak (2011), I compute the correlation between my high prime ARM share state dummy and a U.S. state nonrecourse dummy variable that is based on the classification of Ghent and Kudlyak (2011)'s classification of 11 U.S. states as having nonrecourse mortgages. This correlation stands at a negligible 4.8%; the correlations between the nonrecourse U.S. state dummy and the intermediate and low prime ARM share state dummies are also very low at 1% and -5.5%, respectively. Overall, this unconditional evidence indicates that it is unlikely that the recourse versus nonrecourse nature of mortgages play a meaningful role in driving this paper's results.

Second, complementing the above unconditional evidence, I provide conditional evidence based on re-estimating Equation (8) on a sample that only includes the 40 recourse U.S. states as identified as such in Ghent and Kudlyak (2011). The results from this exercise appear in Figure 14, whose expository structure corresponds to that of Figure 5. It is clear that the baseline results of this paper are robust to excluding the 11 nonrecourse U.S. states as the significantly stronger rise in default rates in the high prime ARM share state continues to hold. We can therefore deduce that the results of this paper are unlikely to be driven by the nature of nonrecourse versus recourse mortgage structure prevalent in U.S. states mortgage markets.

4.5 Conditioning on a Pre-2007 Sample

Given the importance and magnitude of credit supply shocks in the recent financial crisis, there is obvious merit in using a sample that includes observations related to the financial crisis period and its aftermath for proper identification of the state-dependent effects of credit supply shocks. Nevertheless, one may still argue that it is worthwhile confirming that the results of this paper are robust to not conditioning on these observations when running my estimation. Such an argument can be based on two reasons. The first is my intention to search for a potential root cause of the financial crisis which naturally had to originate prior to the onset of the financial crisis. And the second is the potential structural difference between the pre-crisis period and the period covering the financial crisis period and its aftermath (e.g., zero lower bound related difference) which makes it potentially important to distinguish between these periods when trying to identify the effects of credit supply shocks. These two reasons highlight the potential concern that my results may be driven by the inclusion of observations related to the financial crisis period and its aftermath.

To alleviate this concern, I have re-run my estimation conditioning only on pre-2007 observations by restricting my prime ARM share state dummies to obtain 0 after 2006:Q4. Such a truncation is consistent with the timing of the ending of the mid-2000s favorable credit supply shock realizations (see Figure 9), which takes place in 2007:Q1.[35] The results from this exercise

[35] In 2007:Q1 there is still a very favorable -0.85 standard deviation credit supply shock, after which credit supply shock realizations become mostly positive through 2008. My conditioning on only pre-2007 observations through the restriction that the prime ARM share state dummies obtain 0 after 2006:Q4 implies that I only include in my estimation credit supply shock realizations through 2007:Q1 (given the lagged appearance of these dummies in Equation (8)), thus being consistent with truncating the identification at the approximate ending of the mid-2000s credit supply driven boom period.

are shown in Figure 15, whose expository structure corresponds to that of Figure 5. It is apparent that the baseline results of this paper are robust to conditioning only on a pre-2007 sample as the significantly stronger rise in default rates in the high prime ARM share state continues to hold. We can therefore deduce that the results of this paper are unlikely to be driven by the inclusion of the financial crisis period and its associated large adverse credit supply shock realizations.

4.6 Alternative Prime ARM and Prime Share Percentiles

As explained on Page 20, my construction of the prime ARM share state dummies is based on both percentile cut-off values for the prime ARM share distribution as well as percentile cut-off values for the prime share distribution. Specifically, the baseline high (intermediate,low) prime ARM share state dummy obtains 1 if it corresponds to an observation whose ARM share value belongs to the upper quartile (interquartile,lower quartile) range of the distribution of prime ARM shares and whose prime share value belongs to the interquartile range of the prime share distribution. I now examine the robustness of the results to altering these percentile thresholds.

Prime ARM Share Percentiles. I begin by keeping constant the choice of interquartile range of the prime share distribution while experimenting with the following alternative prime ARM share percentile cut-offs for the high, intermediate, and low prime ARM share states: 85th, 85th-15th range, and 15th; 65th, 65th-35th range, and 35th; and 55th, 55th-45th range, and 45th. The results from these alternative thresholds appear in Figures 16a-16c, whose expository structure corresponds to that of Figure 5. The results clearly indicate that the main finding of the significantly stronger rise in default rates in the high prime ARM share state relative to the low one continues to hold also for the considered alternative ARM share percentile thresholds.

Prime Share Percentiles. I now turn to keeping constant the choice of upper and lower quartile thresholds for the prime ARM share distribution while experimenting with the following alternative prime share range choices: 95th-5th range;[36] 85th-15th range; and 65th-35th range. The results from these alternative range choices appear in Figures 17a-17c, whose expository structure corresponds to that of Figure 5. The results clearly indicate that the main finding of the significantly stronger rise in default rates in the high prime ARM share state relative to the low one continues to hold also for the considered alternative prime share range choices.

5 Discussion

The crux of this paper's narrative is that the upward ARM resets of the mid-2000s boom period ultimately drove up mortgage default rates and set the stage for the financial crisis. However, researchers studying the causes of the mortgage crisis have usually assigned a small role for these upward resets in driving the crisis. The headline result supporting this conclusion is the fact reported by Foote et al. (2012) that only 12% of the mortgages that defaulted in 2007-2010 experienced an increase in their payment relative to their original payment before first becoming delinquent.

As explained in Fuster and Willen (2017), looking at just the incidence of such defaults can be misleading for understanding the role of the ARM indexation mechanism for two reasons. First, borrowers with ARMs have a strong tendency to refinance prior to the upward rate reset, in which case they would be removed from the pool of ARMs (likely joining the pool of FRMs, artificially driving up FRM default rates in case they end up defaulting) and thus lead to a fall in ARM default rates that counteracts the rise in default rates arising from the actual reset. Fuster and Willen (2017) demonstrate for a particular 2005:Q1 subprime ARM cohort that these two opposing forces can completely offset one another. While it is true that this refinancing mechanism is likely to be absent in an environment of falling house prices, a significant such decline in prices only began in 2007:Q2 thus making the refinancing mechanism relevant for prime ARMs during the

[36]Results are similar when the 100th-0th percentiles range is used, i.e., when the prime ARM share state dummies are constructed without imposing any restrictions on them to correspond to any range of the prime share distribution.

boom period and even possibly the interim period between the ending of the boom period and the beginning of the housing price decline cycle (i.e., 2006:Q2-2007:Q2).[37]

Second, ARM borrowers that have defaulted prior to the actual upward resets may have done so because of anticipation effects. While it is hard to identify these anticipation effects for upward resets due to the above-mentioned issue of refinancing, Fuster and Willen (2017) do report significant anticipation effects of future *downward* resets (which do not suffer from the refinancing issue) on default hazards. Building on the results from Figure 8, which suggest that being in a high prime ARM share state ultimately led house prices to significantly decline in response to the favorable credit supply shocks of the mid-2000s boom period, it is possible to argue for amplified anticipation effects of future upward resets on prime ARM borrowers in the period coinciding with an already declining house price environment (from roughly mid-2007). The reasoning for this argument is based on the notion that these borrowers, now finding it much more difficult to refinance out of their prime ARMs, perceive default to be a more viable option when facing future upward resets.[38]

Taken together with the results of this paper, these two reasons imply that the above-mentioned 12% number from Foote et al. (2012) need not undermine the validity of this paper's narrative but rather highlight the need for a broader interpretation of this paper's results along two dimensions.

[37]According to Freddie Mac's historical data (covering 1990-2012) on the distribution of loan products (included in Freddie Mac's portfolio) that borrowers chose when they refinanced their existing first-lien mortgage, an average of 93% of borrowers of ARM products opt to transition to an FRM product when refinancing, with the remaining share opting to stay in the same product category (or some other form of ARM relative to their original ARM type) or a Balloon-type product. I.e., conditional on refinancing, an ARM borrower is very likely to switch to an FRM. Moreover, the refinance share from MBA, i.e., the ratio of mortgage origination (in dollars) for refinancing purposes to total mortgage origination, does not exhibit a noticeable fall during the housing bust period although mortgage origination for refinancing purposes does begin to fall considerably in absolute terms from 2007:Q3 onwards. Taken together, these two facts from MBA and Freddi Mac data largely support the notion of a mid-2000s (going up to roughly the middle of 2007) refinancing channel by which prime ARM borrowers opted to switch to FRMs prior to upward rate resets.

[38]As documented in the previous footnote, MBA data indicate that mortgage origination for refinancing purposes only began to fall significantly in absolute terms from 2007:Q3 onwards as total mortgage origination also began to contract significantly. This is largely consistent (timing wise) with the beginning of the bust cycle in house prices and thus lends credence to the view that anticipation effects of future upward rate resets on prime ARM default rates were likely starting to amplify when this bust cycle began to take course.

First, they should be interpreted as encompassing the effects of both actual upward resets as well as anticipated ones, while keeping in mind that a potentially non-negligible share of defaulting FRMs may have actually originated from ARMs that have switched to FRMs prior to the upward resets and that the larger the extent of this switching mechanism the stronger the underestimation of an ARM channel from any analysis that uses data on mortgages rather than borrowers (with this caveat applicable to both my analysis as well as that of Foote et al. (2012)). And second, they should be looked at through the lens of the empirical results from Gupta (2018) on foreclosure contagion where increased foreclosure owing to increased mortgage payments has a significant positive effect on neighboring houses' foreclosures due to lower house prices, reduced credit supply, and peer effects relating to information on defaults costs obtained from observing local defaults. Such spillover effects, in addition to the aforementioned issues of anticipation effects and ARM-FRM pre-upward-reset switching mechanism, can further help explain the significance of the prime ARM channel for setting the stage for the financial crisis as indicated by the results of this paper and as co-existing with the 12% number from Foote et al. (2012).

6 Conclusion

Understanding the root cause of the recent financial crisis is of great value, both from an intellectual curiosity standpoint as well as from a policymaking standpoint. Motivated by the theoretical prediction that the ARM indexation mechanism can be detrimental for mortgage default rates following increases in the risk-free rate, this paper has put forward empirical evidence that supports the narrative that a prime ARM channel of monetary policy played an important role in setting the stage for the crisis. The story coming out of my empirical analysis is that favorable credit supply shock realizations taking place in the mid-2000s boom period induced contractionary monetary policy, which in turn significantly raised default rates on prime ARMs (as well as on other mortgage types through spillover effects) in the period leading up to the financial crisis. Since prime ARMs were quite prevalent during this period, and given that the financial crisis was ultimately triggered by a mortgage default crisis, it is reasonable to argue that this mechanism is a good candidate for being one of the main root causes of the crisis.

The policy implications of the empirical results of this paper are twofold. First, they highlight a somewhat overlooked (at least by academic research) potential root cause of the financial crisis which stresses the importance of both the borrower (prime) and the product (ARM) space of mortgages, not just shifting focus to a prime-borrower-based explanation for the crisis but also emphasizing the crucial role that ARMs play in this context. Second, they suggest that policymakers need not consider the role of systematic monetary policy in linear terms alone, but rather think about this role in broader terms that embody possible non-linear features. The non-linearity of systematic monetary policy advanced in this paper is based on the way by which the initial state of the economy can possibly alter the shock-absorbing capacity of monetary policy owing to the state-dependent behavior of mortgage default rates.

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Appendix A Posterior Distribution of Parameters

Since the Bayesian estimation of Equation (7) can be thought of as a special (and simpler) case of that of Equation (8), I only present here the latter for expositional purposes. Drawing on the notation from Section 3.2, let the set of the parameters (coefficients matrix and residual standard deviation) to be estimated from Equation (8) be given by Q_h and σ_h. Equation (8) can then be written in companion form as follows:

$$Y_{i,h} = X_{i,h}Q_{i,h} + U_{i,h} \tag{10}$$

where i indexes U.S. states, with $i = 1, ..., 51$; h is the regression's rolling horizon with $h = 1, ..., 20$, p is the number of lags; $Y_{i,h} = [y_{i,p+h} - y_{i,p-1}, y_{i,p+h+1} - y_{i,p}, ..., y_{i,T} - y_{i,T-h-1}]'$, with T being the time dimension of the sample; $X_{i,h} = [X_{i,1}, ..., X_{i,T-h}]'$, with $X_{i,t} = \Big[\Big[I^A_{i,t} \times [EBP_t, ..., EBP_{t-p}, \Delta y_{i,t-1}, ..., \Delta y_{i,t-p}, 1]\Big],$ $\Big[I^B_{i,t} \times [EBP_t, ..., EBP_{t-p}, \Delta y_{i,t-1}, ..., \Delta y_{i,t-p}, 1]\Big], \Big[I^C_{i,t} \times [EBP_t, ..., EBP_{t-p}, \Delta y_{i,t-1}, ..., \Delta y_{i,t-p}, 1]\Big]\Big]'$; $Q_h =$ $[\Xi_{A,h}, \Omega_{A,h}, \Gamma_{A,h}, \alpha_{A,1,h}, ..., \alpha_{A,51,h}, \Xi_{B,h}, \Omega_{B,h}, \Gamma_{B,h}, \alpha_{B,1,h}, ..., \alpha_{B,51,h}, \Xi_{C,h}, \Omega_{C,h}, \Gamma_{C,h}, \alpha_{C,1,h}, ..., \alpha_{C,51,h}]'$; and $U_{i,h} = [u_{i,p-1+h}, ..., u_T]'$. Q_h here represents the coefficient matrix of Equation (8) and σ^2_h is the variance of $u_{i,t+h}$.

I assume the following normal-inverse Wishart prior distribution for these parameters:

$$vec(Q_h) \mid \sigma^2_h \sim N(vec(\bar{Q}_{0,h}), \sigma^2_h \times N_0^{-1}), \tag{11}$$

$$\sigma^2_h \sim IW_k(v_0 S_{0,h}, v_0), \tag{12}$$

where N_0 is a $3(1 + 2p + 51)$ x $3(1 + 2p + 51)$ positive definite matrix; S_0 is a variance scalar; and $v_o > 0$. As shown by Uhlig (1994), the latter prior implies the following posterior distribution:

$$vec(Q_h) \mid \sigma^2_h \sim N(vec(\bar{Q}_h), \sigma_h \times N_h^{-1}), \tag{13}$$

$$\sigma^2_h \sim IW_k(v_h S_h, v_h), \tag{14}$$

where $v_h = 51 \times (T-h) + v_0$; $N_h = N_0 + \sum_i X'_{i,h} X_{i,h}$; $\bar{Q}_h = N_h^{-1}(N_0 \bar{Q}_{0,h} + \sum_i X'_{i,h} X_{i,h} \hat{Q}_h)$; $S_h = \frac{v_0}{v} S_{0,h} + \frac{51\times(T-h+1)}{v_h} \hat{\sigma}_h^2 + \frac{1}{v_h}(\hat{Q}_h - \bar{Q}_{0,h})' N_0 N_h^{-1} \sum_i X'_{i,h} X_{i,h} (\hat{Q}_h - \bar{Q}_{0,h})$, where $\hat{Q}_h = \left(\sum_i X'_{i,h} X_{i,h}\right)^{-1} \left(\sum_i X_{i,h}\right)' Y$ and $\hat{\sigma}_h^2 = \sum_i (Y_{i,h} - X_{i,h}\hat{Q}_h)'(Y_{i,h} - X_{i,h}\hat{Q}_h)/(51 \times (T-h)$.

I use a weak prior, i.e., $v_0 = 0$, $N_0 = 0$, and arbitrary $S_{0,h}$ and $\bar{Q}_{0,h}$. This implies that the prior distribution is proportional to σ_h^2 and that $v_h = 51 \times (T-h)$, $S_h = \hat{\sigma}_h^2$, $\bar{Q}_h = \hat{Q}_h$, and $N_h = \sum_i X'_{i,h} X_{i,h}$. Due to the spatial and temporal correlations of the error term $u_{i,t+h}$, the likelihood function is misspecified which in turn requires that the residual variance estimate $\hat{\sigma}_h^2$ be appropriately modified so as to improve estimation precision (Müller (2013)). Toward this end, I apply a correction to $\hat{\sigma}_h^2$ based on Driscoll and Kraay (1998) which accounts for arbitrary spatial and temporal correlations of the error term and denote the corrected variance estimate by $\hat{\sigma}_{hac,h}^2$.

We are now in position to lay out the posterior simulator for Q_h and σ_h^2, which can be described as follows:

1. Draw σ_h from an $IW_k(51 \times (T-h+1)\hat{\sigma}_{hac,h}^2, 51 \times (T-h+1))$ distribution.

2. Draw Q_h from the conditional distribution $MN(\hat{Q}_h, \sigma_h^2 \times \sum_i (X'_{i,h} X_{i,h})^{-1})$.

3. Repeat steps 1 and 2 a large number of times and collect the drawn Q_h's and σ_h^2's.

Table 1: **Model Parameterization**.

Parameter	Description	Value
α	Housing Stock Share	0.35
δ	Depreciation Rate	0.025
υ	Homeowners' Survival Rate	0.969
μ	Monitoring Cost	0.08
σ	S.D. of Idiosyncratic Productivity	0.13
ρ	Risk-Free Rate Shock Persistence	0.8
$\bar{r}$	Steady State Risk-Free Rate	0.01

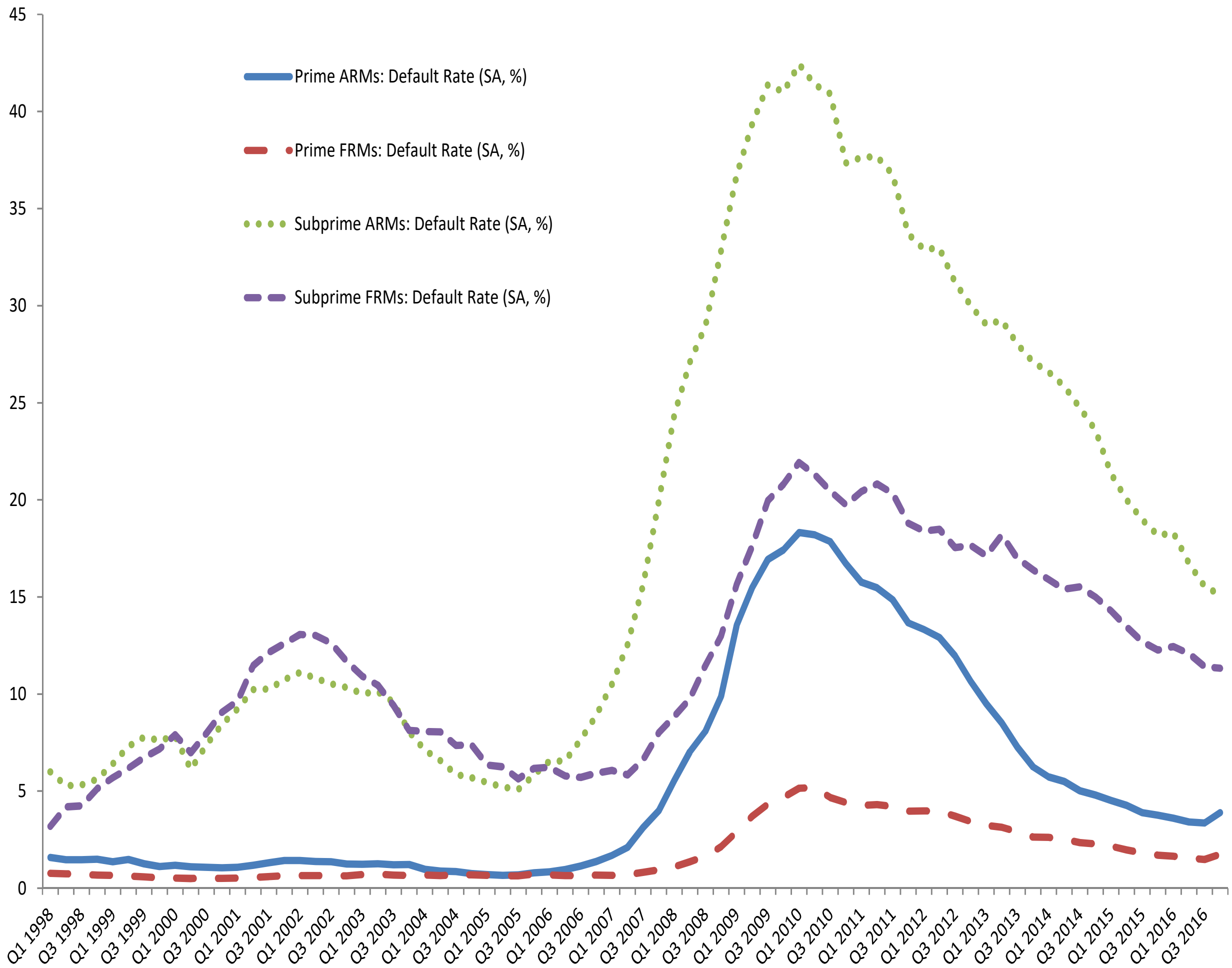
Notes: This table consists of the parameters' values used for the model of Section 2.

Table 2: **State-Dependent Contribution of Credit Supply Shocks to the Pre-Lehman-Shock Rise in Mortgage Default Rates.**

	Absolute Contribution	Relative Contribution
High Prime ARM Share State	44.7% [36.8%,54.6%]	58% [47.7%,70.8%]
Intermediate Prime ARM Share State	7.9% [4%,12%]	10.3% [5.2%,15.5%]
Low Prime ARM Share State	-8.8% [-13.5%,-4.1%]	-11.4% [-17.6%,-5.3%]

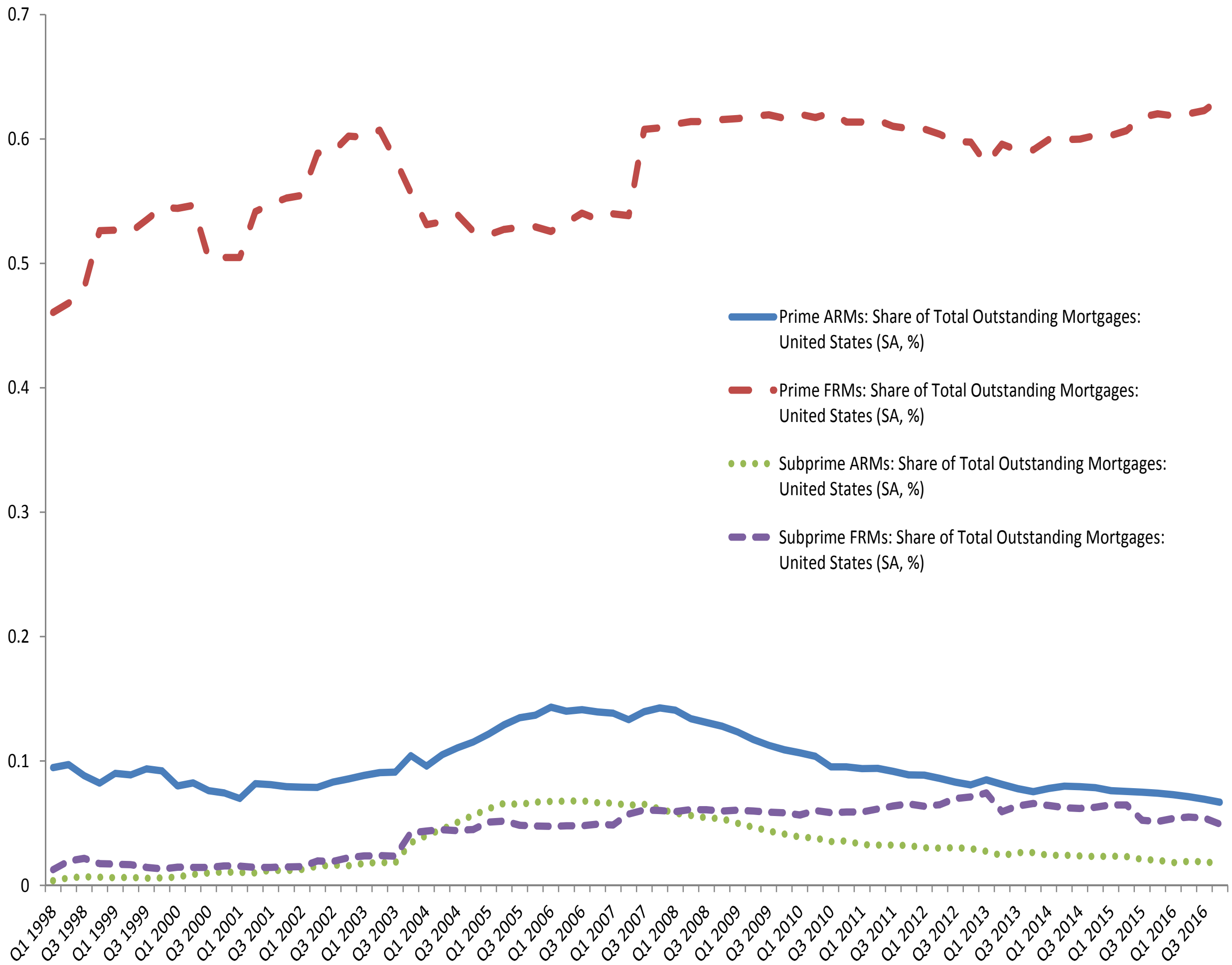
Notes: This table presents the median and 16th and 84th percentiles of the contribution (in %) of the credit supply shock to the change in mortgage default rates in the 2006:Q2-2008:Q3 period, both in absolute terms as well as in relative terms. The latter relative contribution is computed as $\frac{contribution\ of\ shock}{percentage\ change\ in\ default\ rates\ in\ deviation\ from\ steady\ state\ growth}$, where the annual steady state growth rates for default rates is assumed to be 3.4%, which is the sample-average growth rate (averaged across U.S. states). The absolute contribution from the first column of the table is simply the numerator of the above fraction.

Figure 1: **Time Series of Mortgage Default Rates by Borrower and Product Type.**



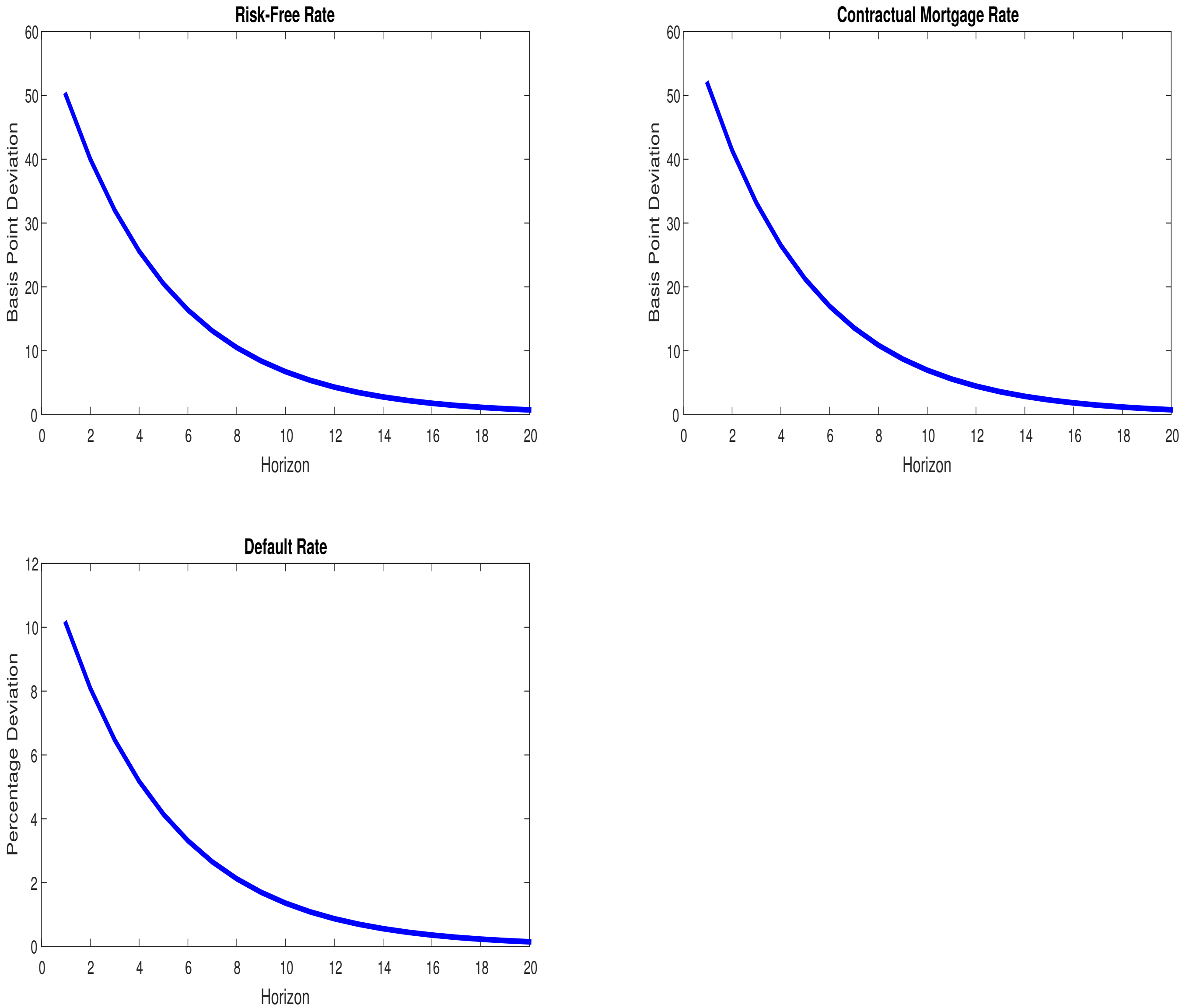
Notes: This figure presents the time series of the seasonally adjusted shares of mortgages out of total outstanding mortgages whose payments are overdue by at least 90 days or in foreclosure process for the following 4 mortgage categories: prime ARM (solid line), prime FRM (dashed line), subprime ARM (round-dotted line), and subprime FRM (square-dotted line). Data are from the Mortgage Bankers Association (MBA) and cover 1998:Q1-2016Q4.

Figure 2: **Time Series of Mortgage Market Shares by Borrower and Product Type.**



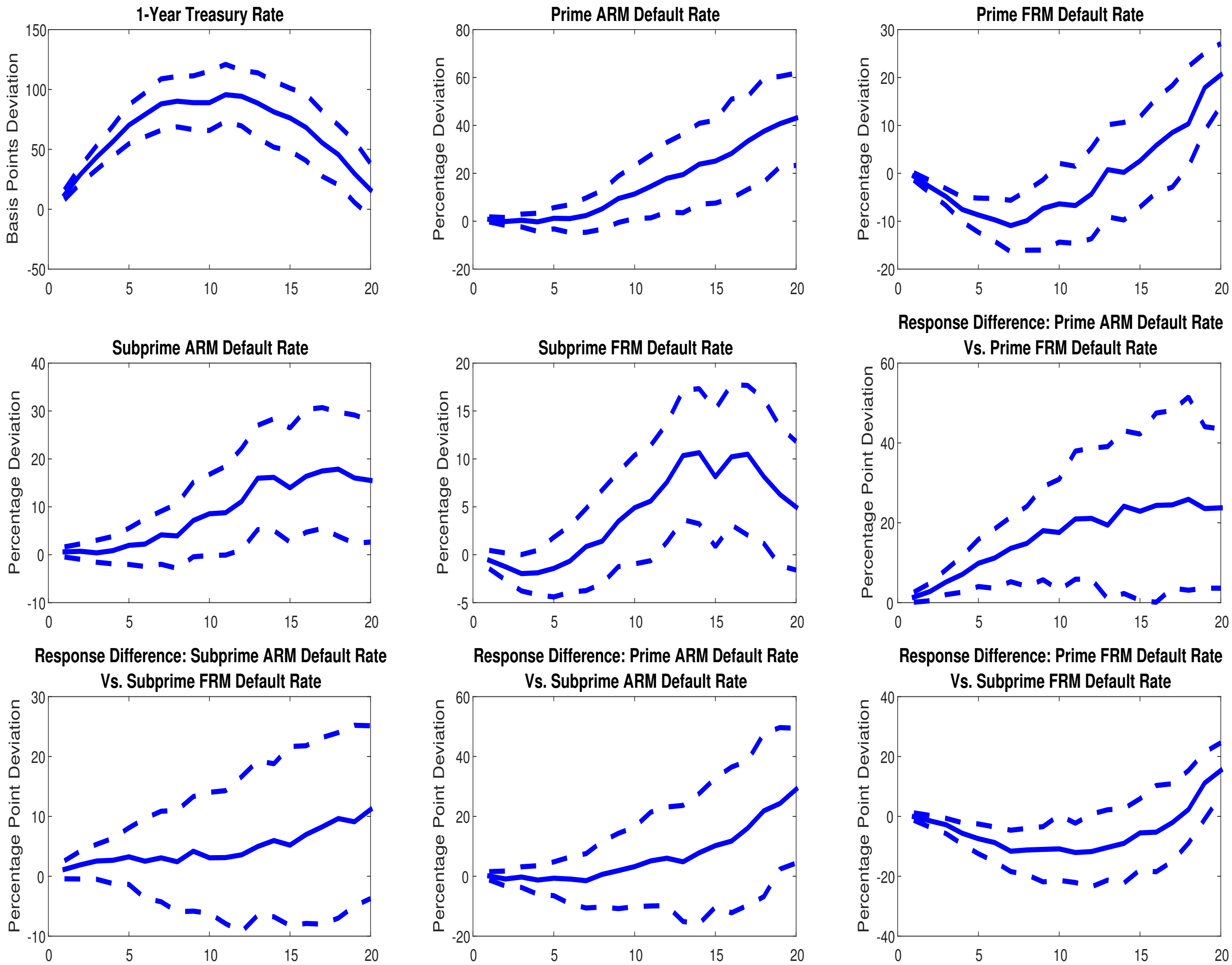
Notes: This figure presents the time series of the seasonally adjusted shares of mortgages out of total outstanding mortgages for the following 4 mortgage categories: prime ARM (solid line), prime FRM (dashed line), subprime ARM (round-dotted line), and subprime FRM (square-dotted line). Data are from the Mortgage Bankers Association (MBA) and cover 1998:Q1-2016Q4.

Figure 3: **Impulse Responses to a 50 Basis-Point Risk-Free Rate Shock**.



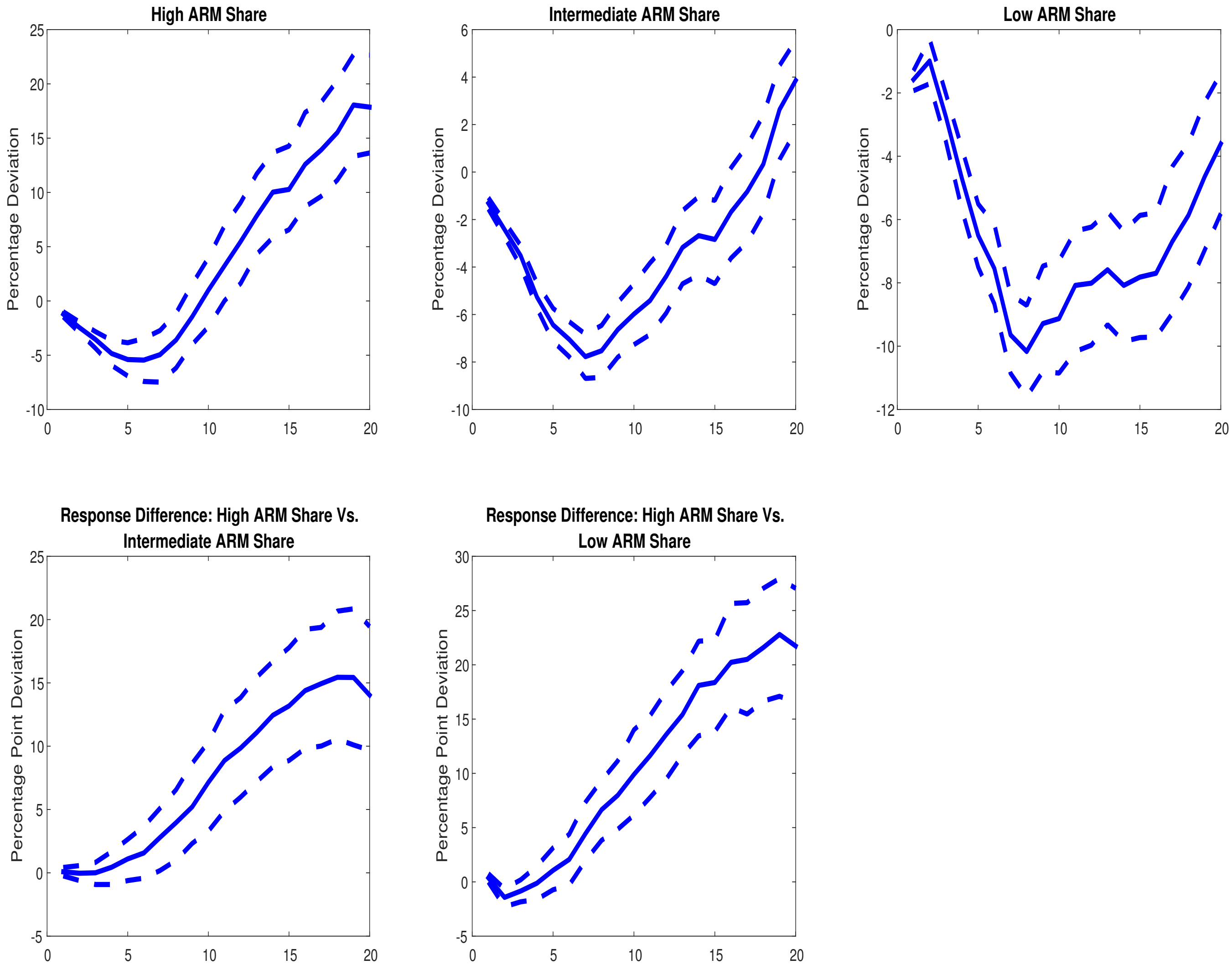
Notes: This figure presents the impulse responses to a 50 basis-point risk-free rate shock from the model presented in Section 2. The responses are shown in terms of deviations from steady state values (basis point deviation for the risk-free and contractual mortgage rates and percentage deviation for the default rate). Horizon is in quarters.

Figure 4: **Effects of Credit Supply Shocks on 1-Year Treasury Rate and Mortgage Default Rates by Borrower and Product Type**.



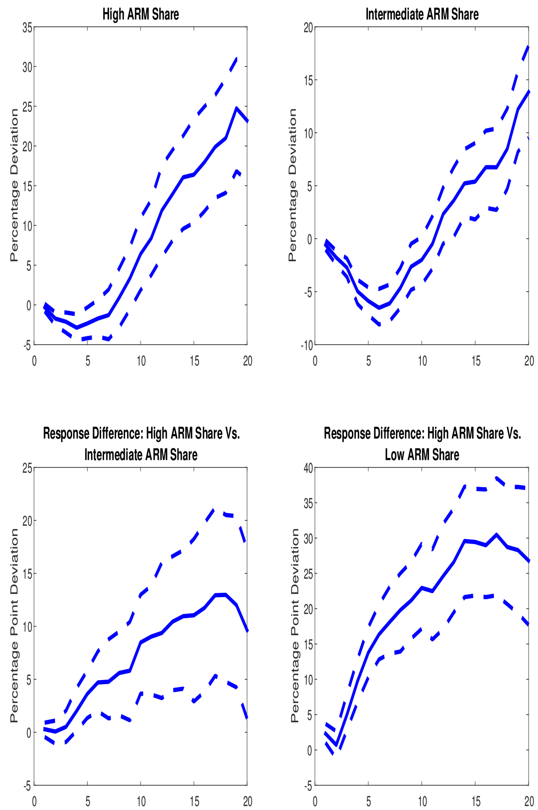
Notes: This figure presents the impulse responses of the 1-year treasury rate and aggregate, U.S. mortgage default rates by borrower and product type (prime ARM, prime FRM, subprime ARM, and subprime FRM) to a one standard deviation credit supply shock. The results are based on estimation of Equation (7); the last 4 sub-figures of the figure show the response difference between default rates on prime ARMs and prime FRMs, subprime ARMs and subprime FRMs, prime ARMs and subprime ARMs, and prime FRMs and subprime FRMs. Solid lines show the median responses while dashed lines represent 68% posterior confidence bands of impulse responses. The responses are shown in terms of deviations from pre-shock values (in basis points deviation for the treasury rate and percentage deviation for the default rate variables). Horizon (on the x-axis) is in quarters.

Figure 5: **State-Dependent Effects of Credit Supply Shocks on Mortgage Default Rates**.

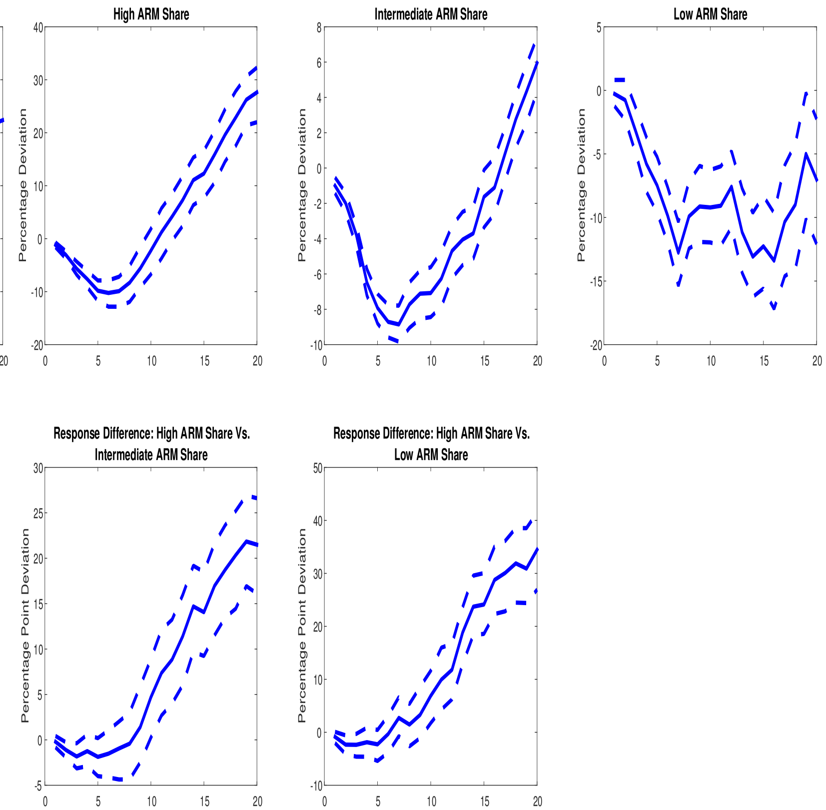


Notes: This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8). The first three sub-figures present the median impulse responses along with 68% posterior confidence bands for the three considered states: high prime ARM share, intermediate prime ARM share, and low prime ARM share. The last two sub-figures show the median response differences along with 68% posterior confidence bands for the high-intermediate prime ARM pair and the high-low prime ARM pair. The responses are shown in terms of percentage deviations from pre-shock values. Horizon (on the x-axis) is in quarters.

Figure 6: **State-Dependent Effects of Credit Supply Shocks: (a) Prime ARM Default Rates; (b) Prime FRM Default Rates**.



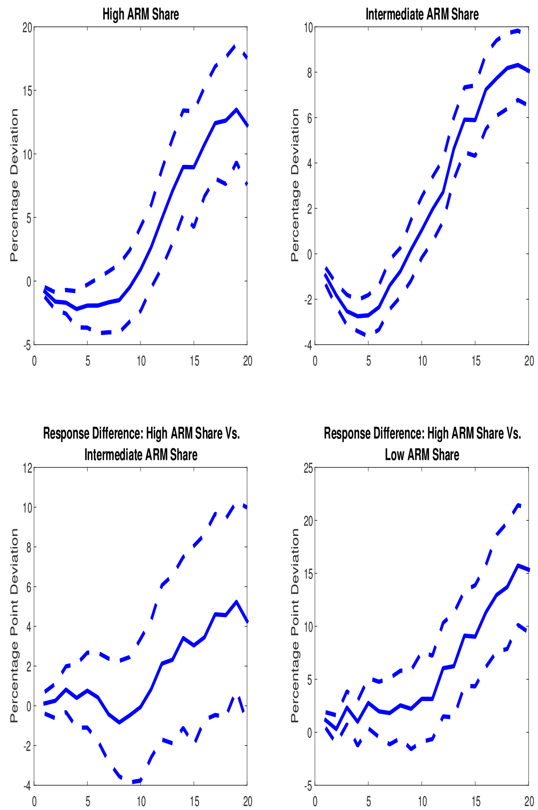
(a) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (Prime ARM Default Rates).



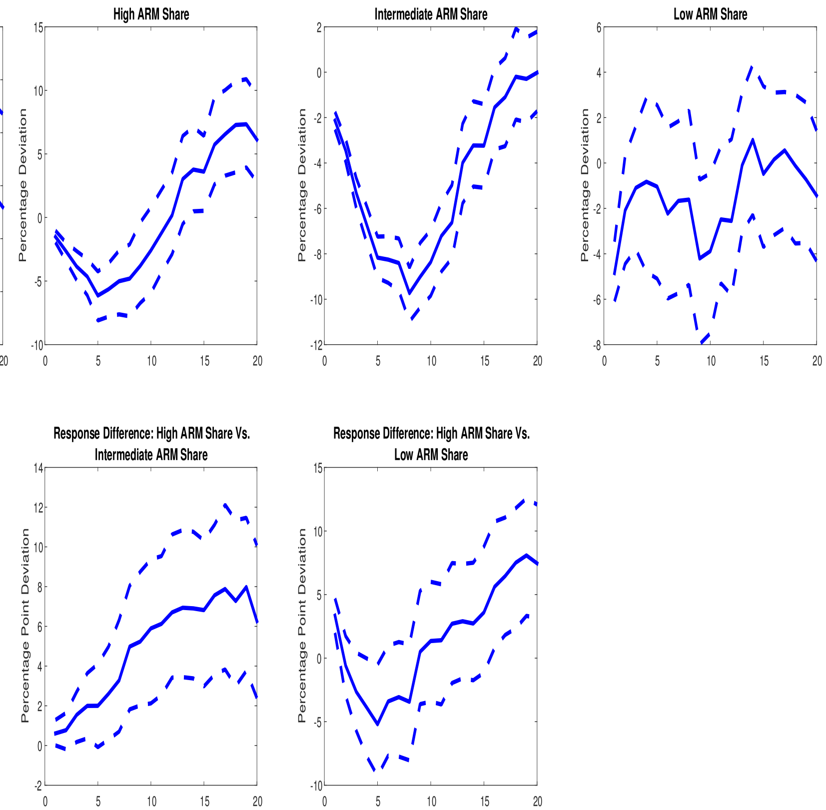
(b) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (Prime FRM Default Rates).

Notes: Panel (a): This figure presents the impulse responses of prime ARM default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8). Panel (b): This figure presents the impulse responses of prime FRM default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8).
See notes from Figure 5 for details on the exposition of the different sub-figures in this figure.

Figure 7: **State-Dependent Effects of Credit Supply Shocks: (a) Subprime ARM Default Rates; (b) Subprime FRM Default Rates**.



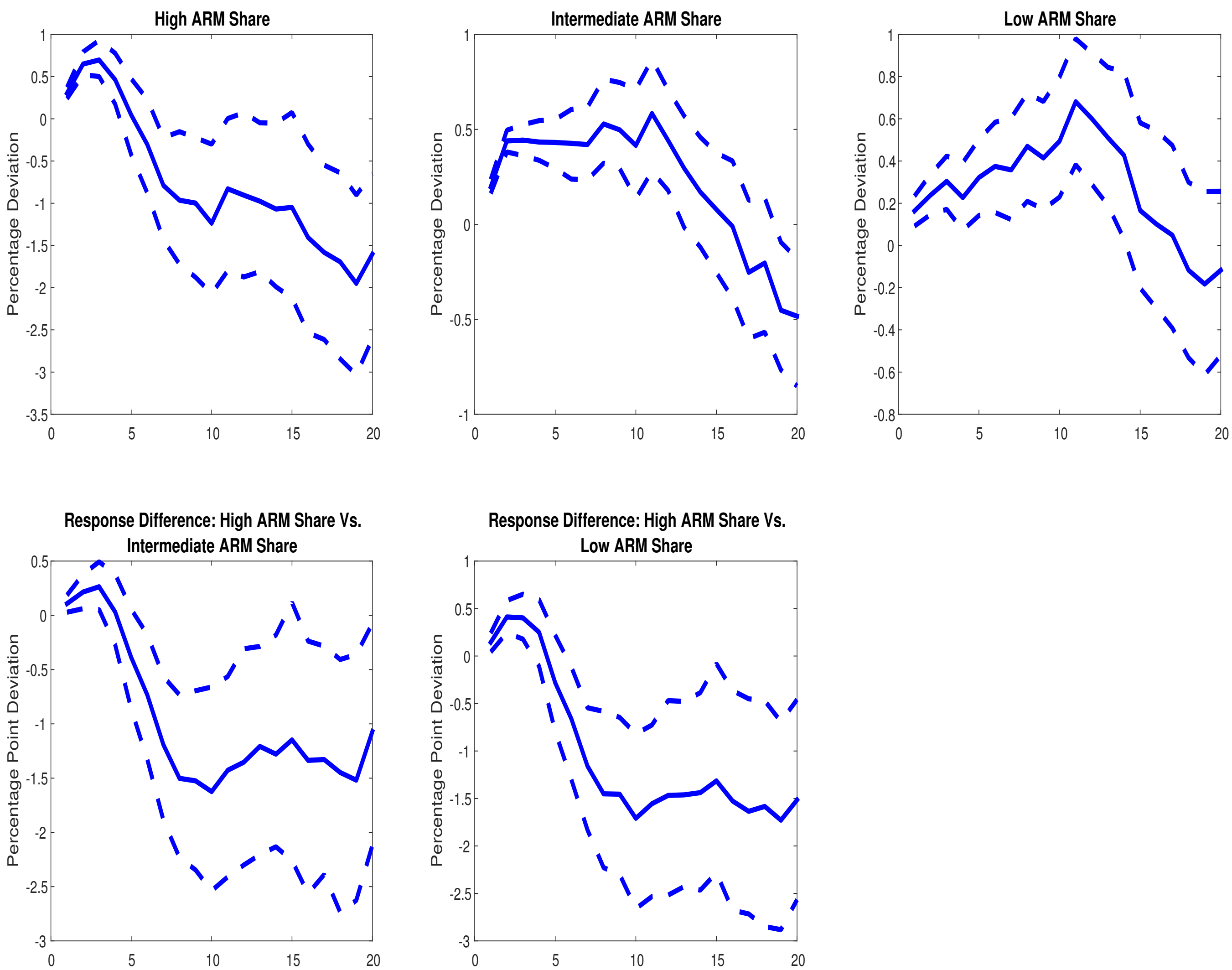
(a) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (Subprime ARM Default Rates).



(b) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (Subprime FRM Default Rates).

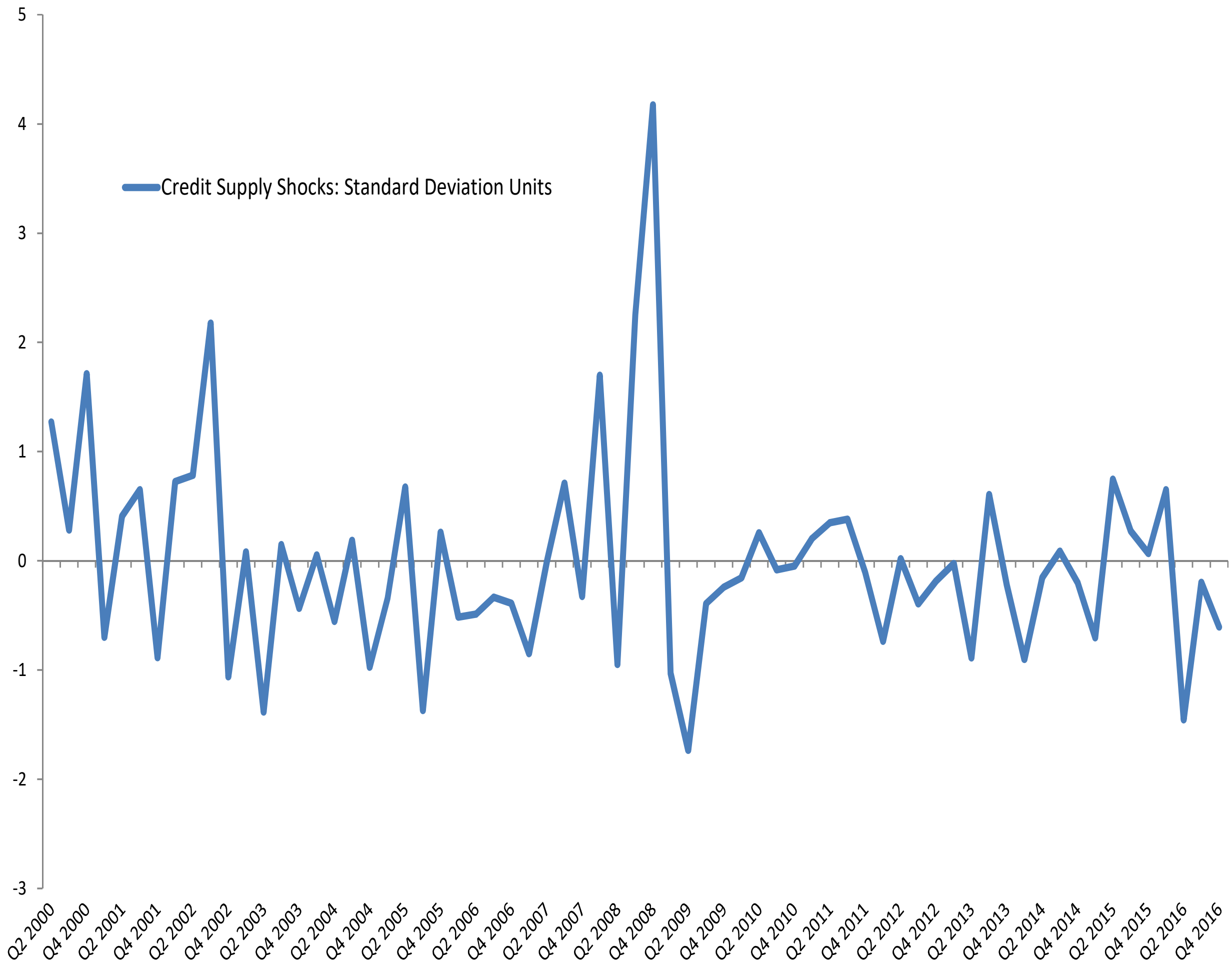
Notes: Panel (a): This figure presents the impulse responses of subprime ARM default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8). Panel (b): This figure presents the impulse responses of subprime FRM default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8).
See notes from Figure 5 for details on the exposition of the different sub-figures in this figure.

Figure 8: **State-Dependent Effects of Credit Supply Shocks on House Prices**.



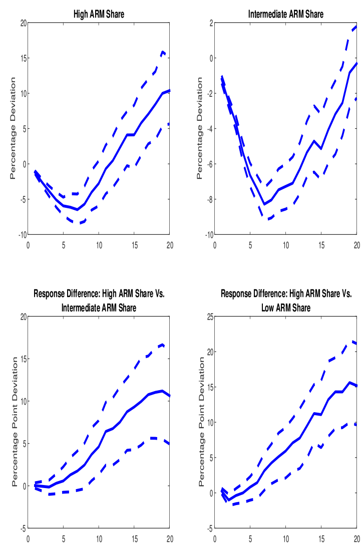
Notes: This figure presents the impulse responses of house prices to a one standard deviation credit supply shock from the non-linear model described by Equation (8). The first three sub-figures present the median impulse responses along with 68% posterior confidence bands for the three considered states: high ARM share, intermediate ARM share, and low ARM share. The last two sub-figures show the median response differences along with 68% posterior confidence bands for the high-intermediate ARM pair and the high-low ARM pair. The responses are shown in terms of percentage deviations from pre-shock values. Horizon (on the x-axis) is in quarters.

Figure 9: **Time Series of Credit Supply Shock Series.**

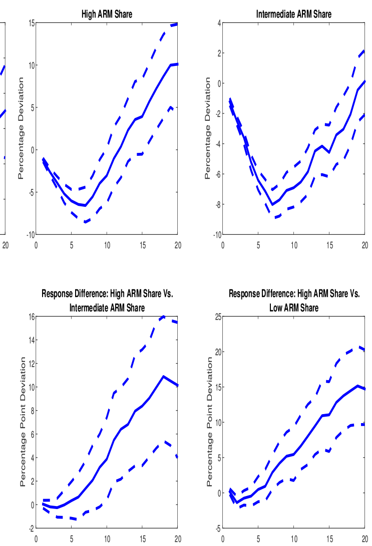


Notes: This figure presents the time series of the median realizations of the credit supply shocks series as estimated from Equation (9). The realizations are shown in standard deviation units and run from 2000:Q2-2016:Q4.

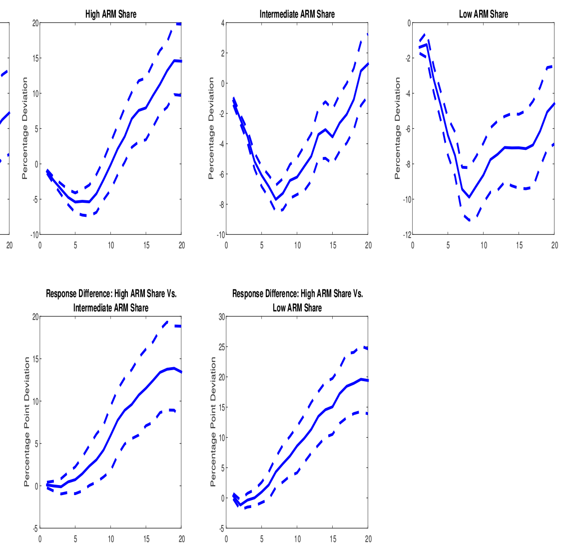
Figure 10: **State-Dependent Effects of Credit Supply Shocks for Different Lag Specifications: (a) 4 Lags; (b) 5 Lags; (c) 6 Lags**.



(a) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (4 Lags).



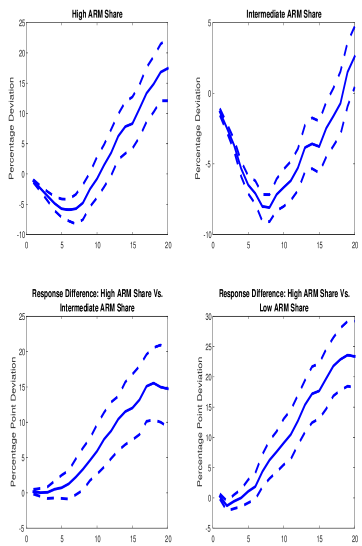
(b) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (5 Lags).



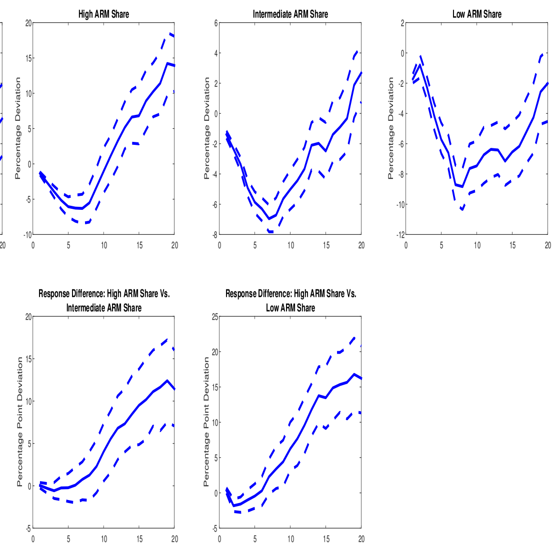
(c) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (6 Lags).

Notes: Panel (a): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with a lag specification of 4. Panel (b): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with a lag specification of 5. Panel (c): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with a lag specification of 6.
See notes from Figure 5 for details on the exposition of the different sub-figures in this figure.

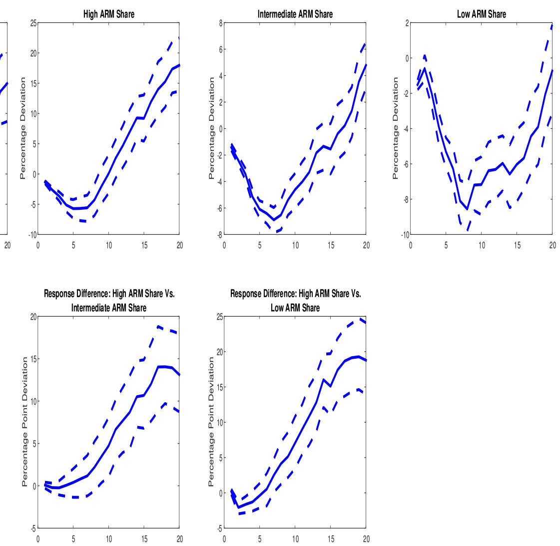
Figure 11: **State-Dependent Effects of Credit Supply Shocks for Different Lag Specifications: (a) 7 Lags; (b) 9 Lags; (c) 10 Lags**.



(a) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (7 Lags).



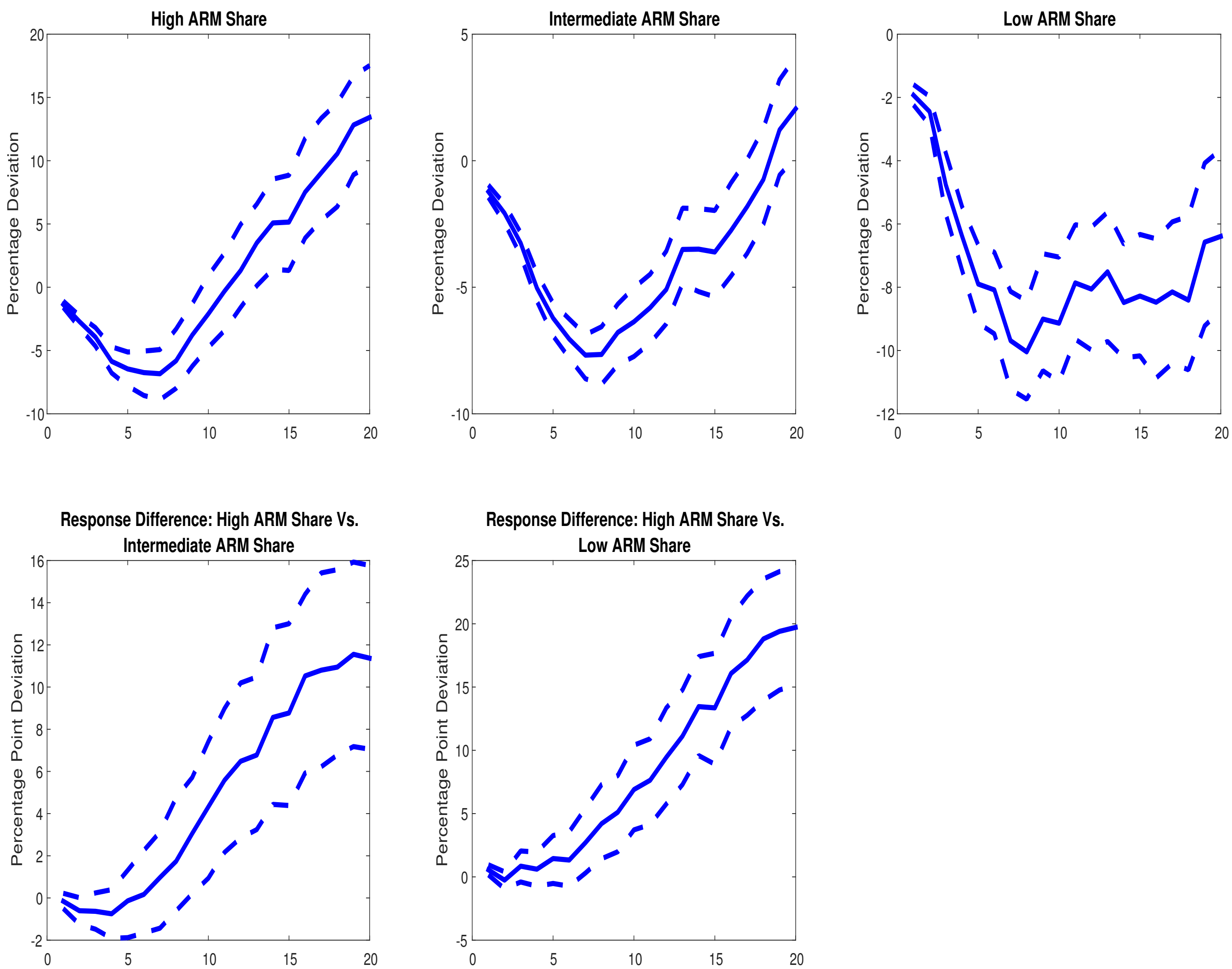
(b) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (9 Lags).



(c) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (10 Lags).

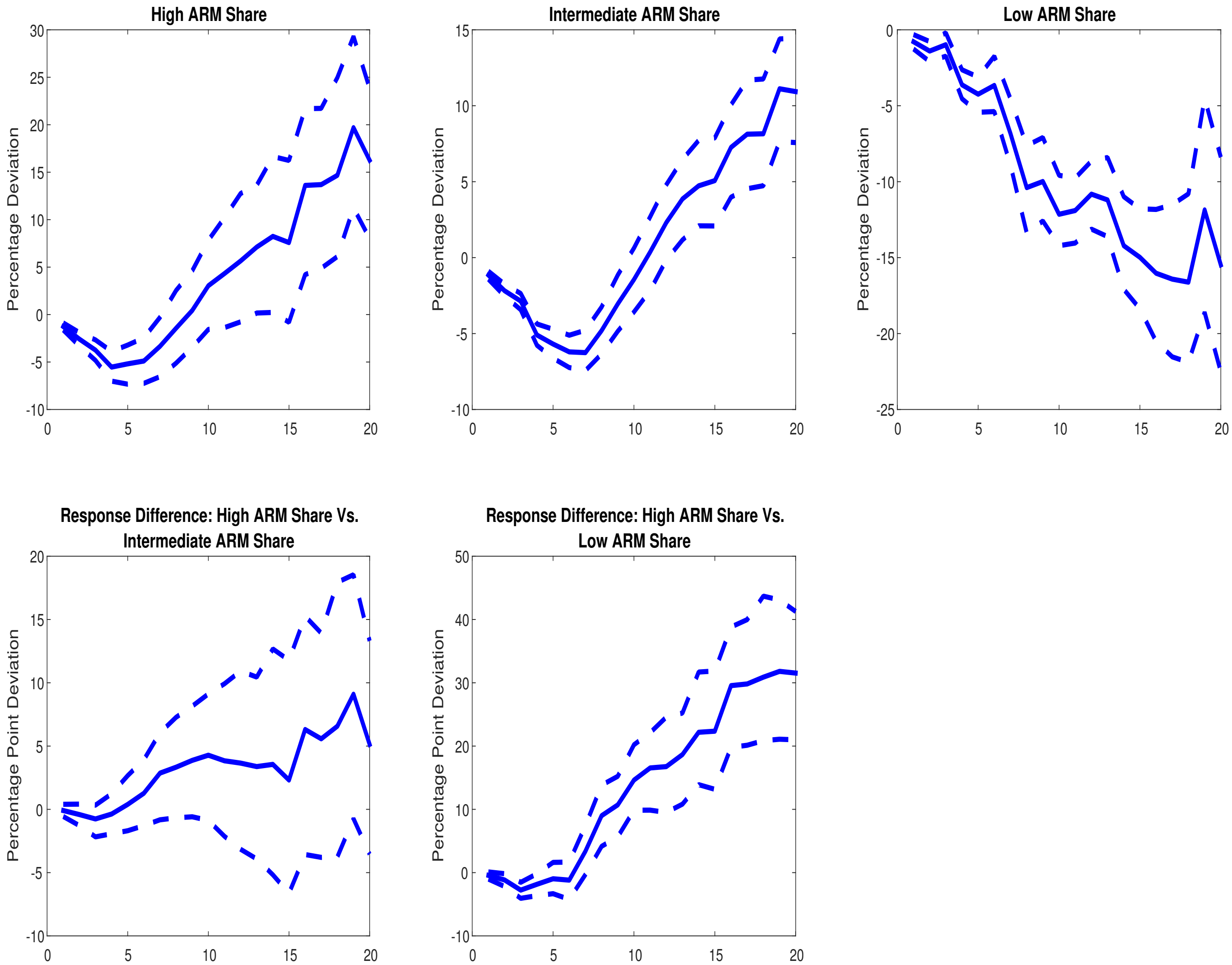
Notes: Panel (a): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with a lag specification of 7. Panel (b): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with a lag specification of 9. Panel (c): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with a lag specification of 10.
See notes from Figure 5 for details on the exposition of the different sub-figures in this figure.

Figure 12: **State-Dependent Effects of Credit Supply Shocks: Removing the Sand States**.



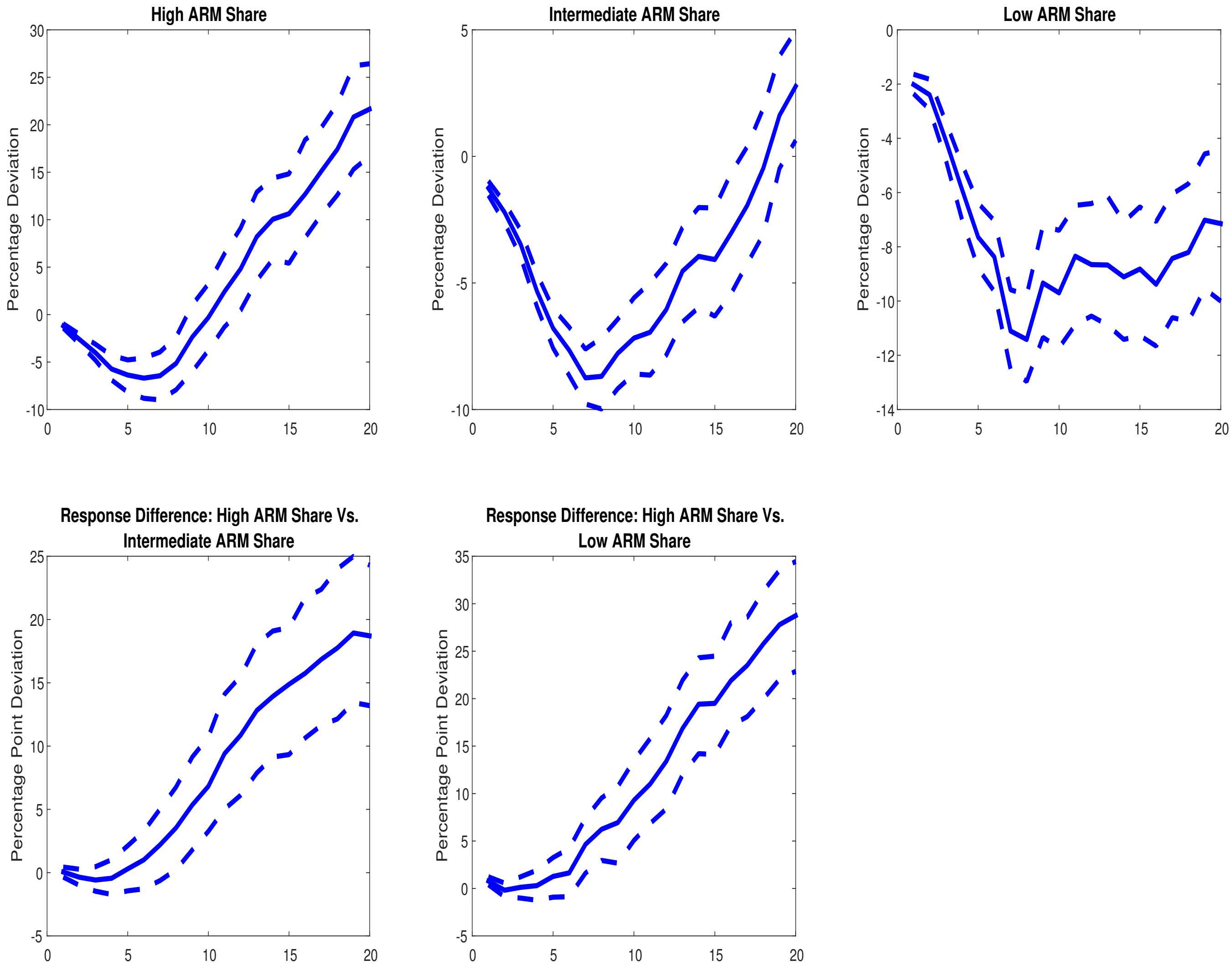
Notes: This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8), where the baseline full sample is replaced by a smaller, 47 U.S. state sample that excludes the four so called 'sand states' (Arizona, California, Florida, and Nevada). The first three sub-figures present the median impulse responses along with 68% posterior confidence bands for the three considered states: high ARM share, intermediate ARM share, and low ARM share. The last two sub-figures show the median response differences along with 68% posterior confidence bands for the high-intermediate ARM pair and the high-low ARM pair. The responses are shown in terms of percentage deviations from pre-shock values. Horizon (on the x-axis) is in quarters.

Figure 13: **State-Dependent Effects of Credit Supply Shocks: Controlling for Leverage**.



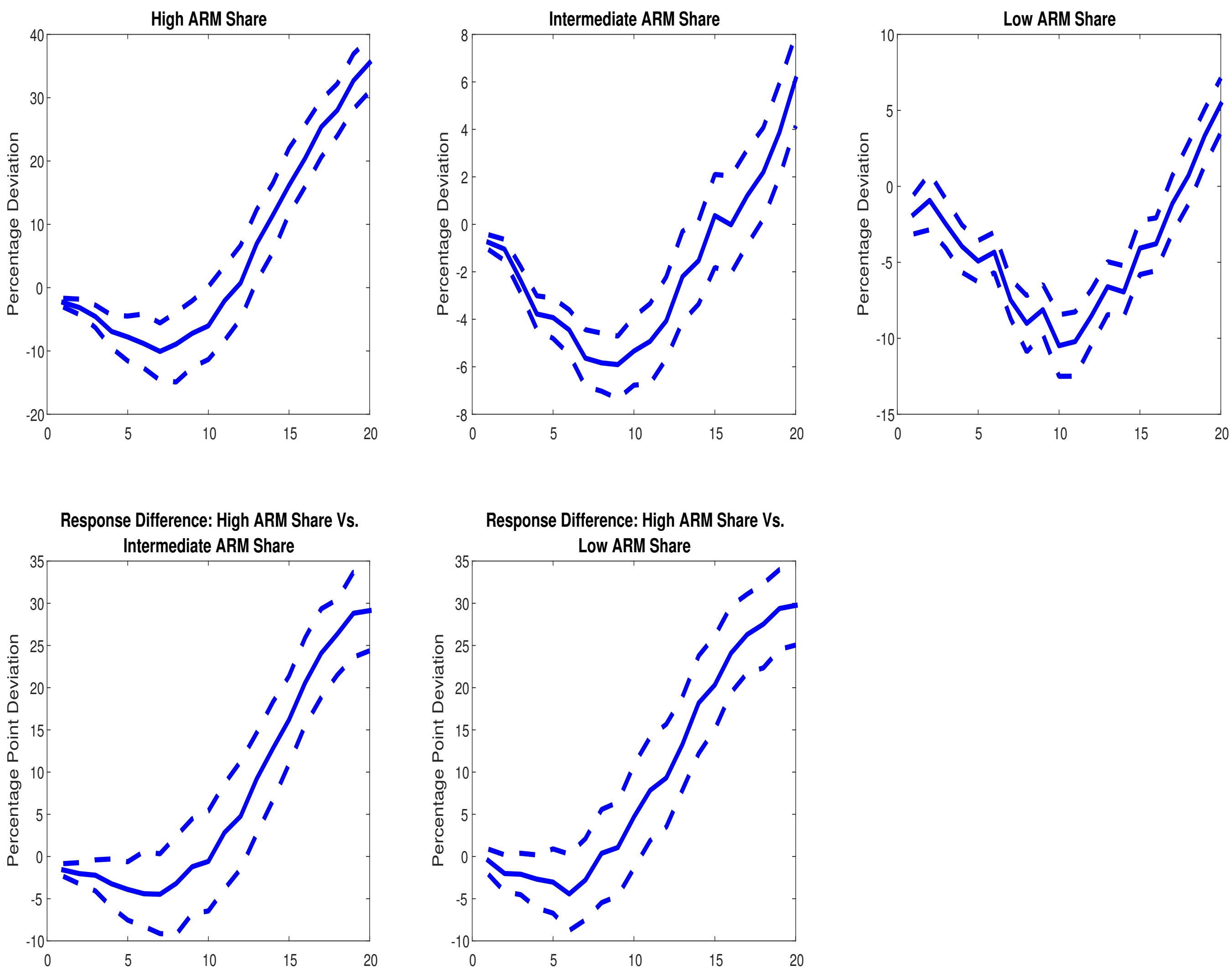
Notes: This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8), where the prime ARM share state dummies are all imposed upon to obtain 0 if corresponding leverage values do not belong to the interquartile range of U.S. states' leverage distribution. The first three sub-figures present the median impulse responses along with 68% posterior confidence bands for the three considered states: high ARM share, intermediate ARM share, and low ARM share. The last two sub-figures show the median response differences along with 68% posterior confidence bands for the high-intermediate ARM pair and the high-low ARM pair. The responses are shown in terms of percentage deviations from pre-shock values. Horizon (on the x-axis) is in quarters.

Figure 14: **State-Dependent Effects of Credit Supply Shocks: Removing Non-Recourse U.S. States**.



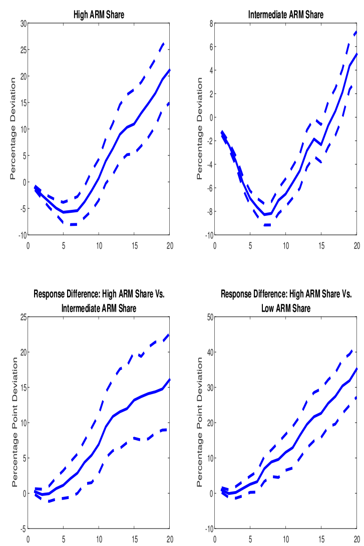
Notes: This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8), where the baseline full sample is replaced by a smaller, recourse-only 40 U.S. state sample. The first three sub-figures present the median impulse responses along with 68% posterior confidence bands for the three considered states: high ARM share, intermediate ARM share, and low ARM share. The last two sub-figures show the median response differences along with 68% posterior confidence bands for the high-intermediate ARM pair and the high-low ARM pair. The responses are shown in terms of percentage deviations from pre-shock values. Horizon (on the x-axis) is in quarters.

Figure 15: **State-Dependent Effects of Credit Supply Shocks: Conditioning on a Pre-2007 Sample**.

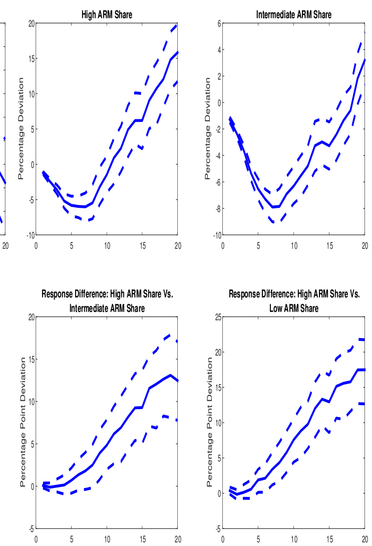


Notes: This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8), where I only condition on pre-2007 observations by restricting the prime ARM share state dummies to obtain 0 after 2006:Q4. The first three sub-figures present the median impulse responses along with 68% posterior confidence bands for the three considered states: high ARM share, intermediate ARM share, and low ARM share. The last two sub-figures show the median response differences along with 68% posterior confidence bands for the high-intermediate ARM pair and the high-low ARM pair. The responses are shown in terms of percentage deviations from pre-shock values. Horizon (on the x-axis) is in quarters.

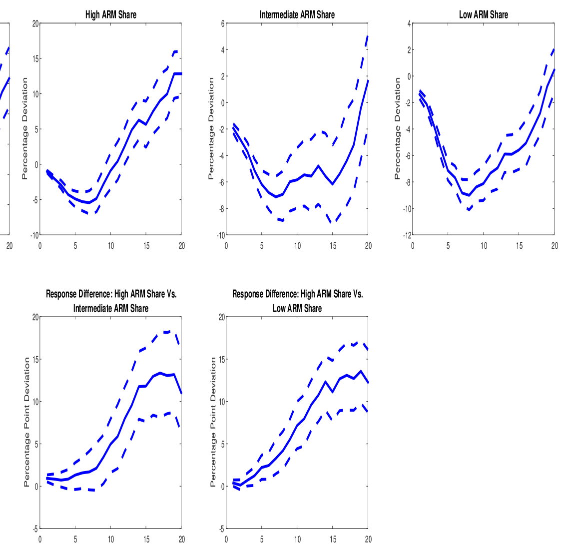
Figure 16: **State-Dependent Effects of Credit Supply Shocks for Different Prime ARM Share Thresholds: (a) 85th-15th Percentiles; (b) 65th-35th Percentiles; (c) 55th-45th Percentiles**.



(a) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (85th-15th Prime ARM Share Percentiles).



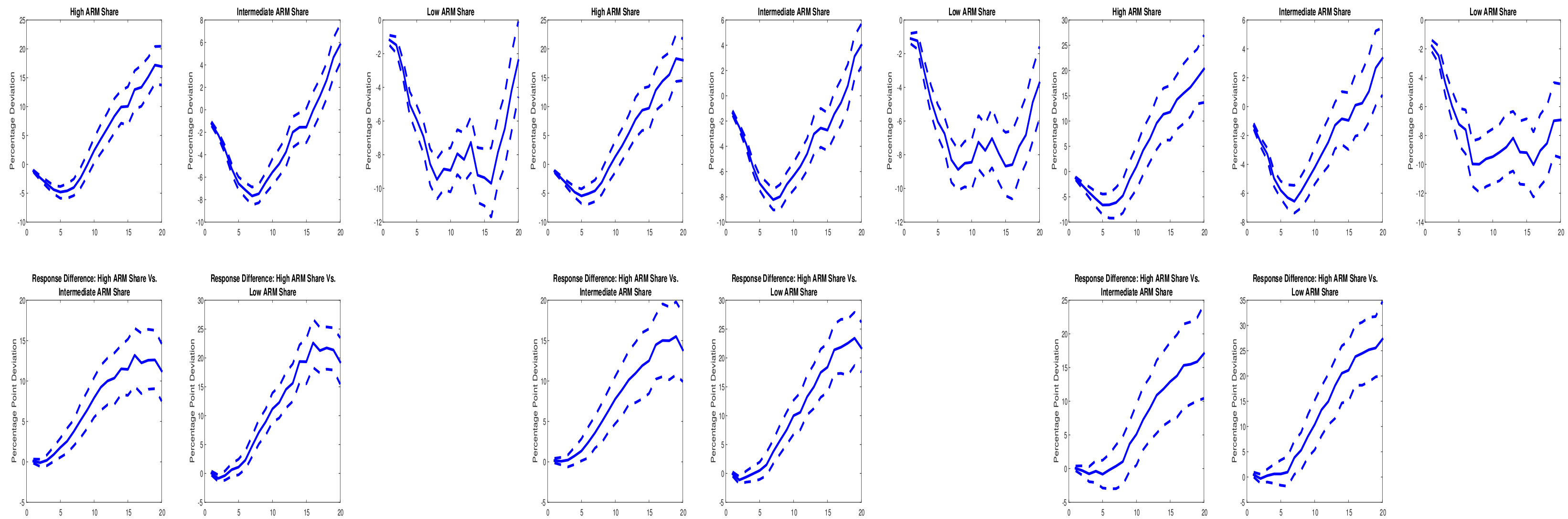
(b) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (65th-35th Prime ARM Share Percentiles).



(c) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (55th-45th Prime ARM Share Percentiles).

Notes: Panel (a): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with the following prime ARM share percentile thresholds: 85th percentile for high prime ARM share state; 85th-15th percentile range for intermediate prime ARM share state; and 15th percentile for low prime ARM share state. Panel (b): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with the following prime ARM share percentile thresholds: 65th percentile for high prime ARM share state; 65th-35th percentile range for intermediate prime ARM share state; and 35th percentile for low prime ARM share state. Panel (c): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with the following prime ARM share percentile thresholds: 55th percentile for high prime ARM share state; 55th-45th percentile range for intermediate prime ARM share state; and 45th percentile for low prime ARM share state.
See notes from Figure 5 for details on the exposition of the different sub-figures in this figure.

Figure 17: **State-Dependent Effects of Credit Supply Shocks for Different Prime Share Range Choices: (a) 95th-5th Percentiles Range; (b) 85th-15th Percentiles Range; (c) 65th-35th Percentiles Range**.



(a) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (95th-5th Prime Share Percentiles Range).

(b) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (85th-15th Prime Share Percentiles Range).

(c) State-Dependent Impulse Responses to a One Standard Deviation Credit Supply Shock (65th-35th Prime Share Percentiles Range).

Notes: Panel (a): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with a 95th-5th percentiles range choice for prime share. Panel (b): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with a 85th-15th percentiles range choice for prime share. Panel (c): This figure presents the impulse responses of mortgage default rates to a one standard deviation credit supply shock from the non-linear model described by Equation (8) with a 65th-35th percentiles range choice for prime share.
See notes from Figure 5 for details on the exposition of the different sub-figures in this figure.