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Nonlinearities of mortgage spreads over the business cycles

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Abstract

This paper provides robust evidence for the non-linear effects of mortgage spread shocks during recessions and expansions in the United States. Estimating a smooth-transition VAR model, we show that mortgage spread shocks hitting in recessionary regimes create significantly deeper and more protracted decrease in industrial production and prices, as well as a persistent fall in house prices. Evidence also suggests that shock propagation is amplified through the interaction of stock prices. Our empirical results complement the theoretical literature which emphasizes the role of occasionally binding collateral constraints and asset prices in explaining macroeconomic asymmetries.

Key words: Mortgage spread shocks, smooth transition vector autoregressions, nonlinearities, financial frictions.

JEL classification: C32, E32, E44, E52.

(1) George Dean Johnson, Jr. College of Business and Economics, University of South Carolina Upstate. Email: jcheng@uscupstate.edu
(2) Bank of England. Email: jeremy.chiu@bankofengland.co.uk

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Publications Team, Bank of England, Threadneedle Street, London, EC2R 8AH
Telephone +44 (0)20 7601 4030 Fax +44 (0)20 7601 3298 email publications@bankofengland.co.uk

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1 Introduction

The financial crisis of 2007 has highlighted the important role played by the housing market in shaping the US business cycles. Large declines in house prices, which were accompanied by severe credit contractions in the mortgage market, had coincided with the onset of the Great Recession. The mortgage spread, which is measured as the spread between the interest rate on newly issued mortgages and the government bond rate of the same maturity, witnessed substantial increases before and after the start of the recession. In an attempt to reduce the mortgage interest rate, the Federal Reserve introduced the mortgage-backed security (MBS) purchase program in 2009, as part of its unconventional monetary policy.

While many studies have argued that housing shocks exert significant impacts on the macroeconomy, very few empirical papers look at the potential non-linear effects of housing shocks. This question is important given that policy makers have repeatedly expressed concern about the recovery of the housing market and its potential downside risks.[1] Any empirical evidence of nonlinearities associated with housing shocks will have vital implications and will prompt policy makers to implement appropriate policies in dealing with future crises. This paper contributes to the literature by *empirically* investigating whether mortgage spread shocks matter more for the real economy during recessions. Our answer is a robust 'yes.'

Theoretically, one may expect that mortgage spread shocks can be amplified during recessions through various channels. The first channel concerns the collateral constraints of the households. Guerrieri and Iacoviello (2016) show that home prices and consumption have a strong positive correlation during recessions. They argue that collateral constraints on housing wealth tend to bind during recessions when home prices are low. The binding collateral constraints amplify the co-movement between home prices and consumption. We hypothesize that if mortgage spread shocks affect house prices and housing wealth, their effects on consumption and output would be larger under recessions due to the housing collateral channel.

To the extent that mortgage spreads can affect asset prices, the second channel involves adverse mortgage spread shocks reducing the borrowing capacities of credit-constrained firms. Recognizing that nearly 70 percent of commercial and industrial loans are secured by collateral assets (real estate), Liu et al. (2013) postulate that a fall in land prices can generate significant fall in investment. Lower land prices caused by mortgage spread shocks can reduce the amount of pledgeable collateral and decrease the ability for firms to obtain credit and engage in investment, leading to deeper and more protracted economic contractions. Besides, firms' balance sheet positions, which tend to be weak during recessions, may further deteriorate in response to falling asset prices, leading to rising corporate credit spreads. This manifests the financial accelerator mechanism described by Bernanke and Gertler (1989) and Bernanke et al. (1999). Consequently, the reduction in in-

[1] For example, Minutes of the Federal Open Market Committee published on August 7, 2007 stated: '*Participants agreed that the housing sector was apt to remain a drag on growth for some time and represented a significant downside risk to the economic outlook.*' Chair Janet Yellen made a similar point in her remarks on May 8, 2014: '*Another risk — domestic in origin — is that the recent flattening out in housing activity could prove more protracted than currently expected rather than resuming its earlier pace of recovery.*'

vestment and output caused by adverse mortgage spread shocks could be more substantial during recessions.

The third channel operates through the financial sector. Brunnermeier and Sannikov (2014) argue that non-linear shock propagation occurs through changes in asset prices caused by portfolio adjustments in response to constraints or precautionary motives (endogenous risks). Moreover, a potential driver of the mortgage spread is the prepayment risk premium, a component not negligible in the US mortgage market (see Gabaix et al. 2007). During recessions the balance sheet of financial institutions is generally under stress, spikes in such premium can worsen their ability to absorb risks and lead to a disproportionately deeper reduction in lending and economic contraction.

Finally, mortgage spread shocks can potentially induce precautionary savings of the unconstrained households. Guerrieri and Lorenzoni (2011) show that, under the context of shocks hitting the financial system that lead to higher credit spreads, even the unconstrained agents will be motivated by the precautionary motive to increase their savings as a buffer against future shocks. This provides another channel to magnify the economic contraction caused by housing market shocks during recessions.

It is important to note that the amplification channels described above rely heavily on the binding of financial constraints during recessions. Figure 1 displays the mortgage spread and the cyclical component of the industrial production over our sample. It is evident that the mortgage spread is countercyclical. More importantly, increases in mortgage spreads are associated with much larger declines in industrial production under recessions than other periods. Table 1 shows the cyclical statistics of the mortgage spread. As the table shows, the mean of the mortgage spread tends to be higher during recessions. Furthermore, the negative correlation between the mortgage spread and industrial production becomes stronger during recessions. It is important to note that the correlation between the mortgage spread and industrial production is positive during the last recession from 2007M12 to 2009M6. However, the positive correlation is likely driven by the Federal Reserve's mortgage-backed security (MBS) purchase program after 2008, and is indeed confirmed by the fifth column which shows the cyclical statistics of the mortgage spread from 2007M12 to 2008M12. As we can see, the correlation between the mortgage spread and industrial production is strongly negative once we exclude the periods when the MBS purchase program was implemented.

To assess the impacts of mortgage spread shocks on the US economy during expansions and recessions, we estimate a smooth transition structural vector autoregression (STVAR) model. The STVAR model has been widely used in empirical macroeconomics, including but not limited to Auerbach and Gorodnichenko (2013), Berger and Vavra (2014) and Caggiano et al. (2014, 2015). Following Walentin (2014)'s study, we construct the mortgage spreads focusing only on the prime mortgage market. Rather than using quarterly data, we construct a monthly dataset which provides us with more information to estimate our non-linear model. Furthermore, we compute the generalized impulse responses functions to endogenously capture the potential regime-switches due to a mortgage spread shock.

We find strong evidence of asymmetric effects. We show that a positive shock to the mortgage spread causes industrial production, consumer prices, home prices and the federal funds rate to fall. The effects of a mortgage spread shock on industrial production and consumer prices are also much larger during recessions. More importantly, the discrepancy in the impacts of mortgage spreads on industrial production under expansions and recessions is statistically significant. We find that a one standard deviation increase in mortgage spreads (corresponding to a 12 basis point rise) leads to a decline in industrial production and consumer prices with peak effects of -0.6 percent and -0.25 percent respectively under recessions, and the impact remains significant after 3 years. However, a shock of similar magnitude is associated with a much smaller and more short-lived economic impact during expansions. Therefore, mortgage spread shocks are more important for output fluctuations during recessions.

Moreover, we find that the policy rate is able to partially counteract the effect of the mortgage spread shocks during expansions, but its stabilizing ability could have been constrained by the zero lower bound problem during the recent recession periods. Our results have vital policy implications for unconventional monetary policy, such as the Federal Reserve's mortgage-backed security purchase program. To the extent that large scale purchases of mortgage-backed securities alter mortgage spreads, our findings suggest that MBS purchase programs would be a more effective tool for stabilizing the economy during recessions than in expansions. Moreover, our results favour the adoption of macro-prudential regulations such as the counter-cyclical capital buffer.

Our results are robust to alternative specifications in our STVAR model. The asymmetric effects of mortgage spread shocks remain even after controlling for the corporate spreads. Moreover, our main results are robust to exclusion of the recent zero lower bound periods that started after the third quarter of 2008. One interesting but important result is that our asymmetric results are amplified when we include aggregate stock prices in our baseline system. This provides strong evidence of shock propagation through the interaction of asset prices and the real economy. As pointed out by Walentin (2014), mortgage spread shocks could potentially be caused by factors such as changes in the prepayment risk premium, changes in financial regulation, changes in the degree of mortgage securitizations and large scale mortgage-backed security (MBS) purchases. However, dissecting the effect of each individual source of mortgage spread shocks is beyond the scope of this paper and we leave that for future studies.

The rest of the paper is organized as follows. Section 2 conducts a literature review, and section 3 estimates the non-linear effects of mortgage spread shocks and discusses the results. Second 4 conducts robustness checks. Section 5 provides further evidence and Section 6 concludes.

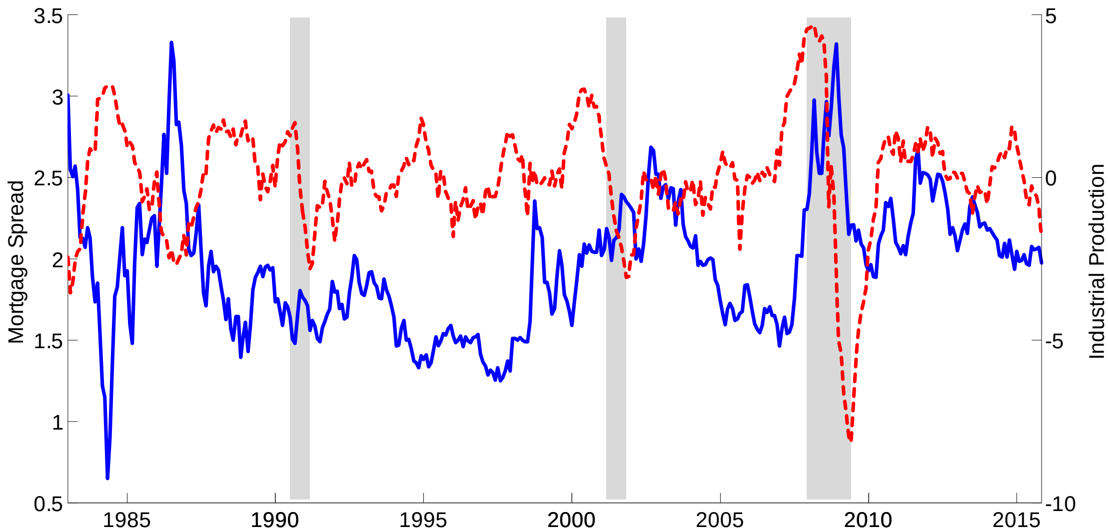

Figure 1: Mortgage spread (solid line), industrial production (dashed line) is measured as the percentage deviation from the Hodrick-Prescott trend, and NBER recession dates (shaded bars). The mortgage spread is computed as the difference between the 30-year fixed rate mortgage rate and the average of the 5-year and the 10-year Treasury bond rate. Data: 1983M1-2015M11.

Table 1

Cyclical statistics of the mortgage spread.

Moment\Period	Whole sample 83M1-15M11	Recession 90M7-91M3	Recession 01M3-01M11	Recession 07M12-09M6	Recession 07M12-08M12
Mean	1.96	1.65	2.21	2.69	2.77
Std. dev.	0.41	0.12	0.14	0.32	0.30
Corr(mspread,IP)	-0.21	-0.44	-0.69	0.14	-0.73
Std. dev. (cspread)	0.73	0.27	0.25	1.20	1.13
Corr(mspread,cspread)	0.82	0.86	0.95	0.43	0.85

Note: The corporate spread ("cspread") is measured as the difference in the interest rates on Moody's Baa-rated corporate bonds and the 10-year Treasury bond. Industrial production ("IP") is in terms of deviation from the Hodrick-Prescott trend.

2 Related Literature

Our paper is closely related to Walentin (2014). Walentin provides convincing empirical evidence that adverse shocks to mortgage spreads have significant and negative impacts on the US output and prices. However, Walentin's analysis was entirely based on linear VAR models, which completely ignored the non-linear effects of mortgage spread shocks. This paper is also related to the empirical literature which identifies housing shocks. Furlanetto et al. (2014) disentangle credit and housing shocks by imposing sign restrictions the responses of the total credit to real estate value ratio. Prieto et al. (2013) estimate a time-varying parameter VAR model to show how the housing sector affects the economy asymmetrically and how housing shocks are more important for the real economy since 2000s. Our paper also adds to the credit spread literature, with the most recent contribution by Gilchrist and Zakrajšek (2012) who provide evidence that the excess bond premium, credit spreads attributable to deviations in the pricing of corporate bonds relative to the measured risk of the issuer, results in a fall in the supply of credit.

Our results complement a growing theoretical literature studying the non-linear relationships between the housing market and the economy. Guerrieri and Iacoviello (2016) estimate a DSGE model with occasionally binding collateral constraints and show that the effects of a housing demand shock on consumption is much larger when collateral constraints become binding. Favilukis et al. (2016) investigate a general equilibrium model where a large number of overlapping generations of homeowners face idiosyncratic and aggregate risks, which cannot be completely insured against because of incomplete financial and collateralized borrowing constraints. They show that a relaxation of financial constraints can lead to large boom in house prices and that the boom in house prices is attributable in the decline in the housing risk premium. To our knowledge, our paper is among the first to empirically investigate the non-linear impact of mortgage spread shocks on the US economy, hence complementing the results found in the theoretical literature.

This paper also pertains to the literature in studying the linear relationship between the housing market and the macroeconomy. Iacoviello (2005) finds that a positive house price shock causes consumption to rise. Iacoviello and Neri (2010) discuss that housing demand and housing technology shocks are responsible for the movements in housing investment and housing prices. They also show that housing market developments have non-negligible effects on consumption. Davis and Heathcote (2005) develop a multi-sector model to explain the dynamics of residential investment. Recently, Liu et al. (2013) argue that positive comovements between land prices and business investment are a driving force behind the broad impact of land-price dynamics on the macroeconomy. Favilukis et al. (2016) stress the importance of wealth distributions in shock transmissions: as a substantial portion of housing demand is attributable to constrained households, any unanticipated shocks to the economy-wide collateral constraints can represent an important source of aggregate risk that cannot be insured away.

Lastly, our work is related to the empirical literature which explores asymmetric macroeconomic implications of structural shocks. Balke (2000) estimates the non-linear economic dynamics of credit using a threshold VAR model and finds that shocks in a tighter credit regime have a larger impact on output. More recently, Caggiano et al. (2014) find that the effect of uncertainty shocks on unemployment dynamics is asymmetric using a smooth-transition VAR model. Caggiano et al. (2015) provide evidence that fiscal spending multipliers in deep recessions are significantly larger when compared to those in strong expansionary periods. Hubrich and Tetlow (2015), by estimating a markov-switching model, provide seminal evidence that shock transmission is significantly different in financial stressful regimes. Ramey and Zubairy (2014) find that the effect of a fiscal shock might not necessarily be stronger when the economy is in a recession. Tenreyro and Thwaites (2016) provide evidence that monetary policy is less potent under recessions and contractionary monetary policy is more effective than expansionary policy. Alessandri and Mumtaz (2014) find that uncertainty shocks exert significantly larger effects on output when the economy is under financial stress. We are among the first papers to empirically quantify the effects of mortgage spread shocks during different phases of a business cycle.

3 Empirical investigations

3.1 Empirical model

We estimate a smooth transition structural vector autoregression (STVAR) model to assess the effects of mortgage spread shocks on the US economy during expansions and recessions.[2] The STVAR system is specified as follows:

$$Y_t = F(z_{t-1})\Phi_R(L)Y_t + [1 - F(z_{t-1})]\,\Phi_E(L)Y_t + \epsilon_t$$

$$\epsilon_t \sim N(0, \Theta_t)$$

$$\Theta_t = F(z_{t-1})\Theta_R + [1 - F(z_{t-1})\Theta_E]$$

$$F(z_t) = \exp(-\gamma z_t)/\left[1 + \exp(-\gamma z_t)\right],\ \gamma > 0, z_t \sim N(0,1)$$

where $Y_t = [Cons_t,\ Houstart_t,\ IP_t,\ CPI_t,\ Mspread_t,\ SFFR_t,\ HPI_t]'$ is the vector of the endogenous variables in the STVAR. $Cons_t$ is the real consumption index, IP_t and CPI_t represent the industrial production index and the consumer price index in the US respectively. $Houstart_t$ represent the housing starts and HPI_t is the real house price index. $Mspread_t$ is the mortgage spread and $SFFR_t$ is the shadow federal funds rate. All variables are in log values, except for the mortgage spread and the shadow federal funds rate, which are in levels. The reduced-form residuals ϵ_t have a time-varying, regime-contingent variance-covariance matrix Θ_t. The variance-covariance

[2] Two other approaches commonly used to capture regime switching processes are threshold vector autoregressions (TVAR) and Markov switching models. However, we prefer STVAR models for two reasons. Firstly, STVAR models generalize TVAR models and do not require us to take a stand on the smoothness of the transition between regimes, whereas TVAR models assume an abrupt transition across states. The smoothness of the transition in our STVAR model is controlled by a parameter which is calibrated based on observed data. Secondly, as is well known, the switch of regimes in Markov-switching models is governed by a latent process. The interpretation of the identified regimes may not always be straightforward. Given that our goal in this paper is to explicitly examine the dynamics across the business cycles, a STVAR model which allows us to specify a threshold variable seems more suitable for our purposes.

matrices in recessions and expansions are denoted by Θ_R and Θ_E respectively. The variable z_t is a transition indicator and $F(z_{t-1})$ is a logistic transition function which captures the probability of being in a recession. Φ_R and Φ_E capture the dynamics of our VAR system during recessions and expansions respectively. The slope parameter γ controls the the pace of transition between recessionary and expansionary phases. A high value of γ induces abrupt transition across the two regimes, while a low value implies a smooth transition.

We follow Walentin (2014) and only employ post-1982 data. This helps us ensure that our result is not affected by the Regulation Q and the Volcker disinflation periods. Specifically, we employ monthly US data from 1983M1 to 2015M11.[3] We use the 30-year fixed mortgage rate in our estimation. The mortgage rate data are based on conventional conforming mortgages from Freddie Mac's Primary Mortgage Market Survey. As in Walentin (2014), we look at the spread between the interest rate on newly issued mortgages and the government bond rate of the same maturity and focus only on the prime mortgage market. Given that the estimated duration of a 30-year fixed rate mortgage in the US is about 7 to 8 years, mortgage spread data are obtained as the difference between the 30-year fixed rate mortgage rate and the average of the 5-year and the 10-year Treasury bond rates. To eliminate the effects of the zero lower bound problem, we adopt the shadow federal funds rate, $SFFR_t$, recently developed by Wu and Xia (2016), as the policy interest rate. This interest rate series materially differ from the actual effective federal funds rate starting from 2009M1; we report our results with the actual federal funds rates in the robustness section.

All data are in log values, except for the mortgage spread and the shadow federal funds rate. Data on the real consumption, housing starts, industrial production and the consumer price index come from the Federal Reserve of St. Louis database. The shadow federal funds rate come from the Federal Reserve of Atlanta database. The real home price index is the Freddie Mac house price index deflated by the consumer price index. As in Caggiano et al. (2015), we select the lag length based on the Akaike information criterion employed to the linear version of our model. The VAR model allows for four lags.[4]

In Auerbach and Gorodnichenko (2012), Berger and Vavra (2014) and Caggiano et al. (2015), the transition variable, z_t, is captured by the standardized moving average of the quarterly real GDP growth rate. Similar to their approach, we adopt the twelve-month backward looking moving average of the monthly growth rate of industrial production to construct $z_{t.}$

As pointed out by Teräsvirta et al. (2010), the estimation of the smoothness parameter γ is affected by identification issues. We follow Caggiano et al. (2015), among others, and calibrate γ

[3] One may be concerned that our model estimation is based on a limited number of recessions. We would like to emphasize that the nonlinearity tests proposed by Terasvirta and Yang (2014) (to be discussed in this section) suggest strong evidence of nonlinearities in the data. Besides, as pointed out by Caggiano et al. (2014), an important advantage of STVAR models is that such class of models exploits information from the entire sample rather than from the observations in recessionary periods only. As a matter of fact, our results provide strong evidence that the asymmetric impact of mortgage spreads shocks is indeed significant based on this relatively short sample. An interesting and important extension is to consider a non-linear panel VAR model, and we leave this idea for future research.

[4] Our results are robust to alternative lag lengths (results available in appendix).

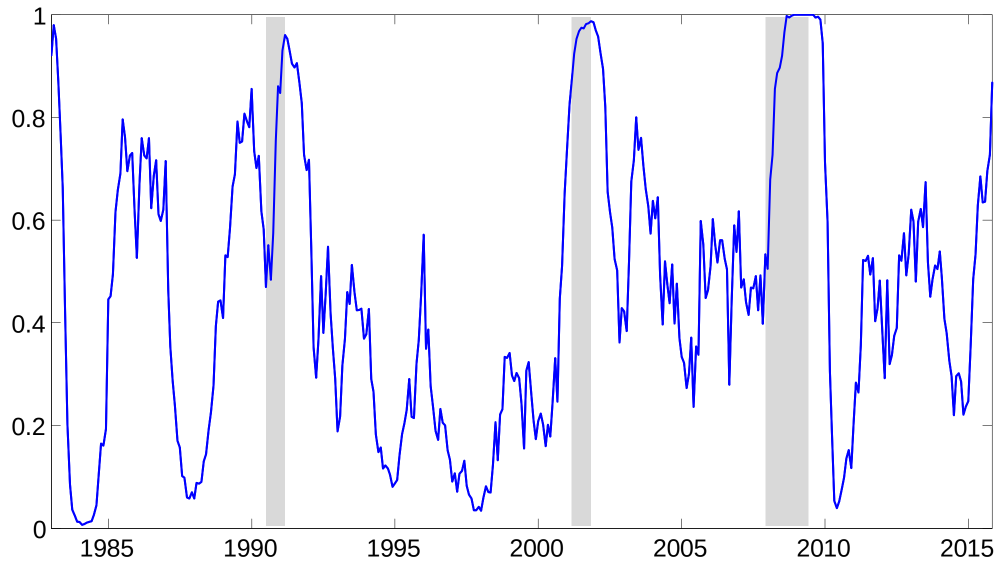

Figure 2: Probability of recessionary regimes. Shaded columns: NBER recessions. The transition function is computed by the standardized 12-month one-sided moving average of the month-on-month industrial production growth rate. Sample period: 1983M1:2015M11.

to match the observed frequency of recessions in our sample. Based on the recession dates released by National Bureau of Economic Research (NBER), approximately 10% of our sample are in the recessionary phase. Thus, in the our model, the economy is considered to be in a recession regime when $F(z_t) \geq 0.9$ and γ is calibrated to ensure that $Pr(F(z_t) \geq 0.9) = 0.1$. This approach leads to a calibration $\gamma = 2.2$. Figure 2 displays the transition function $F(z_t)$ based on our calibration of γ. As the figure shows, the transition function tracks the recession episodes in our sample very well.

To ensure that the true data generating process is not linear, we employed two tests proposed by Teräsvirta and Yang (2014).[5] Both tests rejected the null hypothesis of linearity strongly at any significant levels that are commonly used in the literature. To identify exogenous mortgage spread shocks, we adopt the widely-used Cholesky decomposition approach. We order mortgage spreads after the aggregate quantities, the consumer price index, but before the house price index and the federal funds rate. These restrictions imply that mortgage spread shocks are only allowed to affect house prices and the federal funds rate contemporaneously. Alternative identification assumptions will be discussed in the robustness check section. Furthermore, given the highly non-linear nature of our model, we estimate the model with the Monte-Carlo Markov-chain (MCMC) algorithm developed by Chernozhukov and Hong (2003), the details of which are discussed in the Appendix.[6]

[5] We employed two tests. The first one is a LM-related test using a third-order approximation of the STVAR model. The second one takes into account that there could be small sample bias and rescales the test statistic of the first test. The results are available in the appendix.

[6] An alternative estimation method is to adopt the Gibbs sampling algorithm proposed by Lopes and Salazar

3.2 Baseline Results

In order to capture any potential nonlinearities in the responses of variables, we follow Koop et al. (1996) to compute the generalized impulse response functions (GIRFs) which endogenise the evolution of the probability $F(z)$.[7] Figure 3 shows the estimated impulse responses of the variables to a one standard deviation mortgage spread shock with our linear and non-linear models.

Several findings are warranted. First, our linear model predicts that a positive one standard deviation mortgage spread shock causes industrial production and consumer prices to fall. Both variables reach their maximum contractions of -0.4 percent and -0.1 percent respectively after 15 months. Consumption and the federal funds rate also decline after an adverse mortgage spread shock. Interestingly, the underlying dynamics of real home prices are more nuanced. There is a mild reduction in the real home price index, followed by a strong increase, after the positive shock. Overall, the qualitative results from our linear model are largely consistent with those obtained in Walentin (2014). It is important to note that the impact on industrial production and consumer prices predicted by the linear model is larger than our non-linear model's predictions during expansions. However, the opposite is true when we compare it to the predictions under recessions.

Second, it is evident that the estimated declines in consumption, industrial production, consumer prices and house prices are persistently larger under recessions. Industrial production falls after an adverse mortgage shock in expansions, but the effect is short-lived and much smaller when compared to recessions. Moreover, the figure shows that, under expansions, consumption drops slightly on impact, but it quickly rebounds after the shock. A similar behavior is observed for house prices. The figures also indicates that the federal funds rate drops after the shock as the Federal Reserve implements expansionary policy in an attempt to raise output. However, the decline in the policy rate is milder under recessions.

Is the response of output to a mortgage spread shock in expansions significantly different from that under recessions? Figure 4 displays the estimated responses along with the 68 percent probability bands from our non-linear models. The figure makes clear that industrial production and consumer prices in recessions drop much more than that in expansion regime and the discrepancy is statistically significant. Moreover, the fall in output and prices remain significant for an extended period of time, as compared to the very short-lived impact when shocks hit at expansion regimes. The fall in real house prices is also significant for 20 months.

As can be seen, the impact on the real and price variables as well as real land prices are significantly more severe when such shocks hit in recessions. Our conclusion that mortgage spreads exert asymmetric effects on the US economy during recessions and expansions remains robust.

We have shown that the effects of a mortgage spread shock on industrial production and prices during expansions are significantly different from recessions. Meanwhile, our model also estimates

(2006). It will be an interesting exercise to compare the estimation efficiency between the two methods and we leave this for future research.

[7] The procedures of computing the GIRFs are found in the appendix.

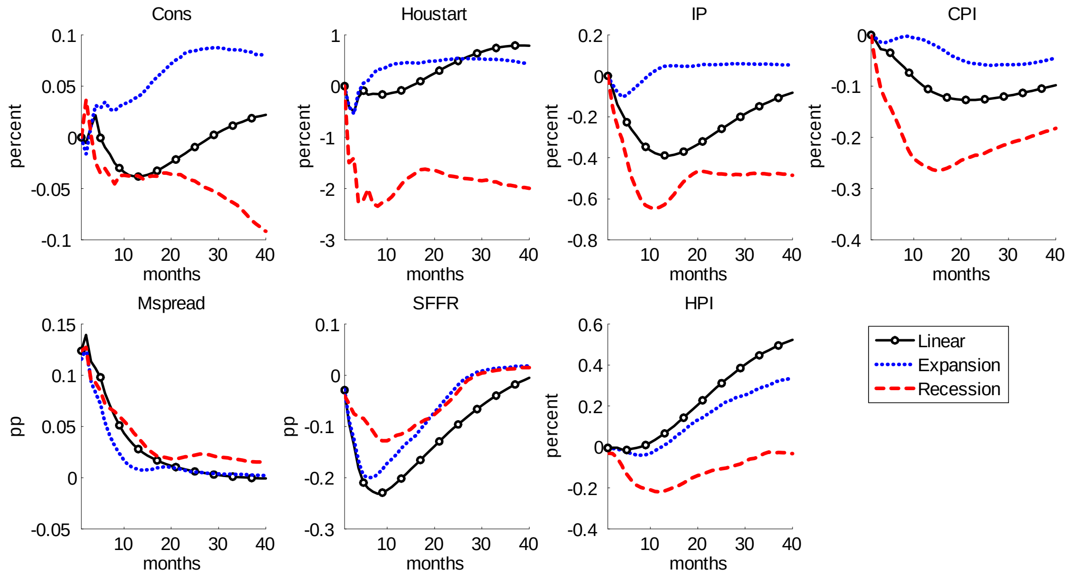

Figure 3: Generalised impulse responses to a one-standard deviation mortgage spread shock: linear model, recessions, expansions. Sample period: 1983M1:2015M11.

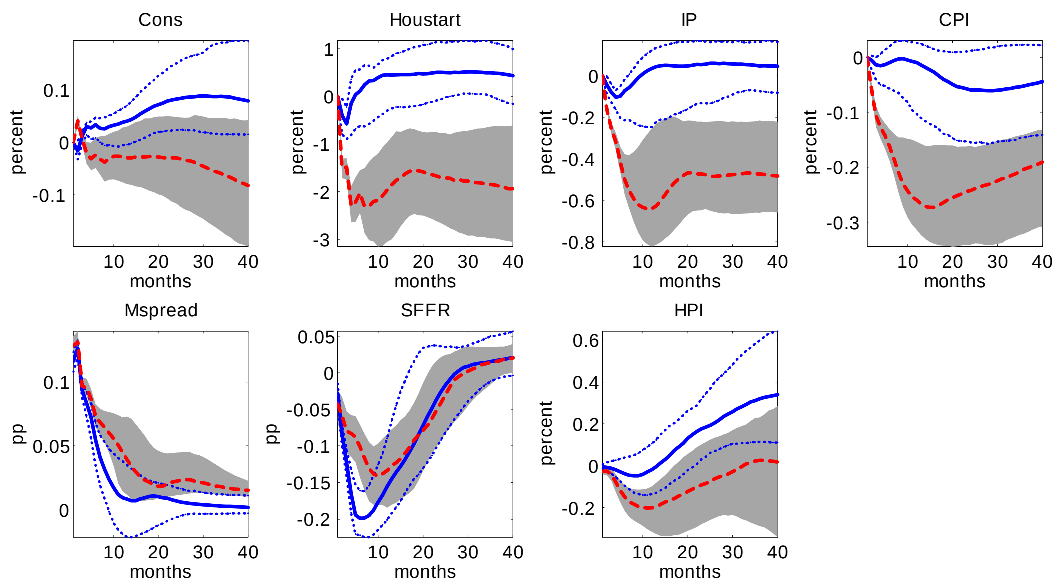

Figure 4: Generalised impulse responses to a one-standard deviation mortgage spread shock under our *baseline model*. Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability. Sample period: 1983M1:2015M11.

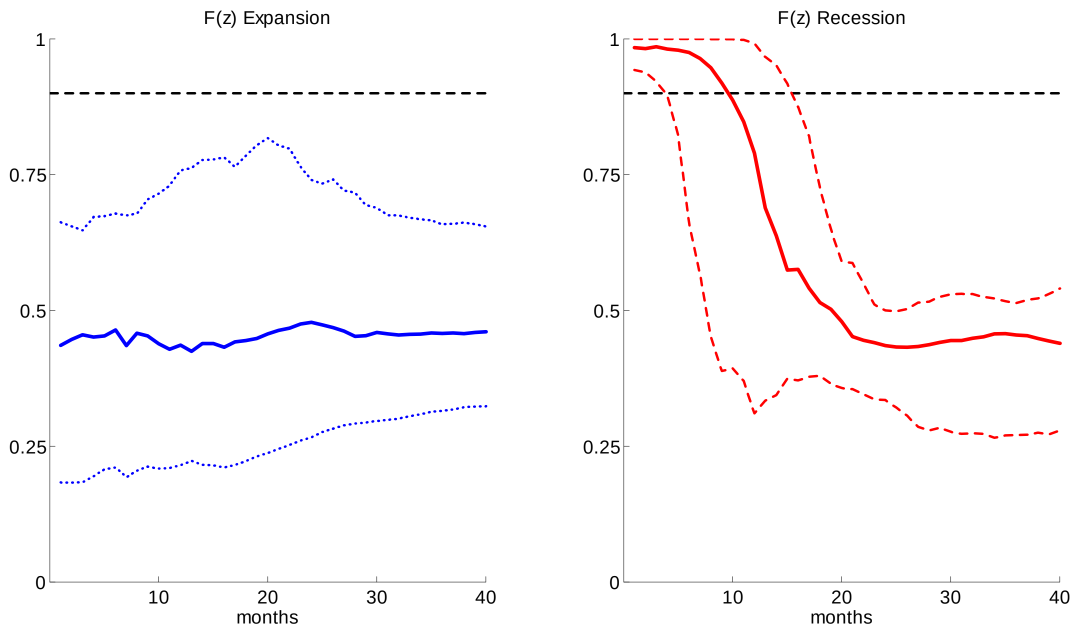

Figure 5: The probability of being in a recessionary phase F(z) after a one- standard deviation mortgage spread shock.

the impact of a mortgage spread shock on the probability of being in a recession. Figure 5 shows the estimated transition function from our model, $F(z)$. As we can see from the figure, when the economy starts out in a recession regime, a mortgage spread shock keep the economy in a recession for an extended period of time. The estimated probability $F(z)$ in recession regime shows that the probability falls below the threshold value of 90 percent after 10 months. On the other hand, when the economy starts at an expansionary phase, the negative impact of a mortgage spread shock is not strong enough to put the economy into a recession and never switches to a recession.

Table 2

Elasticity of variables to mortgage spread shocks from the baseline VAR model.

Phase\Variables	Cons	Houstart	IP	CPI	SFFR	HPI
Linear	-0.3	-4.0	-3.1	-1.0	-1.9	-0.1
Expansion	-0.1	-4.7	-0.9	-0.5	-1.7	-0.3
Recession	-0.8	-18.9	-5.2	-2.1	-1.0	-1.8

Note: Computed as maximum negative response of variable/ standard deviation of shock.

Figure 6: Mortgage spread innovations. 2007M1-2010M3. Solid line: mortgage spread innovations. Units are in terms of standard deviations. The standard deviation is 12 basis points. The first five months of MBS purchase program are marked in red. Dashed line: mortgage spread.

Table 3

Peak effects of MBS purchase program.

Variables\Models	Non-Linear (baseline)	Linear
Consumption	0.4	0.2
Housing starts	9.4	2.0
Industrial production	2.6	1.5
Consumer prices	1.1	0.5
House prices	0.9	0.1

Note: Units are in percent.

To faciliate the comparison between our results with those from other studies, we compute the "elasticities" to a mortgage spread shock. Table 3 displays the magnitudes of the responses of our key variables to a unit-sized shock to mortgage spreads. The table shows that a 100 basis point increase in mortgage spreads would depress industrial production by about 5 percent during recessions, but only 1 percent during expansions. Moreover, consumer prices are lower by 2 percent under recessions and only 0.5 percent under expansions. The predicted effects on industrial production and consumer prices from our linear model are lower (higher) than those under recessions (expansions). Compared with the findings in Walentin (2014), the estimated elasticities of consumption and house prices from our linear model are slightly smaller, but our estimated elasticity of policy rate to a mortgage spread shock is approximately the same.

We display the estimated mortgage spread innovations from our STVAR model in Figure 6. The first five months of the Federal Reserve's mortgage-backed security purchase program, which consisted of buying $1.25 trillion ($500 billion initially) of MBS between January 2009 and March 2010 are marked in red. As one can see, our model is able to correctly capture the mortgage spread innovations. And it also indicates that the MBS purchase program had substantial impacts on the mortgage spread. Indeed, the estimated innovations imply that the MBS purchase program lowered the mortgage spread after 2009 with a peak effect of 44 bps.[8]

Table 3 displays the approximated quantitative effects of the MBS purchase program on the key macroeconomic variables under our non-linear and linear models.[9] The predicted peak effects of the MBS purchase program from our STVAR model are much larger than from the linear model, especially for the effect on housing starts and industrial production.[10]

4 Robustness checks

Thus far, our baseline results show that the effect of mortgage spread shocks on the US industrial production and prices under recessions and expansions are significantly different. In this section, we conduct a series of robustness checks.

4.1 Using the actual federal funds rate

As noted in the previous section, we adopted the shadow federal funds rate to eliminate the zero lower bound problem. In this exercise, we re-estimate our STVAR model with the actual federal funds rate, instead of the shadow federal funds rate, from 1983M1 to 2015M11. In other words, the federal funds rate that we employ in this exercise includes the zero lower bound started after 2008. The generalized impulse responses are displayed in Figure 7. The effects on industrial production and consumer prices are very similar to the baseline model. However, the response of the federal funds rate after an adverse mortgage spread shock is smaller under both expansion and recession. The negative effect on home prices is larger and more persistent, especially under recession. Overall, the generalized impulse response functions indicate the asymmetric effects of mortgage spreads under expansions and recessions.

[8] The effects of a one standard deviation mortgage spread shock on the mortgage spread are 12 bps, 13 bps, 9 bps, 9 bps and 8 bps for the first five months respectively. The mortgage spread innovations in the first five months of the MBS purcahse program are -1.0, 0, -0.4, -1.1 and -1.5 standard deviations, which add up to a peak effect of 44 bps.

[9] The peak effects of the MBS purchase program are calculated as follows. We sum the mortgage spread innovations in the first five months of the program, which amounts to 4 standard deviations. We then multiply the sum of the innovations by the peak effect of one standard deviation under our non-linear and linear models respectively.

[10] Theoretically, the non-linear impulse responses to a mortgage spread shock may depend on the sign or the size of the shock. However, we conducted simulations and confirmed that the role played by the size or the sign of a mortgage shock in explaining the non-linear effects is negligible.

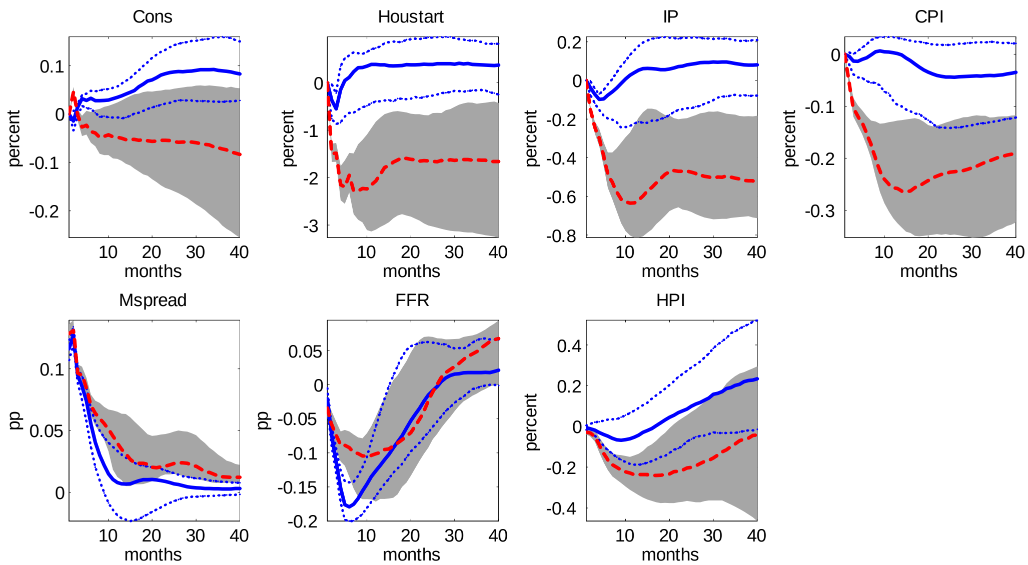

Figure 7: Generalised impulse responses to a one-standard deviation mortgage spread shock, *using the actual federal funds rate that includes the data corresponding to the period of zero-lower-bound interest rate*. Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability. Sample period: 1983M1:2015M11.

4.2 Different calibration for the slope parameter

We examine our results to alternative calibrations of the slope parameter γ in this subsection. More specifically, we set γ to alternative values, ranging between 2.2 to 3.2, which correspond to the number of recessions in our sample equals 10% and 20% respectively. Figure 8 displays the responses of our model when γ is calibrated to 3.2. The results for other calibrations of γ are displayed in the appendix.

Overall, the results are similar to the baseline specification, except that the negative impact on industrial production and consumer prices during recessions is less severe in the current exercise. However, the difference in the responses between recessionary and expansionary phases remains statistically significant.

4.3 Different Cholesky ordering

In this subsection, we test the robustness of our results by examining the results with alternative ordering. In particular, the mortgage spread is ordered last in the model. This implies that mortgage spread shocks do not have contemporaneous effect on the quantity variables, the price indexes and the federal funds rate, but all other shocks can impact mortgage spreads within the same period. Figure 9 displays the generalized impulse responses of the model. The results are very similar to our baseline model. Mortgage spread shocks exert asymmetric effects during expansions and recessions.

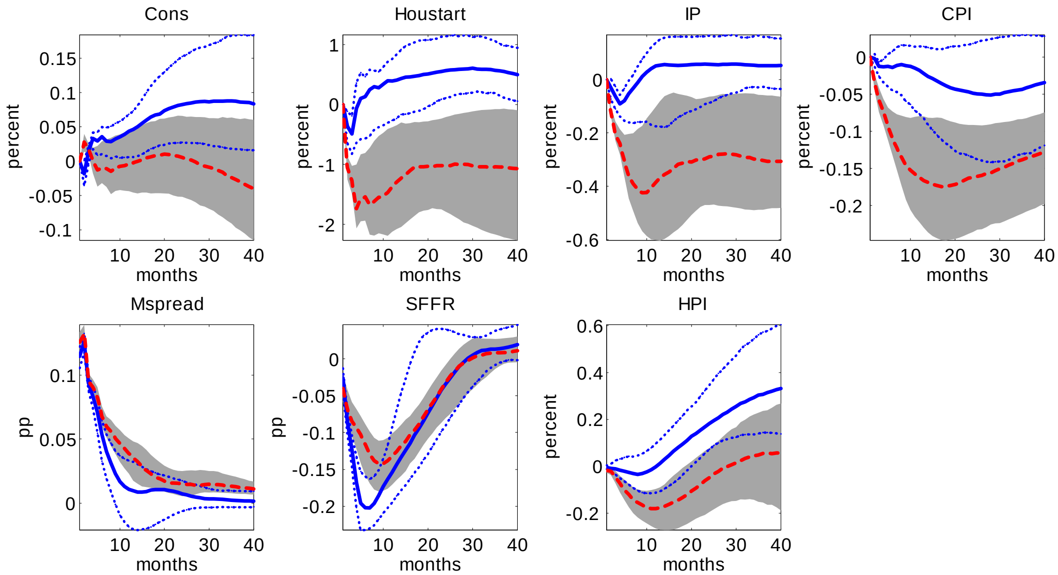

Figure 8: Generalised impulse responses to a one-standard deviation mortgage spread shock *with an alternative slope parameter value* ($\gamma = 3.2$). Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability. Sample period: 1983M1:2015M11.

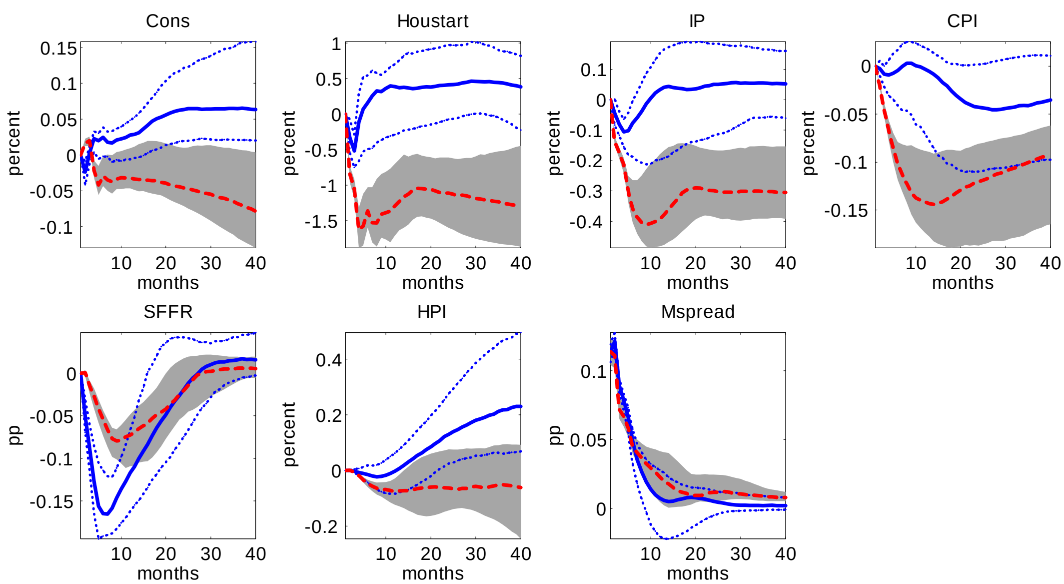

Figure 9: Generalised impulse responses to a one-standard deviation mortgage spread shock *when mortgage spreads are ordered last*. Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability. Sample period: 1983M1:2015M11.

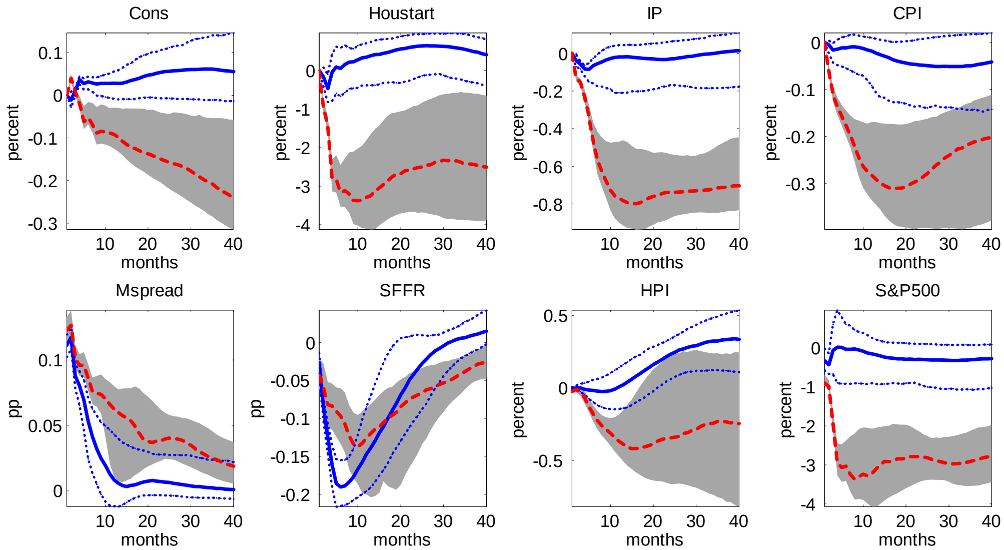

Figure 10: Generalised impulse responses to a one-standard deviation mortgage spread shock *when S&P 500 is included in the baseline model*. Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability. Sample period: 1983M1:2015M11.

4.4 Stock market prices

We introduce the logarithm of S&P500 index to our baseline model in this exercise to capture the financial wealth-related effects created by mortgage spread shocks through stock prices. Figure 10 displays the generalized impulse responses from the modified model. As we can see from the figure, consumption, housing starts and home prices drop substantially after a mortgage spread shock. The responses of industrial production and consumer prices in the current model are much *larger* than our baseline results. This indicates that the contractionary effects of an adverse mortgage spread shock are amplified by the interaction of equity prices.

4.5 Corporate bond spreads

Gilchrist and Zakrajšek (2012) find that excess corporate bond premium shocks are important for business cycle fluctuations. Since mortgage spreads and corporate bond spreads are highly correlated, it is important to for us to investigate the effects of mortgage spread shocks in a model that controls for the corporate spread.

More specifically, we estimate a STVAR in which the vector of endogenous variables, $x_t = [Cons_t, Houstart_t, IP_t, CPI_t, Cspread_t, Mspread_t, SFFR_t, HPI_t]'$. As in Walentin (2014), corporate spreads, $Cspread_t$, are measured as the difference between interest rates on BAA-rated corporate bonds and the 10-year Treasury bond. The corporate spread is ordered before the mortgage spread in our VAR model, such that mortgage spread shocks do not impose on-impact effect

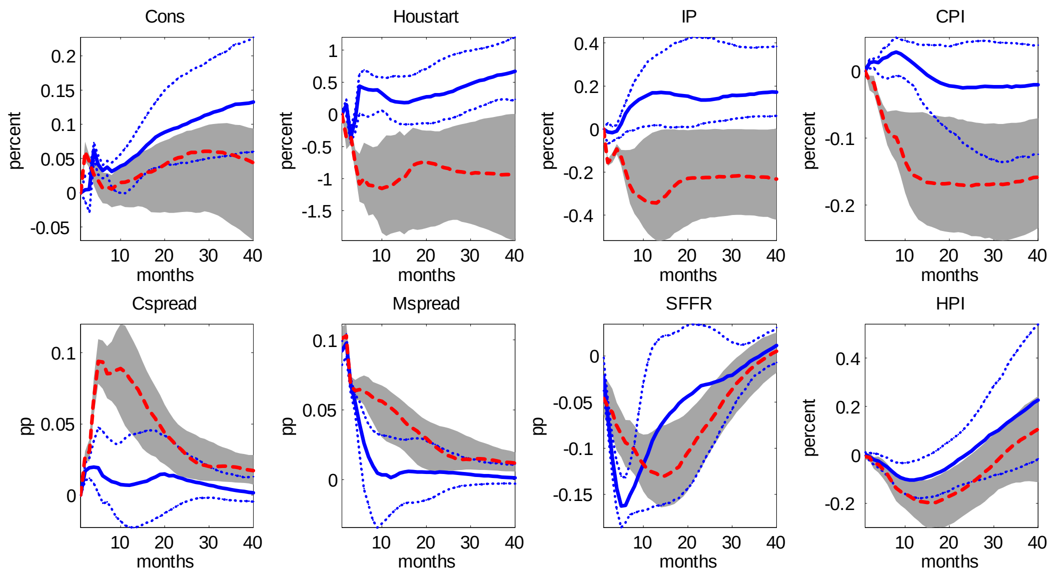

Figure 11: Generalised impulse responses to a one-standard deviation mortgage spread shock, *with the inclusion of corporate bond spreads to our baseline model.* Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability. Sample period: 1983M1:2015M11.

on the corporate spread.

Figure 11 displays the estimated impulse responses of the modified model to a positive mortgage spread shock during recessions and expansions. The figure makes clear that industrial production, consumer prices and real home prices drop significantly after an adverse mortgage spread shock. Compared with the baseline results, the decline in industrial production and consumer prices are less pronounced. Moreover, consumption rises moderately after the shock under the recessionary regime in the current model.

The corporate spread rises significantly after a positive mortgage spread shock. It is also evident that the impact of mortgage spread shocks on the corporate spread is much larger during recessions. The response of the federal funds rate is also more persistent. Overall, the results suggest that mortgage spread shocks may play a smaller role if one controls for the corporate spread shocks. However, our results support that mortgage spread shocks exert asymmetric effects on the US economy during recessions and expansions, even after controlling for corporate spread shocks.

4.6 Financial uncertainty

Caldara et al (2014) point out that financial stress and uncertainty are related. To control for the effects of uncertainty on house prices and the economy, we introduce an uncertainty index to our baseline model in this exercise. Following Bloom (2009), we use the VXO index to capture financial uncertainty in the economy. More specifically, we estimate a STVAR in which the vector

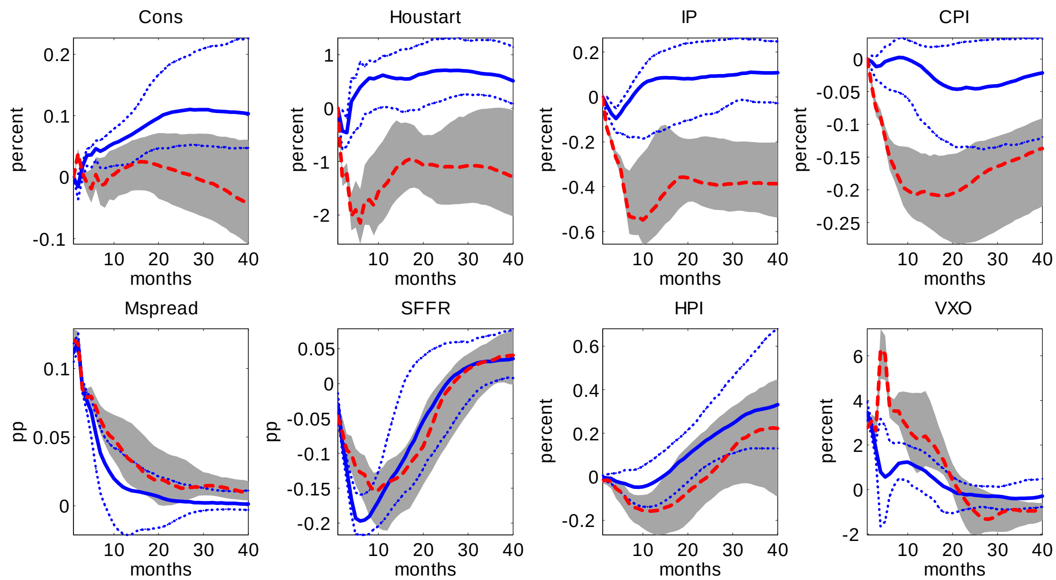

Figure 12: Generalised impulse responses to a one-standard deviation mortgage spread shock *when the VXO index is included in the baseline model*. Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability. Sample period: 1983M1:2015M11.

of endogenous variables, $x_t = [Cons_t,\, Houstart_t,\, IP_t,\, CPI_t, Mspread_t,\, SFFR_t,\, HPI_t,\, VXO_t]'$.

Figure 12 display the estimated generalized impulse responses for the modified model. As the figure shows, the responses are very similar to our baseline results. However, it is important to note that an adverse mortgage spread shock raises uncertainty in the financial market. The VXO index rises substantially after the shock. In fact, the increase in the VXO index is significantly larger under recessions. The figure shows that the difference in the responses of industrial production and consumer prices are statistically significant. Our results remain robust even after controlling for the effect of uncertainty.

4.7 Other robustness checks

In the appendix, we provide further evidence that our results are robust to (i) different VAR lag length; (ii) different calibration values for the slope parameter; (iii) alternative subsample period; (iv) alternative transition variables.

4.8 Systematic Monetary Policy Effectiveness

Our results show that the federal funds rate drops significantly after an adverse mortgage spread shock under both expansions and recessions. However, what would have happened if the federal funds rate had not reacted to mortgage shocks? In this subsection, we attempt to understand the extent to which conventional monetary policy could alleviate the impacts of mortgage spread

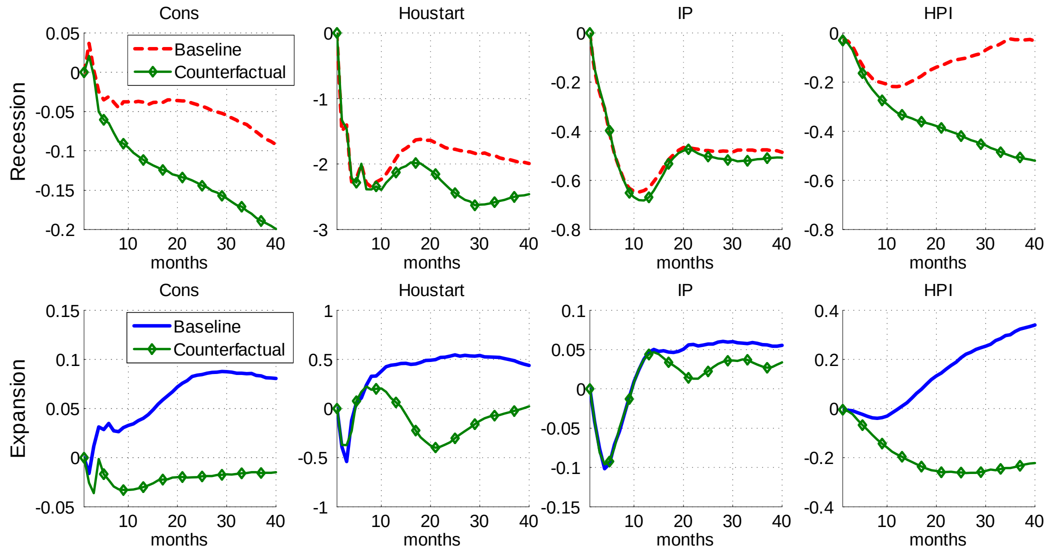

Figure 13: Generalised impulse responses to a one-standard deviation mortgage spread shock *with unconstrained/constrained monetary policy.* Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Green-diamonded lines: counterfactual responses conditional on a fixed federal funds rate. Sample period: 1983M1:2015M11.

shocks. To answer the question of interest, we conduct a counterfactual experiment on our STVAR model by shutting down the systematic response of the federal funds rate after a mortgage spread shock.[11]

Figure 13 compares the responses of the key variables conditional on a fixed federal funds rate with our baseline results. Several features of the figure stand out. First, the declines in house prices and housing starts after a mortgage spread shock are much larger when policy makers are not allowed to lower the policy rate. Similarly, consumption displays a larger fall when the federal funds rate is fixed. These two features reinforce the importance of the housing collateral channel, emphasized by Guerrieri and Iacoviello (2016), in the transmission of a mortgage spread shock.

On the other hand, compared with the baseline result, the negative effect of a mortgage spread shock on industrial production is only slightly larger in our counterfactual experiment. This implies that conventional monetary policy might not be an effective tool to offset the impacts of mortgage spread shocks on real production. One explanation can be that the stabilizing effect of an accommodative policy rate is undermined by the increase in prepayment risks as households tend to refinance their mortgages when interest rates are falling. But we leave this hypothesis for further research.

[11] To conduct the counterfactual simulation, we follow the approach used in Sims and Zha (2006) and Caggiano et al. (2016) and set all the coefficients of the federal funds rate equation in our VAR model to zero.

5 Conclusion

This paper provides robust evidence of nonlinearities of mortgage spreads on the US economy. Using a STVAR model, we find that a positive shock to mortgage spread leads to more severe contraction in industrial production, prices and house prices during recessions. We also show that shock propagations are amplified through the interaction of stock prices. Our results also have important implications for unconventional monetary policy measures, such as the Federal Reserve's mortgage-backed security (MBS) purchase program, which is shown to reduce significantly mortgage spreads and hence could be an effective tool to stabilize the economy during recessions.

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6 Statistical appendix

This appendix presents details in testing model nonlinearities, the computation of STVAR and the generalized impulse responses. The materials are drawn heavily from Caggiano et al. (2015, 2016).

6.1 Statistical evidence in support of nonlinearities

We apply the statistical test proposed in Teräsvirta and Yang (2014) to identify the non-linear relationship among our endogenous variables.

Consider a STVAR model:

$$Y_t = \Phi_0' X_t + \Sigma_{i=1}^n \Phi_i' X_t z_t^i + \varepsilon_t$$

where X_t is a $m \times 1$ vector of endogenous variables, $X_t = [Y_{t-1}\ Y_{t-2}\ ...\ Y_{t-k}\ \beta]$ is a $(l \times m + q) \times 1$ vector of exogenous variables, β is a column vector of constants, z_t is a transition variable, and Φ_0 and Φ_i are coefficient matrices. m is the number of endogenous variables, q is the number of exogenous variable and l is the number of lags. In our case, $m = 7, q = 1, l = 4$.

The procedure of the Teräsvirta-Yang test for non-linear model is as follows:

Step 1: Regress Y_t on X_t and estimate a restricted model in which $\Phi_i = 0, \forall t$. Retrieve the residuals Ξ and the residual sum of squares $RSS_0 = \Xi'\Xi$.

Step 2: Regress Ξ on $(X_{t,} Z_n)$ where $Z_n = [X_t' z_t\ X_t' z_t^2\ ...\ X_t' z_t^n]$. Retrieve the model residuals Ω and compute the residual sum of squares $RSS_1 = \Omega'\Omega$.

Step 3: Compute the test-statistic

$$LM = T \times tr[RSS_0^{-1}(RSS_0 - RSS_1)]$$

The test statistic has a χ^2 distribution with $m(ml + q)$degrees of freedom. For n = 3, the test statistic for our model is 900 which corresponds to a p-value near zero. The null hypothesis of linearity can also be rejected for n = 2.

We also compute the following rescaled LM test statistic:

$$F = \frac{mT - l}{Q\ \times mT} LM$$

where Q is the number of restrictions. The rescaled test statistic has a $F(Q, mT - l)$ distribution. In our model, we receive $F = 10.34$, with p-value near zero.

6.2 Estimation of the smooth-transition VARs

We employ maximum likelihood methods to estimate our STVAR model. The log-likelihood function is as follows:

$$\log L = const + \frac{1}{2}\sum_{t=1}^{T}\log|\Theta_t| - \frac{1}{2}\sum_{t=1}^{T}\epsilon_t'\Theta_t^{-1}\epsilon_t$$

where the vector of residuals $\epsilon_t = Y_t - F(z_{t-1})\Phi_R(L)Y_t - (1-F(z_{t-1}))\Phi_E(L)Y_t$. Conditional on the calibrated value of γ, the parameters that we need to estimate are $\Gamma = \{\Theta_R, \Theta_E, \Phi_R(L), \Phi_E(L)\}$.

Notice that for an initial guess on $\{\Theta_R,\ \Theta_E\}$, the coefficient matrices $\Phi_R(L)$ and $\Phi_E(L)$ can be estimated by minimizing $\frac{1}{2}\sum_{t=1}^{T}\epsilon_t'\Theta_t^{-1}\epsilon_t$, since the model is linear in $\{\Phi_R(L),\ \Phi_E(L)\}$ when $\{\gamma,\ \Theta_R,\ \Theta_E\}$ are known. The procedure involves simulating over different sets of values for Θ_R and Θ_E. In order to ensure positive definiteness of the matrices, we focus on the Cholesky decomposition of Θ_R and Θ_E. In other words, we search for a vector of parameters $\Omega = \{chol(\Theta_R), chol(\Theta_E), \Phi_R(L), \Phi_E(L)\}$, where *chol* represents Cholesky decomposition.

The Markov Chain Monte Carlo (MCMC) algorithm, developed by Chernozhukov and Hong (2003), is adopted for the estimation of the model. Given an initial value, the procedure draws chains of parameter values based on the following steps:

Step 1. Consider Ω^n as the current state and ζ^n is a vector of *i.i.d* shocks drawn from $N(0, \Theta_\Omega)$, where Θ_Ω is a diagonal matrix. Draw a candidate vector of parameter values $\Upsilon^n = \Omega^n + \zeta^n$ for the chain's n +1 state.

Step 2. With probability $min\left\{1, \frac{L(\Upsilon^n)}{L(\Omega^n)}\right\}$,set $\Omega^{n+1} = \Upsilon^n$ in the n +1 state of the chain, where $L(\Upsilon^n)$ and $L(\Omega^n)$ are the values of the likelihood function conditional on the candidate vector and the current state of the chain respectively. Otherwise, set $\Omega^{n+1} = \Omega^n$.

We conduct N = 50,000 draws for our estimates and discard the first 80% as burn-in. A scale factor is adjusted to ensure that the acceptance rate is close to 30 percent. The estimate of $\overline{\Omega} = \frac{1}{N}\sum_{n=1}^{N}\Omega^n$ is shown to be consistent under standard regularity assumptions by Chernozhukov and Hong (2003). The covariance matrix, $var(\Omega)$ is then calculated by $\frac{1}{N}\sum_{n=1}^{N}(\Omega^n - \overline{\Omega})^2$.

6.3 Generalized Impulse Response Functions

Following the approach by Koop et al. (1996), the generalized impulse responses functions for our STVAR are computed as follows.

Step 1. Construct the set of all possible histories Ψ of length $p = 12$ (the number of moving average terms) based on our sample from 1985M1 to 2015M11. Each history is denoted as $\varphi_i \in \Psi$.

Step 2. Divide the set of possible histories into two subsets: recessionary and expansionary histories. For each history, calculate the transition variable z_{φ_i}. If $z_{\varphi_i} \leq \overline{z}$, then $\varphi_i \in \Psi_R$, where Ψ_R is the set of recessionary histories, $\overline{z}$ is the threshold value based on our calibration. Similarly, if $z_{\varphi_i} > \overline{z}$, then $\varphi_i \in \Psi_E$, where Ψ_E is the set of expansionary histories.

Step 3. Randomly select a history φ_i from the recessionary set Ψ_R. Then compute $\widehat{\Theta}_{\varphi_i} = F(z_{\varphi_i})\widehat{\Theta}_R + \left[1 - F(z_{\varphi_i})\right]\widehat{\Theta}_E$ for the the selected history φ_i. Note that $\widehat{\Theta}_R$ and $\widehat{\Theta}_E$ are the estimates from the generated MCMC chain. This is to eliminate any potential estimation bias.

Step 4. Apply Cholesky decomposition to the estimated variance-covariance matrix $\widehat{\Theta}_{\varphi_i}$ to obtain a lower triangular matrix $\widehat{C}_{\varphi_i}$ where $\widehat{\Theta}_{\varphi_i} = \widehat{C}_{\varphi_i}\widehat{C}'_{\varphi_i}$.To get the structural shocks by orthogonalizing the estimated residuals,

$$\mathbf{e}^k_{\varphi_i} = \widehat{C}^{-1}_{\varphi_i}\widehat{\epsilon}$$

Step 5. Draw with replacement from $\mathbf{e}_{\varphi_i}$ to get a h seven-dimensional shocks and form a vector of bootstrapped shocks

$$\mathbf{e}^{k*}_{\varphi_i} = \left\{\mathbf{e}^*_{\varphi_i,t},\ \mathbf{e}^*_{\varphi_i,t+1},...,\mathbf{e}^*_{\varphi_i,t+h}\right\}$$

Step 6. Perturb the j_{th} shock in $\mathbf{e}^{k*}_{\varphi_i}$ by δ and form another vector of bootstrapped shocks $\mathbf{e}^{k\delta}_{\varphi_i}$.

Step 7. Construct residuals as follows:

$$\widehat{\epsilon}^{k*}_{\varphi_i} = \widehat{C}_{\varphi_i}\mathbf{e}^{k*}_{\varphi_i}$$

$$\widehat{\epsilon}^{k\delta}_{\varphi_i} = \widehat{C}_{\varphi_i}\mathbf{e}^{k\delta}_{\varphi_i}$$

Step 8. Use the constructed residuals to simulate the movements of $Y^{k*}_{\varphi_i}$ and $Y^{k\delta}_{\varphi_i}$. The generalized impulse response functions, $GIRF^k(h, \delta, \varphi_i)$ are equal to $Y^{k*}_{\varphi_i} - Y^{k\delta}_{\varphi_i}$.

Step 9. Conditional on history φ_i, repeat the procedure and get $GIRF^k(h, \delta, \varphi_i)$ for $k = 1, ..., Z$ where Z is set to 500. Then calculate the GIRF as

$$\widehat{GIRF}^i(h, \delta, \varphi_i) = Z^{-1}\textstyle\sum_{k=1}^{Z} GIRF^{ik}(h, \delta, \varphi_i)$$

Step 10. Repeat the steps above for 500 histories in the recessionary history set, $\varphi_i \in \Psi_R$. Obtain $\widehat{GIRF}^{i,R}(h, \delta, \varphi_{i,R})$ for $i = 1, ..., 500$.

Step 11. Use the average of $\widehat{GIRF}^{i,R}(h, \delta, \varphi_{i,R})$ to obtain the $\widehat{GIRF}^R$ under recessions.

Step 12. Repeat step 3 to 11 for 500 histories in the expansionary set to obtain $\widehat{GIRF}^E$ under expansions.

Step 13. Use the 16th and 84th percentile of the densities $\widehat{GIRF}^{1:500,R}(h, \delta, \varphi_{i,R})$ and $\widehat{GIRF}^{1:500,E}(h, \delta, \varphi_{i,E})$ to construct the 68% probability bands.

7 Appendix: Further robustness exercises

Different lag length. Our baseline model is estimated with four lags. Here we estimate the model with three lags. Figure A1 displays the results

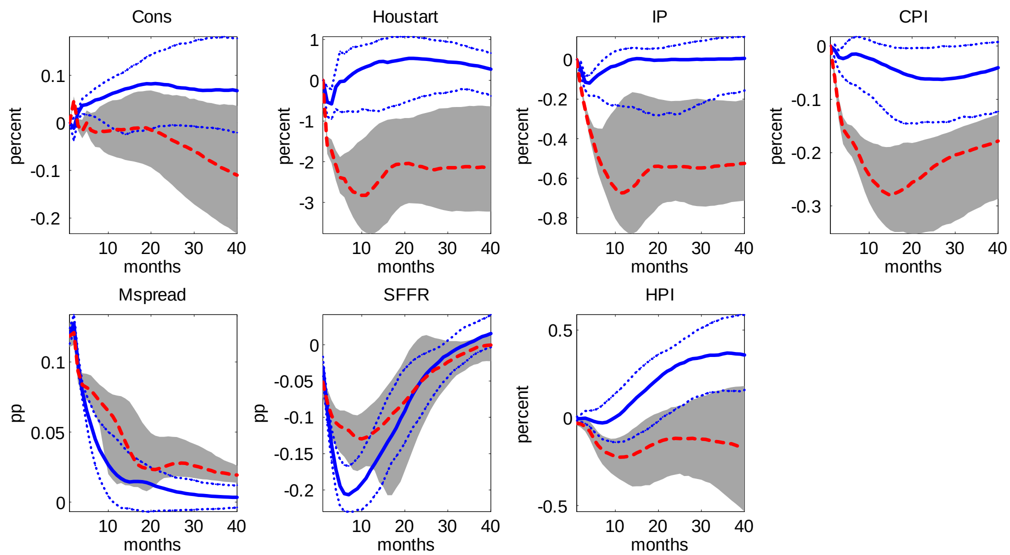

Figure A1. Generalised impulse responses to a one-standard deviation mortgage spread shock *when the baseline model is estimated with 3 lags*. Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability. Sample period: 1983M1:2015M11.

Different calibrations for slope parameter. We calibrate the smoothness parameter $\gamma = 3.0$ such that the recession frequency in our sample is equal to 15 percent. Figure A2 displays the results based on this calibration.

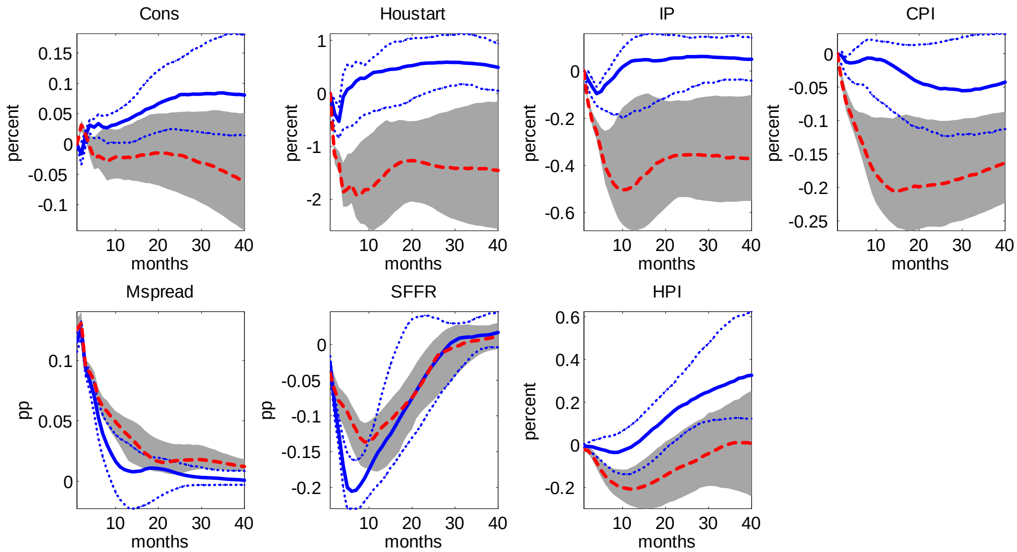

Figure A2. Generalised impulse responses to a one-standard deviation mortgage spread shock *with an alternative slope parameter value* $\gamma = 3.0$. Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability. Sample period: 1983M1:2015M11.

Subsample 1985M1 to 2008M9. In this robustness exercise, we end the sample in 2008M9 to avoid the zero lower bound and any possible non-linearity due to the intensification of the recent financial crisis. Figure A2 displays the generalized impulse responses for the subsample. As the figure shows, the effect of an adverse mortgage spread shock on industrial production and prices are much smaller. However, it is still evident that mortgage spread shocks exert asymmetric effects under recessions and expansions.

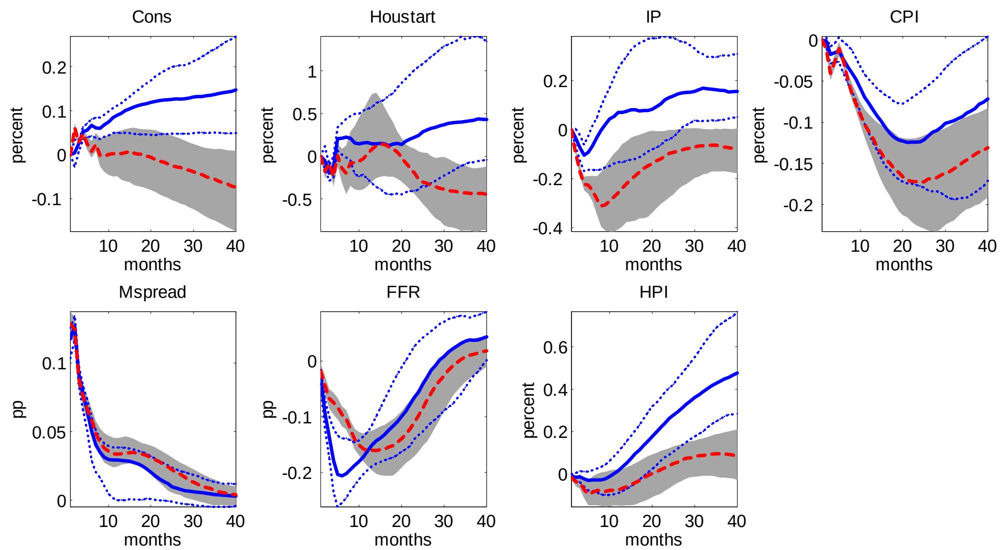

Figure A3. Generalised impulse responses to a one-standard deviation mortgage spread shock *estimated with the sample from 1985M1 to 2008M9.* Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability.

Transition variable with nine-month moving average of the industrial production growth rate. In this exercise, we compute the transition variable z_t, using nine month backward looking moving average of the growth rate in industrial production. Figure A5 displays the corresponding transition function $F(z_t)$ based on the nine month moving average. Figure A6 displays the impulse responses.

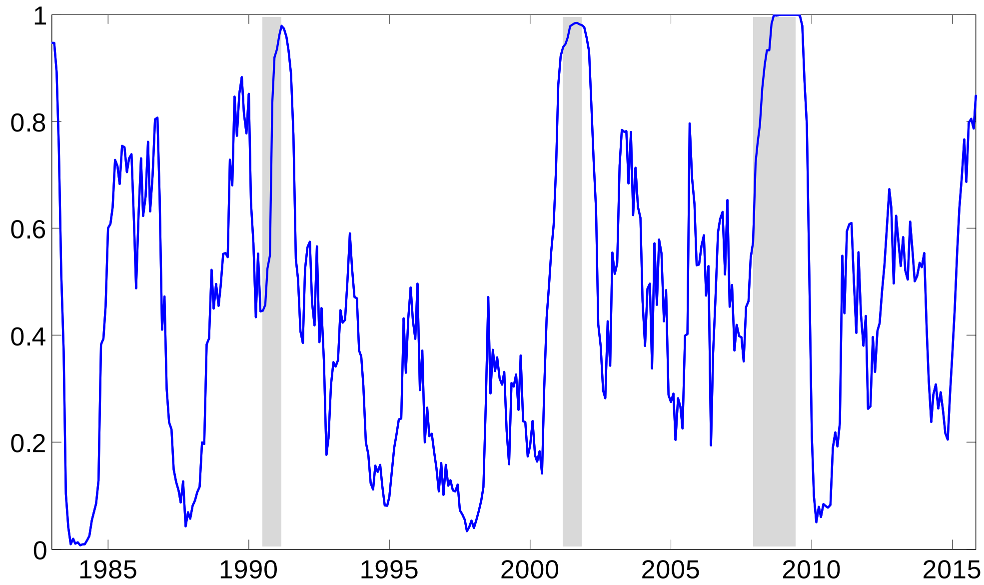

Figure A5. Probability of Being in a Recessionary Phase. Shaded columns: NBER recessions. The transition function is computed by using the standardized 9-month one-sided moving average of the month-on-month industrial production growth rate. Sample period: 1983M1:2015M11.

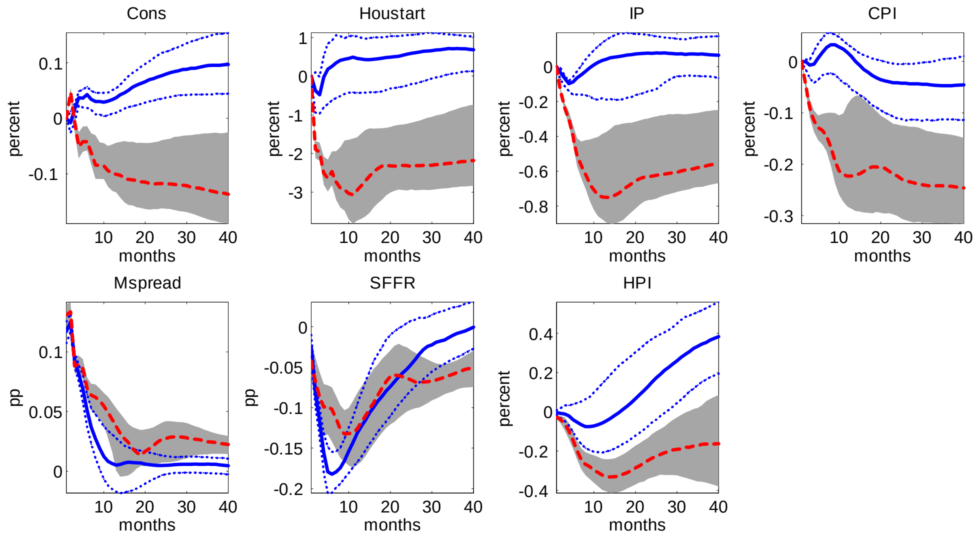

Figure A6. Generalised impulse responses to a one-standard deviation mortgage spread shock using a *9-month moving average industrial production growth rate as the transition variable.* Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability. Sample period: 1983M1:2015M11.

Unemployment rate as transition variable. In this exercise, we estimate a STVAR model augmented with the unemployment rate. We employ the rate of change of the unemployment rate as the transition variable of the business cycle. More specifically, we define the periods in which the growth of twelve month moving average of the unemployment rate is above one standard deviation as recessionary. Figure A7 displays the generalized impulse responses.

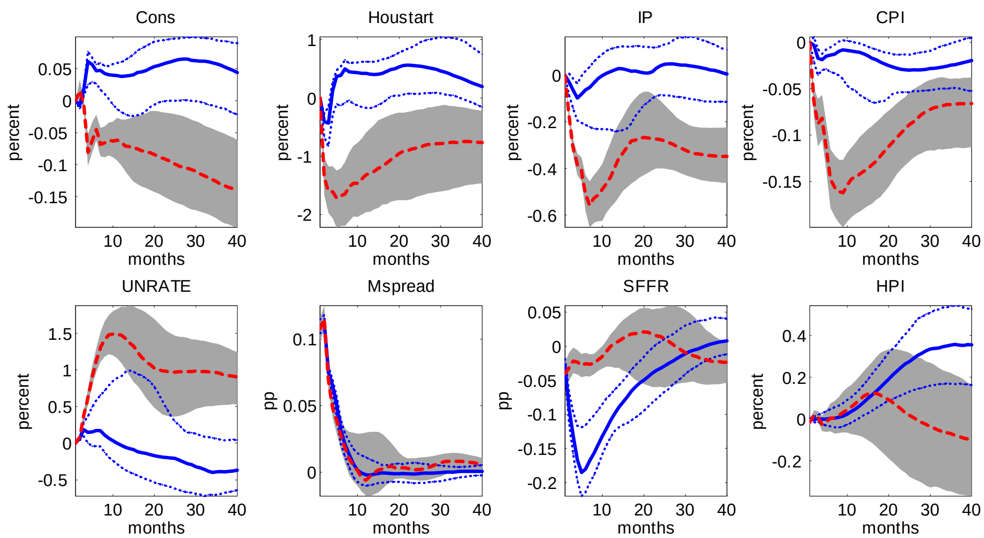

Figure A7. Generalised impulse responses to a one-standard deviation mortgage spread shock when the unemployment rate is included in the baseline model and is also used as the transition variable. Solid lines: median responses under expansions. Dashed lines: median responses under recessions. Error bands are of 68 percent probability. Sample period: 1983M1:2015M11.

Mortgage spreads and Corporate spreads

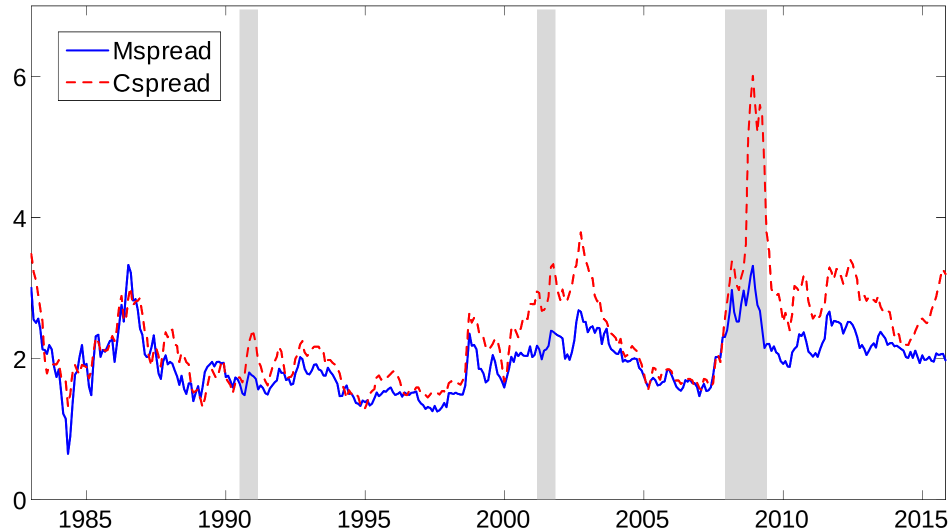

Figure A8. Mortgage spread (solid line), corporate spread (dashed line) and NBER recession dates (shaded columns). The mortgage spread is computed as the 30-year fixed rate mortgage rate minus the average of the 5-year and the 10-year Treasury bond rate. The corporate spread is defined as the difference between the interest rates on Moody's Baa-rated corporate bonds and the 10-year Treasury bonds.