Housing Market Connectedness and Transmission of Monetary Policy*

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Abstract

This paper examines whether the degree of interconnectivity among local housing markets affects the effectiveness of the monetary transmission mechanism in the U.S. economy. We construct measures of housing market connectedness and use a state-dependent local projection method to estimate nonlinear empirical impulse responses of macroeconomic variables to a monetary policy shock. The primary finding is that monetary policy has a greater impact when regional housing markets are more synchronized. This implies that a spillover effect among local housing markets may magnify the effectiveness of monetary policy. Moreover, analyses reveal two additional findings: monetary policy is more effective i) during high-connectedness periods with expansions, and ii) when house price fluctuations are predominantly driven by a national factor rather than regional factors.

JEL Classification: R31, E52, E32

Keywords: Housing market, connectedness; monetary policy

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1 Introduction

U.S. regional housing markets are synchronized, but with varying levels of synchronization over time (Landier, Sraer and Thesmar, 2017; Choi and Hansz, 2021). Such interconnectivity among local housing markets potentially performs a crucial role in monetary transmission mechanisms because changes in regional-level economic conditions triggered by monetary policy shocks could spill over into other regions. Since this spillover effect may either amplify or dampen the effects of monetary policy, it remains uncertain whether monetary policy is more or less effective when regional housing markets are more synchronized. Policymakers may face the challenge of tailoring monetary policy to achieve desired economic outcomes in light of this uncertainty. Against this backdrop, the objective of this paper is to examine how housing market connectedness influences monetary transmission mechanisms within the U.S. economy.

To begin with, we measure the degree of interconnectivity among state-level housing markets by utilizing the methodology developed by Diebold and Yilmaz (2014). This involves measuring the connectedness index through the variance decomposition matrix associated with an N-variable vector autoregression (VAR). We use data on the average house prices from the Freddie Mac House Price Index (FMHPI) for all 50 states and Washington, D.C. in the United States, covering the period from 1976:m1 to 2020:m12. We then identify which periods constitute the low- or high-connectedness state based on the connectedness measures.[1] We next empirically document whether the transmission of monetary shocks depends on the housing market connectedness. To this end, we employ state-dependent local projection methods, proposed by Jorda (2005). Our empirical methodology is comparable to those of Tenreyro and Thwaites (2016) and Alpanda and Zubairy (2019), as they investigate how monetary policy influences economies in times of recession or when households have high debt levels. As such, our study contributes to the existing literature on the effects of monetary shocks, which can vary depending on the economic conditions.

The primary finding is that the impact of federal funds rate shocks is stronger during periods with high levels of housing market connectedness compared to those with low levels of connectedness. More specifically, the impact of a monetary shock on GDP, consumption, residential investment, housing prices, and employment is substantially greater when the initial level of housing market con-

[1] We find that these episodes of low or high connectedness do not necessarily align with business cycles.

nectedness is higher than its long-run average. These results are robust to employing different definitions for the state of the economy, alternative monetary policy shocks, and other various specifications. In particular, our baseline estimation is designed to avoid the impact of the Great Recession and the Zero Lower Bound (ZLB) periods, and thus, the sample period is limited to 1981:q1-2007:q4. However, expanding the sample period and including additional data still yield robust results.

In our investigation of the underlying mechanism behind these findings, we examine the impact of monetary policy shocks on house prices across different local housing markets and how the degree of market connectedness influences these dynamics. The findings suggest that local house prices tend to move together and increase in response to expansionary monetary policy shocks when regional housing markets are more synchronized. In contrast, the response of local house prices is muted and more diverse during low-connectedness episodes. The results indicate that the existence of a national factor that reflects the synchronized behavior of all housing markets could be essential for enhancing the effectiveness of monetary policy in a high-connectedness state. To quantify this, we estimate a national factor using the 51 housing price return series. Our analysis reveals that monetary policy is more effective when the fluctuations in house prices are primarily driven by a national factor rather than regional factors. Furthermore, upon analyzing the effects of monetary shocks on episodes that intersect both business cycles and housing market connectedness cycles, we discover an intriguing finding: monetary policy is most potent in a high-connectedness/boom state.

The significance of this paper lies in providing insight into whether the spillover effect among local housing markets intensifies or mitigates the effects of monetary policies. Changes in interest rates potentially affect housing markets in several ways. One of these is by lowering mortgage rates, which can make it easier for potential homebuyers to finance their purchases. Additionally, increased demand for housing in one region can spill over to other regions, further increasing aggregate demand. Our findings suggest that this effect can be even more pronounced in synchronized housing markets.

This paper contributes to the extensive body of research that investigates how the state of economies affects the effectiveness of monetary policy. The literature provides mixed evidence regarding the effectiveness of monetary policy during different phases of the business cycle. Weise (1999) and Lo and Piger (2005) suggest that the impact of money supply shocks on output is stronger during recessions or periods of low output growth than during expansions, while Tenreyro and Thwaites (2016) find that the response of U.S. output to monetary policy shocks is stronger during expansions due to larger responses of consumer durables and business investment expenditure.

In recent years, there has been a growing focus on how leverage affects the effectiveness of monetary policy. Jorda, Schularick and Taylor (2020) and Alpanda and Zubairy (2019) find that the effects of monetary policy are greater during credit booms and weaker during periods of high household debt, respectively. Using state-dependent local projection methods and data from 18 advanced economies, Alpanda, Granziera and Zubairy (2021) also demonstrate that the impact of monetary policy shocks on output and other macroeconomic and financial variables is weaker during economic downturns, and periods of low household debt and high interest rates.

While the existing literature extensively examines how the state of the economy affects the effectiveness of monetary policy, scant research has been conducted on the relationship between regional markets and monetary policy. Previous studies have examined the regional effects of U.S. monetary policy (Furceri, Mazzola and Pizzuto, 2019), the influence of the regional distribution of housing equity on the consequences of monetary policy (Beraja et al., 2018), and the integration of national monetary and regional housing markets via mortgage rates (Fratantoni and Schuh, 2003). Using a dynamic factor model and state-level data from 1986 to 2005, Del Negro and Otrok (2007) find that movements in house prices are mainly driven by the local component. In contrast, the present study focuses specifically on the role of interconnectedness among local housing markets in shaping the effectiveness of monetary policy.

The paper is organized as follows. Section 2 outlines the empirical methodology and dataset used in this study. Section 3 presents the key findings, and Section 4 discusses issues including local housing market dynamics, the relationship between connectedness and the national factor, and the relationship between connectedness and the business cycle. We perform a sensitivity analysis in Section 5, and finally, in Section 6, we offer concluding remarks and suggestions for future research.

2 Econometric Methodology

This section provides a brief overview of the empirical approach used to study how the degree of connectedness among housing markets affects the transmission of monetary policy. To this end, we take two steps. First, we follow the Diebold and Yilmaz (2014) approach to measure the level of housing market linkage. Second, we use state-dependent local projection methods to empirically document whether the transmission of monetary shocks depends on housing market connectedness.

2.1 Measuring Housing Market Connectedness

To measure the housing market connectedness index, we employ the connectedness approach proposed by Diebold and Yilmaz (2014). Accordingly, the connectedness index can be computed using the variance decomposition matrix associated with an N-variable vector autoregression (VAR). Consider a covariance stationary N-variable VAR(p):

$$X_t = \sum_{m=1}^{p} \Phi_m X_{t-m} + \varepsilon_t,$$

where $\varepsilon_t \sim (0, \Sigma)$. The moving average (MA) representation can be written as:

$$X_t = \sum_{m=0}^{\infty} A_m \varepsilon_{t-m},$$

where the $N \times N$ coefficient matrices A_m follows the recursion:

$$A_m = \Phi_1 A_{m-1} + \Phi_2 A_{m-2} + .. + \Phi_p A_{m-p},$$

with $A_0 = I_N$ and $A_m = 0$ for $m < 0$. In VAR model estimation, the number of parameters to be estimated increases with the number of variables, which is the so-called *curse of dimensionality*. To address this problem, we adopt the elastic net estimator developed by Zou and Hastie (2005). This is a hybrid of shrinkage and selection methods. The elastic net estimator, $\hat{\beta}_{Enet}$, solves the following:

$$\hat{\beta}_{Enet} = \arg\min_{\beta} \left[\sum_{t=1}^{T} \left(y_t - \sum_{k=1}^{N} \beta_k x_{kt} \right)^2 + \lambda \sum_{k=1}^{N} \left(\alpha \left| \beta_k \right| + (1-\alpha)\beta_k^2 \right) \right].$$

The elastic net estimator combines Least Absolute Shrinkage and Selection Operator (LASSO) penalty and the Ridge penalty. There are two tuning parameters, λ and $\alpha \in [0, 1]$. If $\alpha = 1$, it becomes LASSO penalty, and if $\alpha = 0$, it becomes a Ridge regression. We follow Bostanci and Yilmaz (2020) and set α to be equal to 0.5 without cross validation,[2] while λ is chosen by 10-fold cross validation.

Variance decomposition, which includes coefficients in the MA representation and transformations such as impulse response functions, is crucial in understanding dynamics. This is because the variance decomposition matrix enables the evaluation of the portion of future uncertainty in market i

[2] α can be selected by cross validation, but it substantially increases computational burdens.

that is caused by shocks in market j, for all $i \neq j$. The identification of forecast error variance decomposition (FEVD) is one of the critical steps when measuring connectedness. In this regard, we utilize the generalized approach of Pesaran and Shin (1998), which is independent of variable ordering and allows for correlated shocks.[3] We will first define highly granular pairwise directional connectedness. The contribution of market j to the Q-step-ahead generalized forecast error variance of market i, $\theta^g_{ij}(Q)$, for Q = 1, 2, ..., is defined as:

$$\theta^g_{ij}(Q) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{Q-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{Q-1} (e_i' A_h \Sigma A_h' e_i)},$$

where σ_{jj} is the standard deviation of the disturbance of the jth equation, and e_l is a selection vector in which only the l-th element is one and zeros otherwise. $\theta^g_{ij}(Q)$ is interpreted as *cross variance shares*: the fractions of the Q-step-ahead error variances in forecasting market i due to shocks to market j. Having selected the generalized identification method for the variance decompositions, the sum of each row may not necessarily equal one (i.e., $\sum_{j=1}^{N} \theta^g_{ij}(Q) \neq 1$) since the shocks to each market are not orthogonalized. Considering this we normalize each entry of the generalized variance decomposition matrix by its respective row sum. Pairwise directional connectedness from market j to market i, $C_{ij}(Q)$, is defined as:

$$C_{ij}(Q) = \frac{\theta^g_{ij}(Q)}{\sum_{j=1}^{N} \theta^g_{ij}(Q)}.$$

By construction, $\sum_{j=1}^{N} C_{ij}(Q) = 1$ and $\sum_{i,j=1}^{N} C_{ij}(Q) = N$. Finally, we obtain the *system-wide* connectedness, $\mathcal{C}$, by summing all non-diagonal entries of the normalized variance decomposition matrix:

$$\mathcal{C} = \frac{\sum_{i,j=1,i\neq j}^{N} C_{ij}(Q)}{\sum_{i,j=1}^{N} C^H_{ij}(Q)} = \frac{1}{N} \sum_{i,j=1,i\neq j}^{N} C_{ij}(Q). \tag{1}$$

Accordingly, this total connectedness is an index that measures the interdependence of the entire housing market. It ranges from 0 to 1.

[3] As is well-known in the literature, Cholesky factorization is not robust to variable ordering, which can potentially cause a problem when trying to obtain both system-wide and directional connectedness measures.

2.2 Local Projection Method

Our econometric model closely resembles the methodology employed by Tenreyro and Thwaites (2016), Ramey and Zubairy (2018) and Alpanda and Zubairy (2019). We apply the local projection technique proposed by Jorda (2005) to estimate impulse responses to exogenous monetary policy innovations in both linear state-dependent models. The impulse response of variable y_t at horizon $h \in \{0, 1, 2, ...\}$ to the identified monetary shock, and ε_t, is estimated as the coefficient β_h in the following linear model:

$$y_{t+h} = \alpha_h + \boldsymbol{\gamma}'\boldsymbol{x}_t + \beta_h \varepsilon_t + u_{t+h}, \tag{2}$$

where α_h is a constant, and $\boldsymbol{x}_t$ is a vector of control variables. The coefficient β_h is the response of y at time $t+h$ to the shock at time t.[4] Thus, the local projection method simply requires the estimation of a series of regressions for each horizon, h, and for each variable of interest.

The linear projection model can be easily adapted to estimate a non-linear, state-dependent model. For the model that allows state-dependence, we estimate a set of regressions for each horizon h as follows:

$$y_{t+h} = D_{H,t-1}\left[\alpha_{H,h} + \boldsymbol{\gamma_{H,h}}'\boldsymbol{x}_t + \beta_{H,h}\varepsilon_t\right] + D_{L,t-1}\left[\alpha_{L,h} + \boldsymbol{\gamma_{L,h}}'\boldsymbol{x}_t + \beta_{L,h}\varepsilon_t\right] + u_{t+h}, \tag{3}$$

where $D_{s,t-1}$ is a dummy variable that indicates the state of the economy in terms of housing market connectedness before a monetary policy shock hits, $s \in \{L, H\}$.[5] For example, $D_{L,t-1}$ takes a value of 1 in the low-connectedness state and 0 otherwise. We will discuss in more detail how we construct this dummy variable in the next subsection. Notably, all the coefficients in the non-linear model vary depending on the state of the economy.

[4] We also include deterministic trends (linear and quadratic time trends).

[5] L denotes low connectedness while H denotes high connectedness.

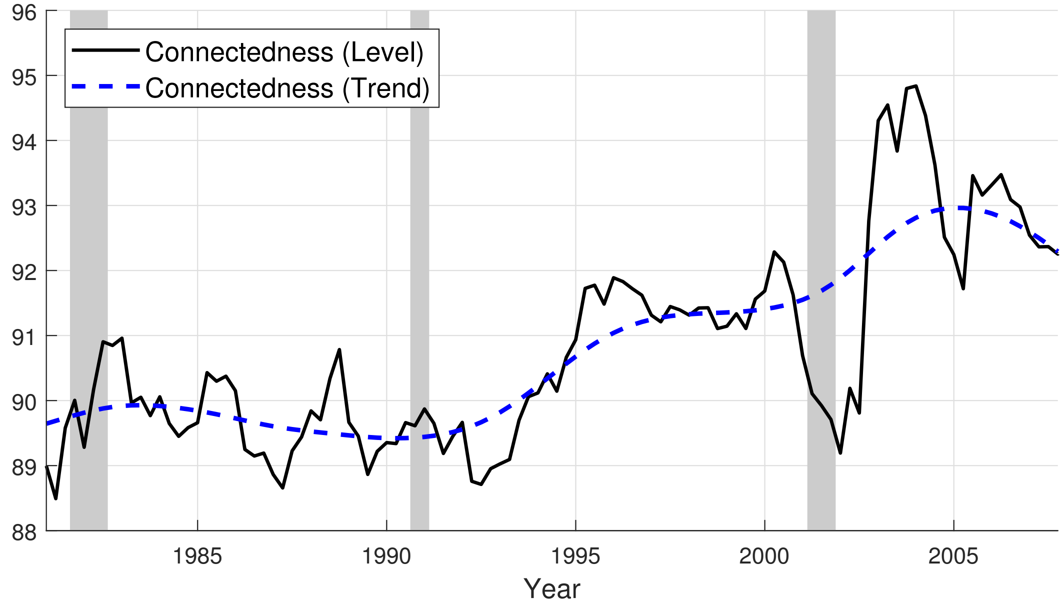

Figure 1: CONNECTEDNESS INDEX: TREND AND CYCLICAL COMPONENTS
Note: The trend and level of the connectedness index. The gray-shaded regions indicate NBER recession periods.

2.3 Defining Low- and High-Connectedness States

To study whether monetary policy effectiveness varies according to housing market connectedness, we need to identify which periods constitute the low- or high-connectedness state. We base our state variable on the *system-wide* connectedness, $\mathcal{C}_t$, in Equation (1). We construct a measure for housing market connectedness using the Freddie Mac House Price Index (FMHPI), which is a measure of typical monthly price inflation for houses across all 50 states and Washington, D.C. in the U.S.[6] The sample period used for the connectedness index runs from January 1976 to December 2020. The connectedness index is computed using an Elastic net LASSO-VAR(1) with a rolling-window analysis, where the forecast horizon is 10 months and the rolling window size is 120 months.[7] We then convert our monthly measures into quarterly ones. Next, we define the states of the economy in terms of housing market connectedness as a deviation from a smooth trend. Detrended measures are constructed based on a Hodrick and Prescott filter (HP filter) with the usual smoothing parameter for quarterly data (i.e., $\lambda = 1,600$). We use sample periods from 1981q1 to 2007q4 in the baseline estimation.[8]

Figure 1 presents the level and trend of the connectedness index for the baseline sample period

[6] The main results remain robust when excluding Alaska, Hawaii, and Washington, D.C.
[7] In a later section, we investigate the robustness of our results to each of these choices.
[8] Our sample ends in 2007q1 to avoid the Zero Lower Bound (ZLB) period on the federal funds rate. We will expand our sample period later to see if the results remain robust when recent periods are included.

(1981:q1 to 2007:q4). We identify a period as a high-connectedness state (low-connectedness state) if the deviation from the trend in that period is positive (negative). Notably, 53% of the sample consists of positive connectedness gaps (i.e., high-connectedness states). The identification of low- or high-connectedness episodes does not coincide with business cycles, as the housing market connectedness does not exhibit a cyclical behavior: the correlation between housing market connectedness and output fluctuations is close to zero (-0.08).[9]

2.4 Identifying Monetary Policy Shocks

To estimate impulse response functions using the local projection methods outlined earlier, it is necessary to specify the assumptions necessary for identifying the monetary policy shocks. As our baseline identification, we follow Alpanda and Zubairy (2019) and consider a standard identification approach employed in a structural VAR model with timing restrictions where GDP and inflation are ordered before the federal funds rate. Accordingly, the key identifying assumption in our baseline estimation is that contemporaneous GDP and inflation are included in the information set of the central bank. To this end, we include contemporaneous and lagged values of GDP and inflation in Equations (2) and (3) along with contemporaneous federal funds rates as the shock and the lagged values of the federal funds rate as part of controls. This is equivalent to the aforementioned identification in the three-variable VAR model. Given the well-known serial correlation problem induced by the successive leading of the dependent variable in the Jorda's method, we apply the correction method proposed in Newey and West (1987) to our standard errors. As a robustness check, we will also use the monetary policy shock measures developed by Romer and Romer (2004).

3 Empirical Results

In this section, we report results from the local projection model on the state-dependent effects of monetary policy shocks. We first present our baseline results, where we identify the monetary policy shock using a Choleski identification scheme (or timing restrictions). Furthermore, we explore

[9] For a depiction of the specific comovement between the cyclical components of the connectedness index and GDP, please refer to Figure A.1 in the appendix.

whether our baseline results are robust to alternative identification of monetary policy shocks following Romer and Romer (2004).

3.1 Baseline Results

Figure 2 displays the impulse responses of GDP, the Personal Consumption Expenditures (PCE) deflator, and the federal funds rate (FFR) to a 100 basis point expansionary shock for our baseline specification. In the first column, the point estimates of the impulse responses for the three models are shown: high connectedness (lines with triangles), low connectedness (lines with squares), and a linear model (lines with circles). In the second column, the impulse response and 68 percent confidence intervals for the linear model are displayed, while the third column shows the impulse response functions and 68 percent confidence intervals for the high- and low-connectedness states to a monetary shock.

We will first discuss the results from the linear model shown in the second column of Figure 2. The linear model presents a familiar picture. Following an expansionary monetary shock, i) the level of output begins to increase, with its response peaking at approximately 0.5 percent above baseline between 16 and 18 quarters after impact, ii) the price level shows a sticky initial response for the first few quarters but eventually increases by 0.8 percent, and iii) the response of the federal funds rate is negative on impact.

Regarding the state-dependent impulse responses, the third column of Figure 2 clearly shows a sharp difference between high- and low-connectedness episodes. The responses of GDP and the price level are significantly larger in the high-connectedness state. More specifically, the GDP response peaks at approximately 0.7 percent in response to a 100 bps shock in the high-connectedness state, which is larger than the 0.5 percent in the linear model. The price level responds more strongly in the high-connectedness state than in the linear model, with a maximum increase of approximately 1.5 percent in the high-connectedness state. In contrast, in the low-connectedness state, the responses of GDP and the PCE deflator are not significantly different from zero at most horizons. These results may suggest that there might be stronger demand effects in the high-connectedness state than in the low-connectedness state. Notably, the responses of the federal funds rate in both states are similar at most horizons (particularly for horizons after 4 quarters), which implies that the larger responses of GDP and the price level in the high-connectedness state, particularly at medium-run horizons

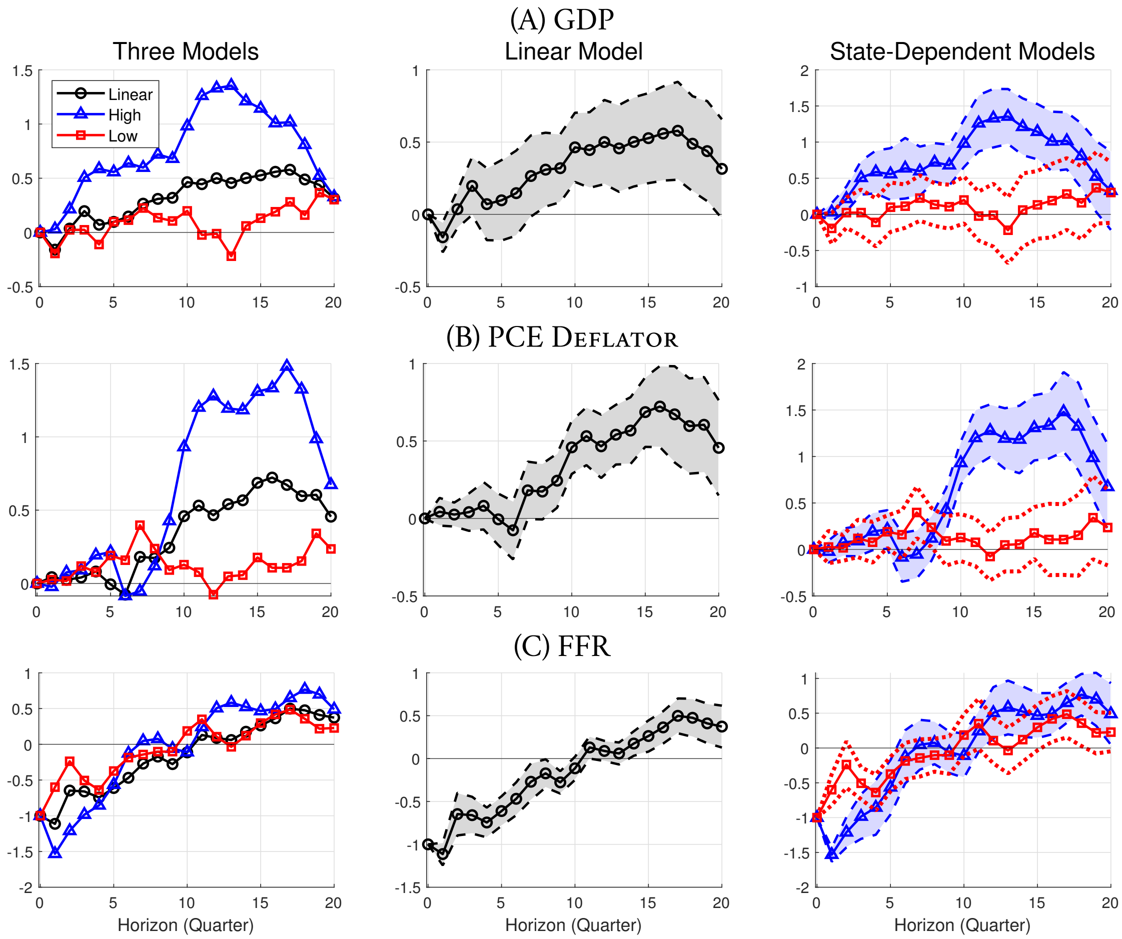

Figure 2: Impulse Response of Headline Variables: Baseline Specification

Note: The impulse responses of GDP, the personal consumer expenditure (PCE) deflator, and the federal funds rate (FFR) to a 100 basis points (bps) expansionary shock for our baseline specification. The first column displays the point estimate of the impulse response of the three models: high connectedness (lines with triangles), low connectedness (lines with squares), and a linear model (lines with circles). The second column shows the impulse response and 68 percent confidence intervals for the linear model, while the third column shows the impulse response functions and 68 percent confidence intervals for the high- and low-connectedness states.

(between 10 and 15 quarters), are not attributable to a bigger fall in the federal funds rate.

In Table 1, we formally test whether the cumulative impulse response functions for the level of GDP and inflation in the high-connectedness state are statistically different from those in the low-connectedness state. The results indicate that the cumulative effects on the level of GDP and inflation are significantly larger at standard levels, particularly at longer horizons. The third panel of Table 1 verifies that the cumulative response of the federal funds rate is not statistically different between high- and low-connectedness states at most horizons.

Figure 3 depicts the responses of different components of GDP to the same monetary policy shock mentioned earlier. Specifically, we consider private consumption (nondurable goods and services) and fixed investment (including both residential and nonresidential fixed investment) as two important ex-

Table 1: Statistical Significance: Baseline Specification

	Cumulative impact at horizon				
	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
GDP					
High Connectedness	1.3383	3.8518	8.1047	12.8231	15.5004
Low Connectedness	-0.2570	0.3166	0.5868	0.7497	1.8609
P-value	0.2336	0.2425	0.0725	0.0403	0.0657
PCE Deflator					
High Connectedness	0.3369	0.5327	4.3676	9.3854	13.8484
Low Connectedness	0.2397	1.2247	1.4454	1.8355	2.6728
P-value	0.9085	0.7109	0.2856	0.0148	0.0062
FFR					
High Connectedness	-5.5547	-6.5049	-6.8548	-5.4948	-3.1462
Low Connectedness	-2.9722	-3.9528	-3.8434	-3.3828	-2.2157
P-value	0.0672	0.4166	0.4354	0.5588	0.7616

Note: The cumulative impulse response functions for the level of GDP, inflation, and FFR, and the p-value for the null hypothesis that the cumulative response in the high-connectedness state is equal to that in the low-connectedness state at a given horizon.

penditure aggregates.[10] Similar to the response of aggregate output, the two expenditure aggregates show a much stronger response in the high-connectedness state compared to the linear model. However, in the low-connectedness state, the responses of the two expenditure variables are statistically insignificant at most horizons. We also focus on the response of residential fixed investment, shown in Panel (C) of Figure 3, which is closely related to housing market connectedness. As expected, residential investment exhibits a larger response in the high-connectedness state.

Figure 4 displays the impulse responses of three other macroeconomic variables that can increase understanding of the state-dependent effects of monetary policy shocks. Panel (A) reveals strong evidence that employment responds significantly more when regional housing markets are more synchronized, which is consistent with the GDP response. Furthermore, as shown in Panel (B), the real wage responds more strongly in the high-connectedness state than in the low-connectedness state at most horizons. This could be additional evidence for stronger demand effects in the high-connectedness state, where a larger increase in demand prompts firms to hire more workers. This leads to a greater rise in the real wage rate, as predicted by standard New Keynesian models. The

[10] Our results are robust from a qualitative perspective, even when we include durable consumption.

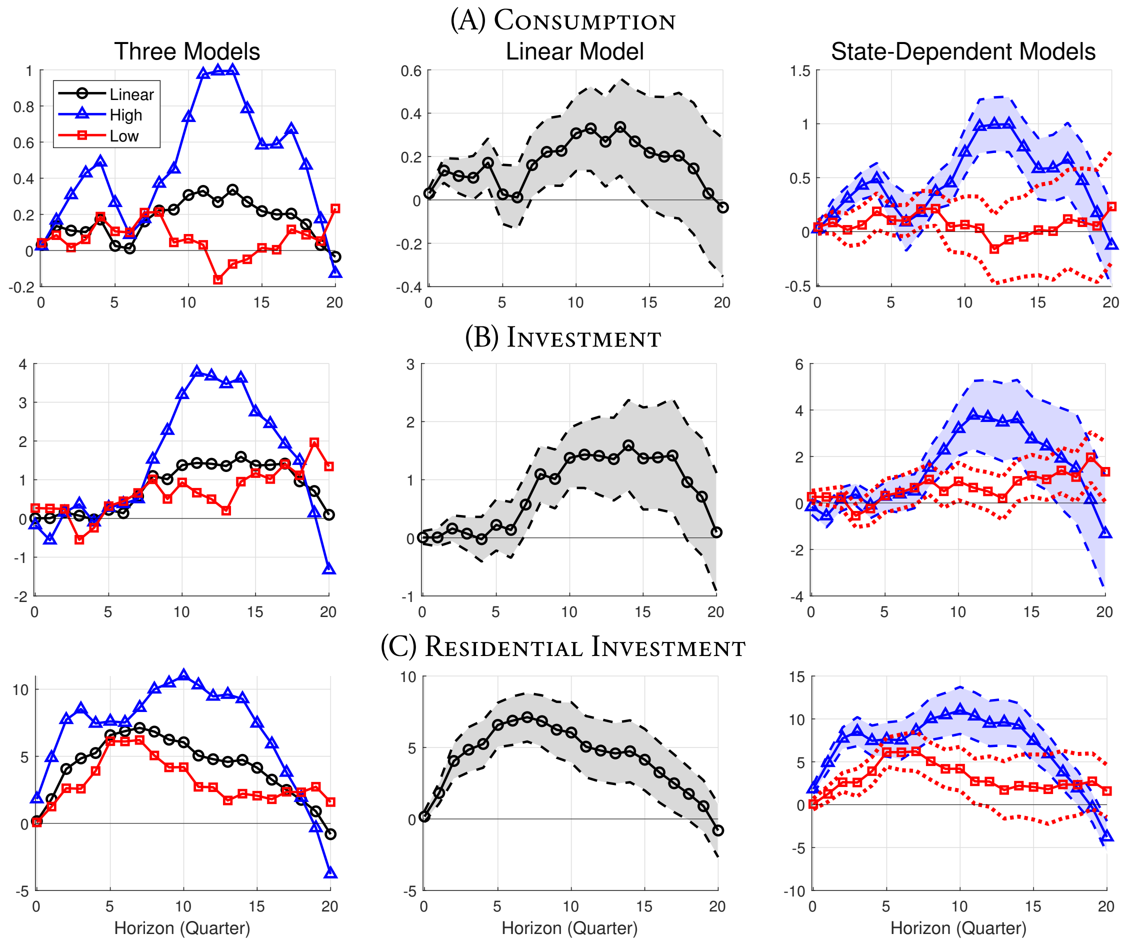

Figure 3: Impulse Response of Expenditure Variables: Baseline Specification
Note: The impulse responses of consumption (nondurable goods and services), private fixed investment, and residential fixed investment to a 100 basis points (bps) expansionary shock for our baseline specification. The first column displays the point estimate of the impulse response of the three models: high connectedness (lines with triangles), low connectedness (lines with squares), and a linear model (lines with circles). The second column displays the impulse response and 68 percent confidence intervals for the linear model, while the third column shows the impulse response functions 68 percent confidence intervals to a monetary shock for the high- and low-connectedness states.

larger demand effect in the high-connectedness state could be attributed to an increase in real house prices through a home equity channel, which operates by relaxing the borrowing constraint as house prices increase.[11] According to Panel (C), the response of real house prices to a monetary shock is significantly greater in the high-connectedness episode than in the low-connectedness episode. This suggests that if a housing market boom is associated with the high-connectedness state, then monetary policy could be more effective in that state.

Our findings elucidate whether spillover effects among neighboring housing markets intensify or mitigate the impact of monetary policy. Changes in interest rates potentially affect the housing market

[11] For an in-depth exploration of the home equity channel, Alpanda and Zubairy (2019) offer a comprehensive analysis, delving into its empirical and theoretical dimensions.

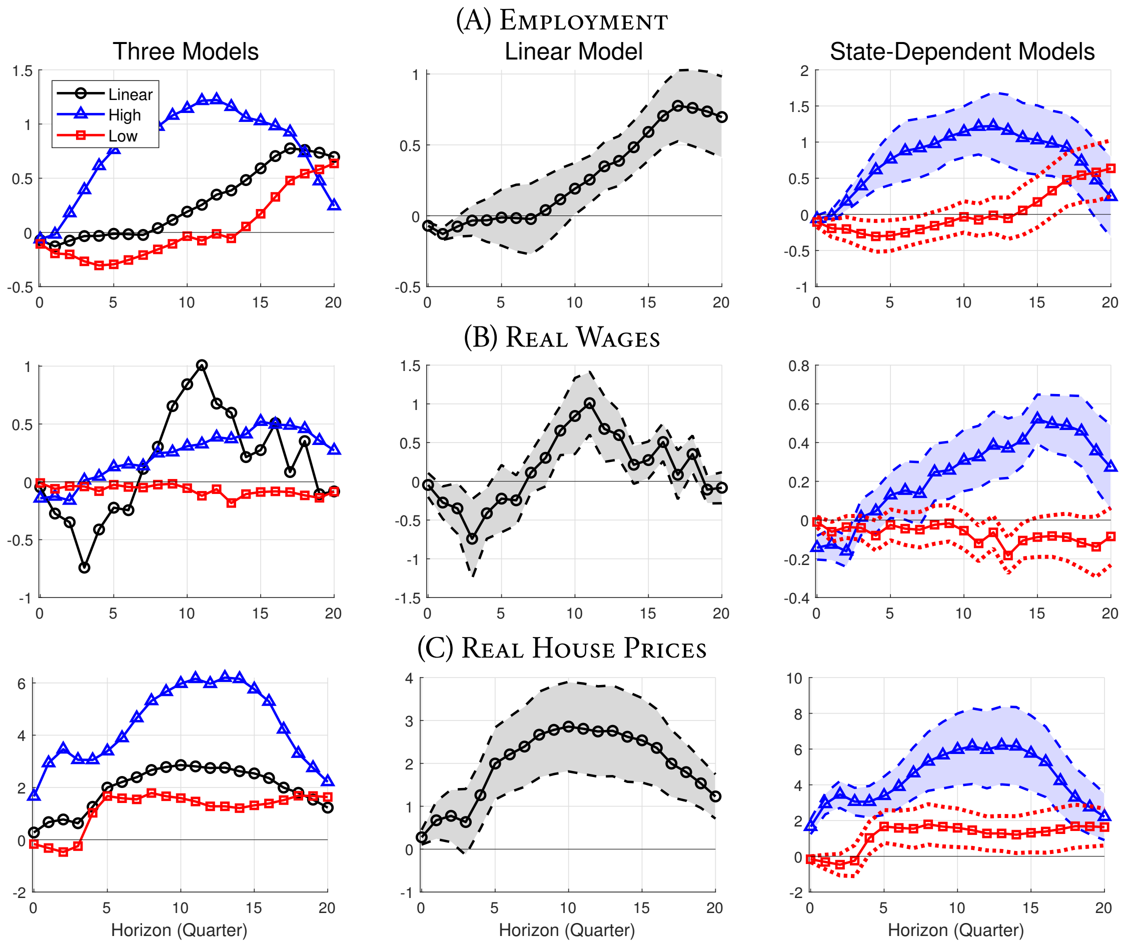

Figure 4: Impulse Response of Other Key Variables: Baseline Specification
Note: The impulse responses of employment, real wages, and real house prices to a 100 basis points (bps) expansionary shock for our baseline specification. The first column displays the point estimate of the impulse response of the three models: high connectedness (lines with triangles), low connectedness (lines with squares), and a linear model (lines with circles). The second column displays the impulse response and 68 percent confidence intervals for the linear model, while the third column shows the impulse response functions 68 percent confidence intervals to a monetary shock for the high- and low-connectedness states.

in various ways, such as by lowering mortgage rates and making it easier for potential homebuyers to finance their purchases. Additionally, increased demand for housing in one region can spill over into other regions, resulting in further increases in aggregate demand. Our study suggests that this effect can be particularly pronounced in synchronized housing markets.

3.2 Alternative Policy Shocks: Romer and Romer (2004)

The monetary policy shocks used in the baseline specification are identified as the structural shocks recovered from a three-variable VAR (GDP, the PCE deflator, and the federal funds rate), using Choleski orthogonalization with the federal funds rate placed last. Alternatively, we use the extended series for

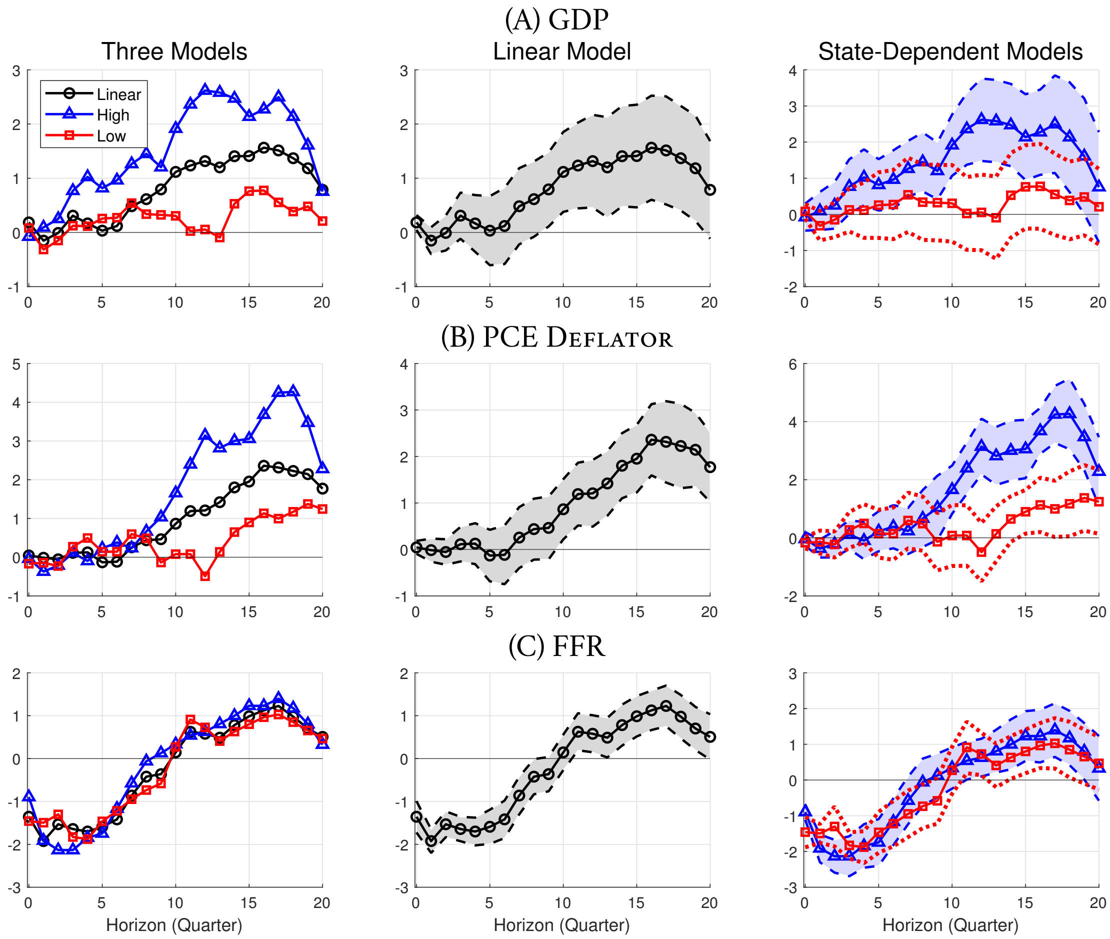

Figure 5: Impulse Response of Headline Variables: Romer and Romer Monetary Shock
Note: The impulse responses of GDP, the personal consumer expenditure (PCE) deflator, and the federal funds rate (FFR) to a 100 basis points (bps) expansionary Romer and Romer (2004) monetary shock. The first column displays the point estimate of the impulse response for three models: high connectedness (lines with triangles), low connectedness (lines with squares), and a linear model (lines with circles). The second column displays the impulse response and 68 percent confidence intervals for the linear model, while the third column shows the impulse response functions' 68 percent confidence intervals to a monetary shock for the high- and low-connectedness states.

the Romer and Romer (2004) monetary shock where measures are obtained as the residuals from an estimated reaction function. The residuals obtained are exogenous with respect to the evolution of economic activity. Using the Romer and Romer (2004) monetary shock, we conduct the same analysis as in the previous subsection.

Figure 5 illustrates the impulse response functions of the key variables (GDP, the PCE deflator, and the federal funds rate) to a Romer and Romer (2004) monetary policy shock. As shown in the second column, in the linear model, the level of output begrins to increase and reaches a maximum four years after the shock. The price level is initially sticky and begins to increase with a delay. The federal funds rate initially falls and reverts towards the conditional mean. The state-dependent effects of the monetary shock on our key variables are reported in the third column of Figure 5. Once again,

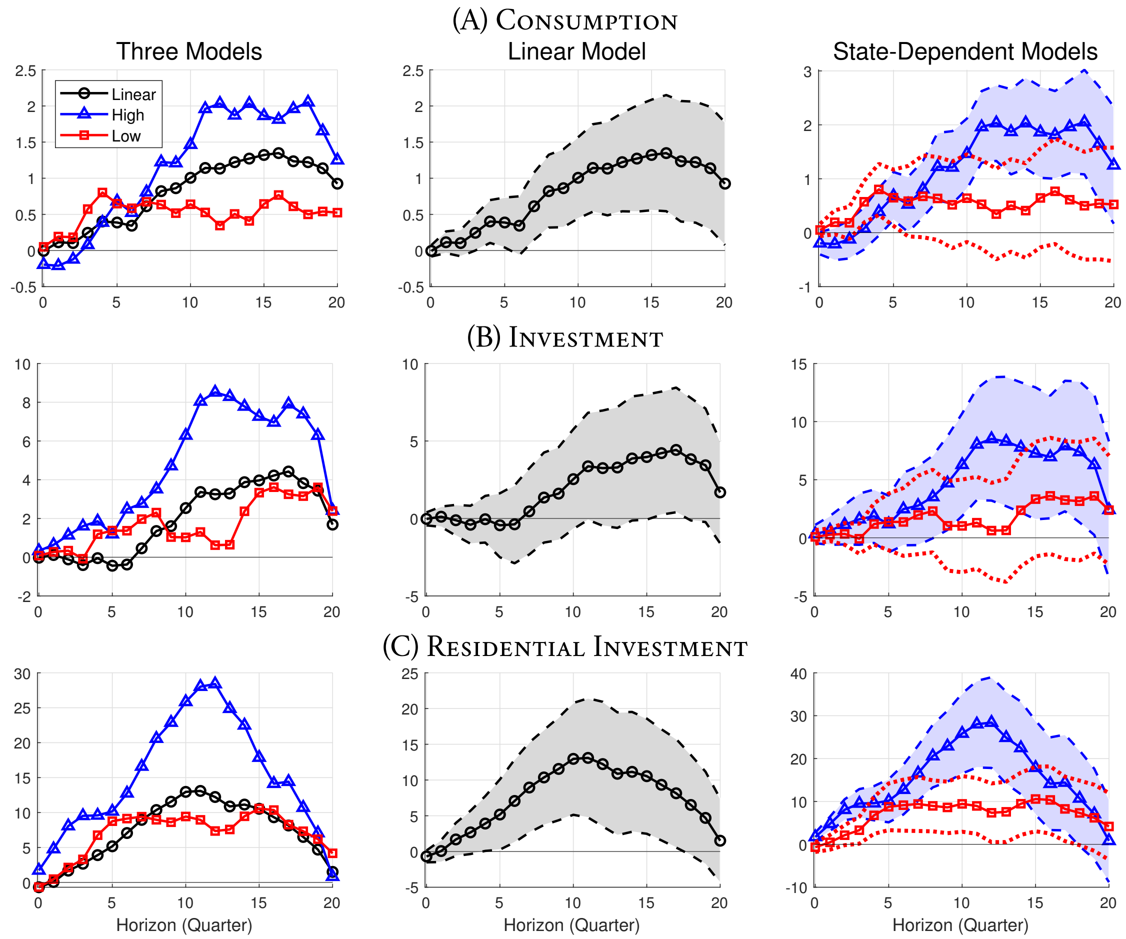

Figure 6: Impulse Response of Expenditure Variables: Romer and Romer Monetary Shock

Note: The impulse responses of consumption (nondurable goods and services), private fixed investment, and residential fixed investment to a 100 basis points (bps) expansionary Romer and Romer (2004) monetary shock for the three models: high connectedness (lines with triangles), low connectedness (lines with squares), and a linear model (lines with circles). The second column presents the impulse response and 68 percent confidence intervals for the linear model, while the third column shows the impulse response functions' 68 percent confidence intervals to a monetary shock for the high- and low-connectedness states.

GDP and inflation show greater responses in the high-connectedness state. Overall, there is very little difference from our baseline results in terms of qualitative perspectives.[12]

Figure 6 displays the impulse response functions of consumption, investment, and residential investment. Although the differences between the two states become much smaller, there is still evidence suggesting that monetary policy shocks result in greater effects on key expenditure variables, particularly on residential fixed investment. Figure 7 presents the effects of monetary shocks on three

[12]Just like we did for the baseline specification, we conduct statistical tests to compare the cumulative impulse response functions for the level of GDP and inflation in the high-connectedness state with those in the low-connectedness state. Our findings indicate that the cumulative effects on the level of GDP and inflation are significantly greater in the high-connectedness state than in the low-connectedness state, particularly over longer horizons. However, there is no statistically significant difference in the cumulative response of the federal funds rate between the two states at most horizons. For further information, refer to Table A.1 in the appendix.

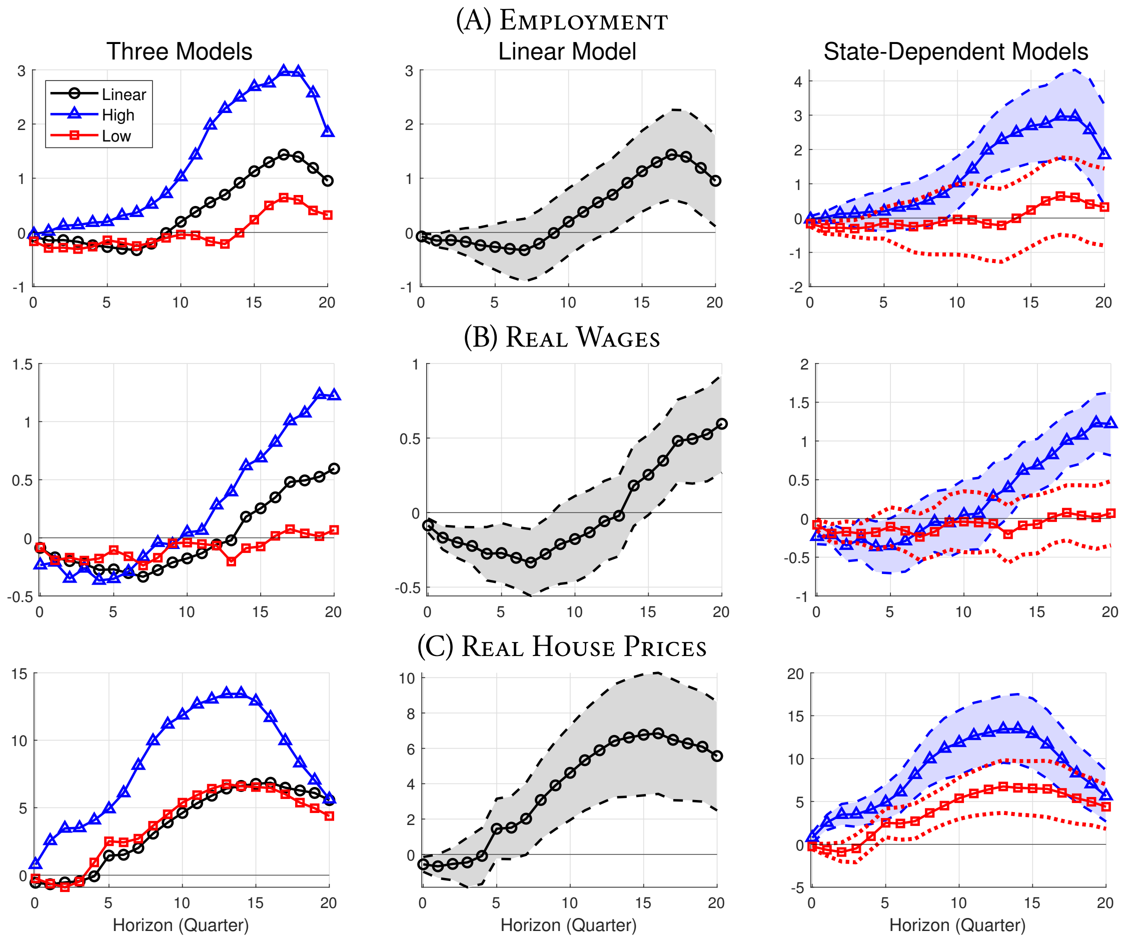

Figure 7: Impulse Response of Other Key Variables: Romer and Romer Monetary Shock

Note: The impulse responses of employment, real wages, and real house prices to a 100 basis points (bps) expansionary Romer and Romer (2004) monetary shock. The first column displays the point estimate of the impulse response of the three models: high connectedness (lines with triangles), low connectedness (lines with squares), and a linear model (lines with circles). The second column displays the impulse response and 68 percent confidence intervals for the linear model, while the third column shows the impulse response functions 68 percent confidence intervals to a monetary shock for the high- and low-connectedness states. Still, there is evidence that the responses of employment, real wages, and real house prices are larger in the high-connectedness state, which might be suggestive evidence for stronger aggregate demand effects in the high-connectedness state.

other macroeconomic variables in the two states. There remains evidence that the responses of employment, real wages, and real house prices are greater in the high-connectedness state, which may indicate stronger aggregate demand effects in that state.

To summarize, our baseline results are robust to shocks identified in the manner of Romer and Romer (2004). Qualitatively, the results retain the message that monetary policy is statistically more expansionary in the high-connectedness state than in the low-connectedness state.

4 Discussion

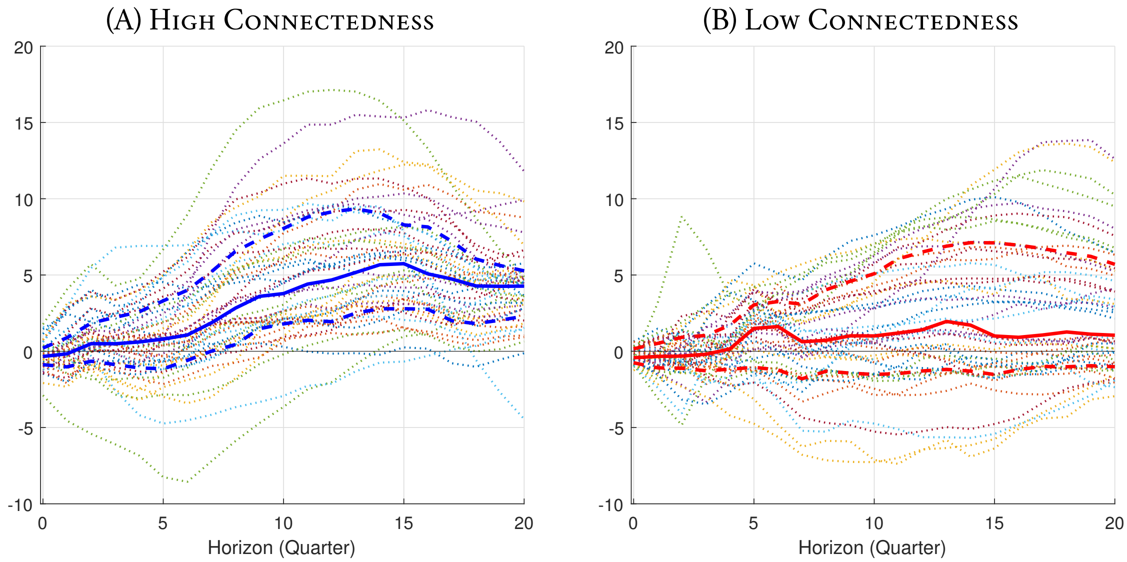

Figure 8: Connectedness and Local Housing Market Dynamics

Note: The response of regional house prices to a monetary policy shock in the high- and low-connectedness states. The solid line represents the median response at each horizon, while the dashed lines indicate the 20th and 80th percentiles at each horizon.

4.1 Connectedness and Local Housing Market Dynamics

This subsection explores potential differences in the impact of monetary policy shocks on housing prices across different local housing markets and how market interconnectedness affects these dynamics. Figure 8 provides a clear visualization of the response of regional house prices to a monetary policy shock in the high- and low-connectedness episodes. The solid line represents the median response at each horizon, while the dashed lines indicate the 20th and 80th percentiles at each horizon. As illustrated in the left panel of Figure 8, local housing prices tend to increase and move together in response to an expansionary monetary policy shock when regional housing markets are more synchronized. At the peak of the total housing price response, which occurs 15 quarters after the shock, all local markets except for one show a positive response. We also examine the correlation and heterogeneity of regional markets, finding an average cross-sectional correlation coefficient of 0.70 and an average cross-sectional coefficient of variation of 0.76 in the high-connectedness state. In contrast, local housing price responses are much more heterogeneous in the low-connectedness state. The right panel of Figure 8 demonstrates that local house prices do not move together in response to an expansionary monetary policy shock when regional housing markets are less synchronized. For instance, 18 local markets exhibit a negative price response 15 quarters after the shock. The average correlation is significantly lower in the low-connectedness state (0.13) than in the high-connectedness state, while the average coefficient of variation is substantially greater (1.22).[13] These indicate that the existence of a national factor that reflects the synchronized behavior of all housing markets could be essential for enhancing the effectiveness of monetary policy in the high-connectedness state. Further elaboration is provided in the upcoming subsection.

4.2 Connectedness and National Factor

In this subsection, we consider a possible explanation for why monetary policy has a large stimulus effect in the high-connectedness state. A natural candidate is a national factor that captures the common movements in all housing markets. In other words, housing markets are more synchronized if a single national factor is the main driver of house price fluctuations rather than idiosyncratic regional-specific factors. To quantify this relationship, we estimate a national factor using the 51 housing price return series and then investigate if monetary policy is more expansionary when the strength of a national factor is relatively high. We take three steps to estimate the average strength of the national factor.

Step 1: Based on the eigenvalue ratio criteria developed in Ahn and Horenstein (2013), we estimate the national factor series using the 51 housing price return series ($R_{i,t}$) for the sample period 1976:m1-2020:m12. We assume that the first factor represents the national factor (GF_t).

Step 2: Using the factors estimated from Step 1, we apply to the 120-month rolling regression method to compute time-varying R-squared measures. Specifically, we regress the ith housing return series on GF_t:

$$R_{i,t} = \alpha_i + \beta_i GF_t + \varepsilon_{i,t} \tag{4}$$

Step 3: We average the 51 R-square values measured at each window point,[14] which is denoted by Υ_t.

Υ_t can capture the overall strength of the national factor, GF_t, relative to regional-specific factors, $\varepsilon_{i,t}$. In principle, individual housing price returns are more synchronized when Υ_t is high. We find that the strength of the national factor, Υ_t, corresponds well to our housing connectedness measure, showing

[13] Additionally, it should be noted that the median response of house prices is greater in the high-connectedness state compared to the low-connectedness state, which is in line with the findings of our analysis at the aggregate level (Figure 4).

[14] We then convert monthly R-squared measures to quarterly ones.

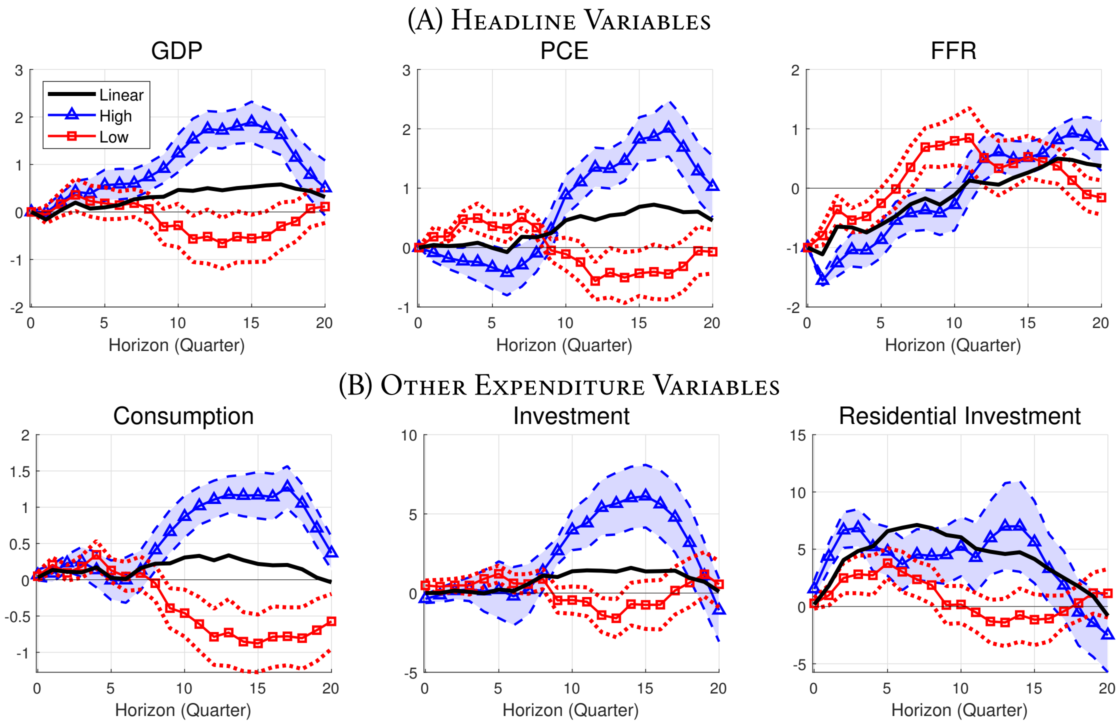

Figure 9: IRFs to a Monetary Shock between Low- and High-strength States

Note: The impulse responses of the headline variables and expenditure variables to a 100 basis points (bps) expansionary monetary shock: high strength (lines with triangles), low strength (lines with squares), and a linear model (solid lines).

a high correlation of 0.7.[15] This result is consistent with observations of Del Negro and Otrok (2007) that the housing price increases before the Great Recession were primarily driven by the national component rather than local ones.[16] We next investigate whether monetary policy is more powerful with higher Υ_t.

We examine whether the transmission of monetary shocks is state-dependent on the strength of the national factor, Υ_t. As in the benchmark specification, we detrend Υ_t using the HP filter and separate it into low- and high-strength episodes.[17] Figure 9 provides an insightful analysis of the impact of state-dependent models on the strength of the national factor as a different state specification. The results demonstrate that the response of output and price level is significantly greater when the national factor is the primary driver of regional housing markets. In terms of GDP components, the

[15] Del Negro and Otrok (2007) show that the role of monetary policy in determining house price dynamics is limited, suggesting that there may be other factors at play. For example, financial integration is one potential factor that may explain the existence of a global factor affecting house prices. According to Landier, Sraer and Thesmar (2017) and Choi and Hansz (2021), the degree of financial integration is strongly correlated with the growth of house prices.

[16] We also find that the national factor's strength has significantly risen since 2000 in comparison to the periods preceding 2000, which is also supported by Del Negro and Otrok (2007).

[17] To compare our baseline results, we set the smoothing to be 1,600 and use sample periods 1981:q1-2007:q4.

second row of Figure 9 highlights a noticeable difference between high- and low-strength states.[18] Notably, consumption, investment, and residential investment display a much stronger response in the high-strength state than in the low-strength one.[19] The results presented provide compelling evidence that the strengthening of the national factor channel could potentially explain the observed increase in monetary policy effectiveness in the high-connectedness state.

4.3 Connectedness and Business Cycles

As discussed previously, there appears to be no discernible cyclicality in housing market connectedness, resulting in a near-zero correlation with output fluctuations (see Figure A.1 in the appendix). However, it is worth exploring whether the degree of housing market connectedness affects the effectiveness of monetary policy during economic downturns. To this end, we analyze the impact of monetary shocks on episodes that intersect both business cycles and housing market connectedness cycles. Analogous to housing market connectedness, we also define a period as a boom state (bust state) if the deviation from the trend during the period is positive (negative).

Figure 10 illustrates the IRFs to a monetary policy shock, distinguishing between booms (the upper panel) and busts (the lower panel), as well as high versus low levels of housing market connectedness. Overall, episodes characterized by a boom and high connectedness exhibit the largest responses in terms of GDP and inflation. Specifically, during a boom period, both GDP and the PCE deflator exhibit more significant responses in the high-connectedness state compared with the low-connectedness state. Conversely, the smallest responses occur when there is a slump coinciding with low connectedness. This indicates that monetary policy is most effective during periods of high connectedness in an economic expansion.

5 Sensitivity Analysis

In this section, we examine the robustness of our baseline results to various specifications. We consider alternative definitions for our state variable, different specifications for housing market connect-

[18] Our statistical tests show that the high-strength state has larger cumulative effects on GDP and inflation than the low-strength state over longer horizons at the 5% significance level. However, there is no difference in the cumulative response of the federal funds rate between the two states.

[19] We also find that employment, real wages, and real house prices respond more strongly in the high-strength state.

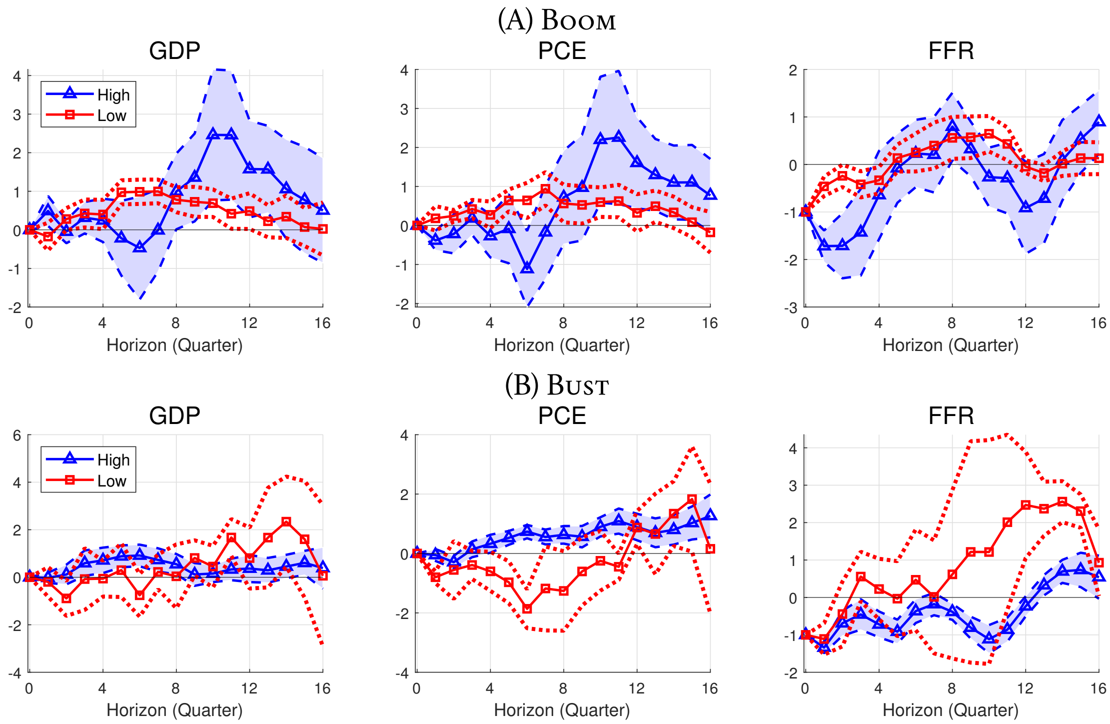

Figure 10: Business Cycles and Connectedness

Note: The impulse responses of the headline variables to a 100 basis points (bps) expansionary monetary shock (A) during boom periods and (B) during bust periods.

edness variables, and also consider a different sample. For these sensitivity analyses, we employ the baseline identification scheme (the identification scheme under timing restrictions) for the monetary shock.

5.1 Smooth Transition between States

We consider the smooth transition-local projection employed in Tenreyro and Thwaites (2016). The impulse response of variable y_t at horizon h in state $s \in \{L, H\}$ is estimated as the coefficient $\gamma_{s,h}$ in the below regression:

$$y_{t+h} = F(z_{t-1}) \left[\alpha_{H,h} + \boldsymbol{\gamma_{H,h}}' \boldsymbol{x}_t + \beta_{H,h}\varepsilon_t\right] + (1 - F(z_{t-1})) \left[\alpha_{L,h} + \boldsymbol{\gamma_{L,h}}' \boldsymbol{x}_t + \beta_{L,h}\varepsilon_t\right] + u_{t+h}, \quad (5)$$

We employ a smooth increasing function of an indicator of the state of the economy, $F(z_t)$:

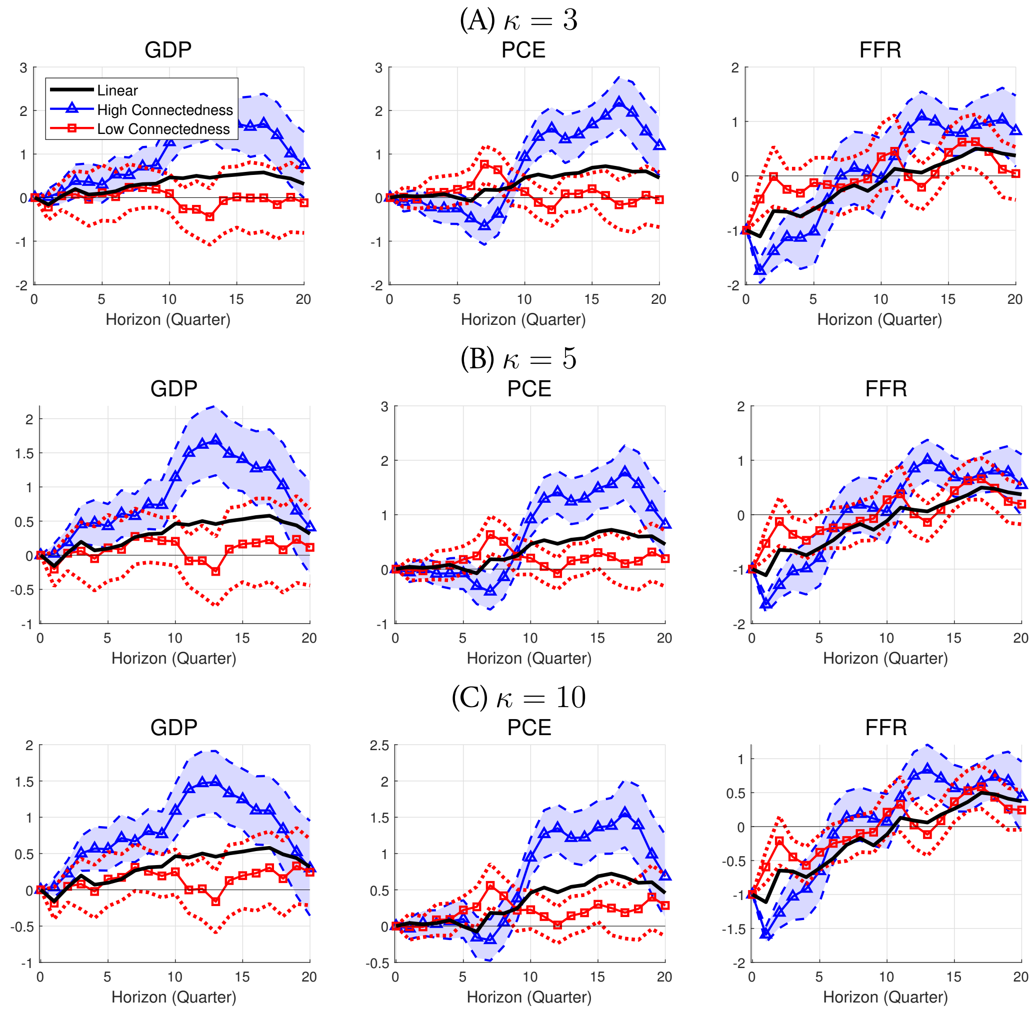

Figure 11: IRFs to a Monetary Shock with Different κ

Note: The impulse responses of GDP, the PCE Deflator, and FFR to a 100 basis points (bps) expansionary monetary shock with 68 percent confidence intervals for linear model (black lines), the high- and low-connectedness states (blue and red lines, respectively).

$$F(z_t) = \frac{\exp(\kappa z_t)}{1 + \exp(\kappa z_t)} \tag{6}$$

where $z_t = \frac{\hat{\mathcal{C}}_t}{\sigma_{\hat{\mathcal{C}}}}$, and $\hat{\mathcal{C}}_t$ and $\sigma_{\hat{\mathcal{C}}}$ are the HP filtered connectedness and its standard deviation, respectively. The parameter κ controls the smoothness of the transition from a high-connectedness state to a low-connectedness state in the economy, affecting the intensity of regime switching. It is important to note that, as κ increases, $F(z_t)$ becomes more similar to a discrete regime-switching setup. In the smooth transition-local projection specification, the quantitative size of the connectedness can be reflected, which differs from the dummy variable used in Equation (3).

Figure 11 demonstrates the effects of monetary shocks on headline variables (e.g., GDP, the PCE deflator, and the federal funds rate) according to the connectedness states with different values of κ. As can be seen in Figure 11, the results for the three different smoothing parameters ($\kappa = 3$, 5, and 10) are very similar to our baseline results.[20] One can see that the responses of GDP and the price level are significantly larger in the high-connectedness state, and the responses of the federal funds rate in both states are similar.[21] The qualitative message of the benchmark analysis remains unchanged: the results are robust to reasonable changes in the intensity of regime switching, κ.

5.2 Including ZLB Period

Since the federal funds rate was near zero from 2008 to 2015, we are forced to end our sample in the fourth quarter of 2007 in the baseline specification. However, it is of interest to evaluate whether our baseline results remain robust if we extend the sample period. To address this issue, we utilize the shadow federal funds rate constructed by Wu and Xia (2016) for the subperiod 2009q1-2016q4. As a result, the extended sample period now spans from 1981q1 to 2016q4.

Figure 12 shows the IRFs from the linear and state-dependent models using our baseline monetary shock specification over the extended sample period. The upper panel presents the response of headline variables (GDP, PCE deflator, and shadow rate) to the monetary policy shock. Again, we see that the results are quite similar to the baseline results. In the linear model, output rises in response to the expansionary monetary policy. The PCE deflator's response is sticky at first, but it begins to rise after a delay. Regarding the state-dependent model, output and the price level respond more strongly in the high-connectedness state than in the low-connectedness state. The state-dependent response of the shadow rate is similar at most horizons.

The bottom panel displays the response of consumption, investment, and residential investment for the longer sample. In the case of the linear impulse response, the GDP components respond to the monetary policy shock with a persistent hump shape. Regarding the state-dependent model, the response of the three variables is overall more significant in the high-connectedness state than in the

[20] Tenreyro and Thwaites (2016) set $\kappa = 3$ and consider a wide range of parameters for the intensity of regime switching from 1 to 10.

[21] Our statistical analyses reveal that, for three specifications, the high-connectedness state has greater cumulative impacts on GDP and inflation than the low-connectedness state, especially over extended periods at a significance level of 10%.

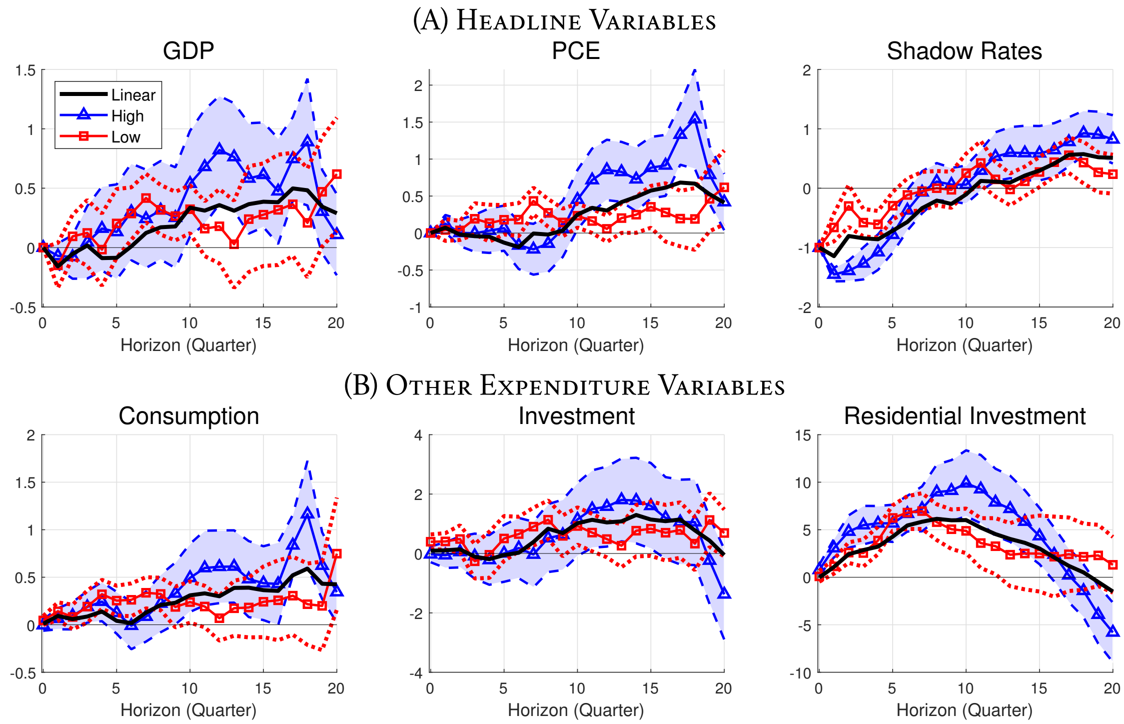

Figure 12: IRFs to a Monetary Shock: Including the ZLB Periods

Note: The impulse responses of the headline variables and expenditure variables to a 100 basis points (bps) expansionary monetary shock with the extended sample period of 1981q1-2016q4.

low-connectedness state, even if the differences between the two states become much smaller.[22]

5.3 Horizon, Window Size, and Lags

As the connectedness measures used in this paper are sensitive to the choice of forecast horizon, we explore whether our baseline results remain robust with different forecast horizons, rolling window sizes, and lag choices. As shown in Figure A.2 in the appendix, we find that the overall qualitative picture from the IRFs remains unchanged.[23]

[22] Although not depicted in this figure, we also find that employment, real wages, and house prices have a significantly greater response in the high-connectedness state than in the low-connectedness state.

[23] In some cases, the response of GDP or inflation is not statistically different across regimes but similar in qualitative terms.

6 Conclusion

This paper examines the impact of housing market connectedness on the monetary transmission mechanism in the U.S. economy. Through the use of state-dependent local projection methods, our study reveals that the efficacy of monetary policy is more pronounced in high-connectedness episodes. Specifically, we observe that the response of key macroeconomic variables (e.g., GDP, consumption, residential fixed investment, employment, and house prices) to a monetary policy shock is significantly greater when the initial level of total connectedness is high compared with its long-term trend. These findings are not only robust to alternative identification methods of monetary policy shocks but also to various modifications of the empirical model. This study also highlights the importance of considering the role of national factors in the transmission of monetary policy. Specifically, our results suggest that strengthening the national factor channel may play a crucial role in generating more effective monetary policy in the high-connectedness state. We also discover a compelling result in the analysis of the effects of monetary shocks on episodes that intersect both business cycles and housing market connectedness cycles, namely that monetary policy is most effective during high-connectedness periods in expansions.

These results have implications for stabilization policy design and development. If monetary policy changes have a limited impact in the low-connectedness state, policymakers may need to rely on unconventional monetary policies or other measures, such as fiscal or financial policies, to achieve the desired expansionary effect. Additionally, these findings call for macroeconomic models that generate a higher sensitivity economic response depending on connectedness among local markets.

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A Appendix

A.1 Data Sources

This subsection explains the data sources used in the paper. All data, except for regional housing prices, the Romer and Romer shocks, and the shadow rate, are drawn from St. Louis Federal Reserve Economic Data (FRED).

A.1.1 Federal Reserve Economic Data (FRED)

- GDP: Real Gross Domestic Product; PCE deflator: Personal consumption expenditures (implicit price deflator) index 2012=100; FFR: Federal funds effective rates; Consumption: The sum of nondurable goods and services; Investment: The sum of private residential fixed Investment and nonresidential fixed investment; Employment: All employees in the nonfarm sector; Real wage: Average hourly earnings of production and nonsupervisory employees in the private sector

A.1.2 Other Sources

- **Freddie Mac**
  - National house price; Regional house price for 50 states and the District of Columbia
- **Federal Reserve Bank of Atlanta**
  - Shadow rate: the Wu-Xia shadow federal funds rate
- **Coibion et al. (2017)**
  - The extended dataset on Romer and Romer's monetary policy shocks.

A.2 Additional Tables and Figures

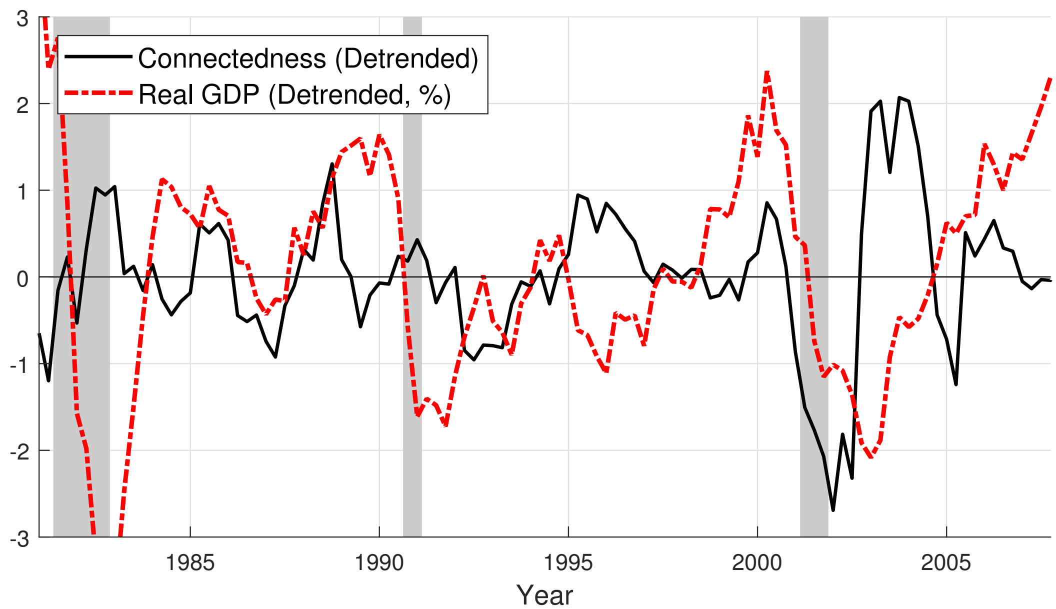

Figure A.1: Detrended Connectedness and GDP

Note: The detrended connectedness index and GDP. The gray-shaded regions indicate NBER recession periods.

Table A.1: Statistical Significance: Romer and Romer Monetary Shock

	Cumulative impact at horizon				
	$h = 4$	$h = 8$	$h = 12$	$h = 16$	$h = 20$
GDP					
High Connectedness	2.7216	5.8171	10.8177	18.0350	24.7595
Low Connectedness	-1.9360	-2.2230	-3.7535	-3.5380	-1.6670
P-value	0.0740	0.1812	0.0985	0.0785	0.0893
PCE Deflator					
High Connectedness	-0.3910	0.4179	6.4303	16.4350	29.9182
Low Connectedness	-1.3117	-2.4938	-4.2794	-3.1886	-0.5928
P-value	0.6143	0.5017	0.0991	0.0092	0.0011
FFR					
High Connectedness	-9.1799	-14.5894	-16.0263	-13.3447	-7.9984
Low Connectedness	-7.4420	-11.1824	-10.5246	-9.5018	-7.2200
P-value	0.4562	0.5256	0.4091	0.5649	0.9061

Note: The cumulative impulse response functions for the level of GDP, inflation, and FFR, and the p-value for the null hypothesis that the cumulative response in the high-connectedness state is equal to that in the low-connectedness state at a given horizon.

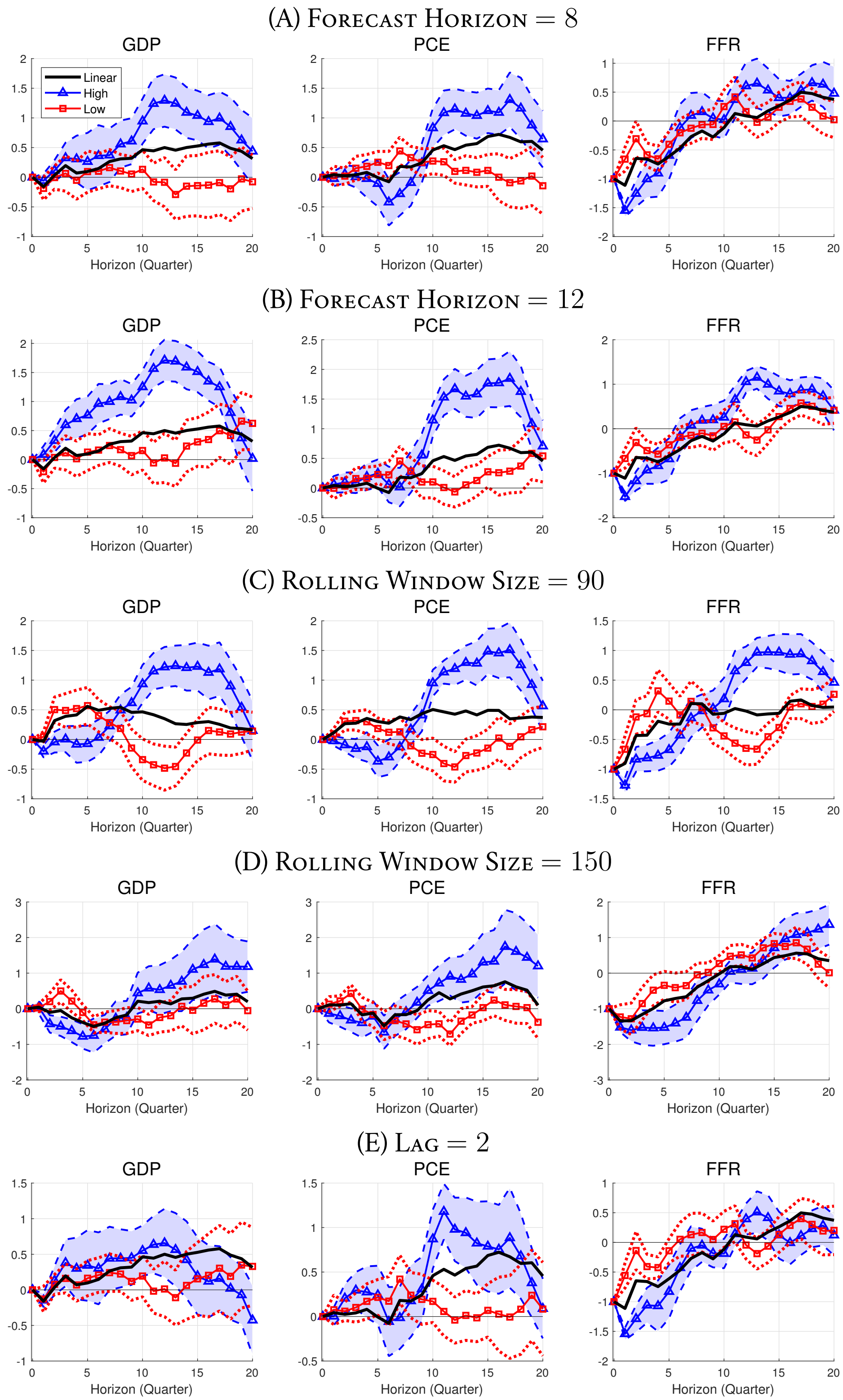

Figure A.2: IRFs to a Monetary Shock with Different Horizons, Windows, and Lags

Note: The impulse responses of GDP, the PCE Deflator, and FFR to a 100 basis points (bps) expansionary monetary shock with 68 percent confidence intervals for linear model (black lines), the high- and low-connectedness states (blue and red lines, respectively).