Housing Deposit Channel of Monetary Policy and Housing Price Double-Dip

Hamed Ghiaie* Philipp Roderweis†

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Abstract. "Rising interest rates lead to a gradual decline in housing prices.", a widely held belief; this paper challenges that conventional wisdom both theoretically and empirically by showing that sustained monetary tightening activates a novel transmission mechanism, i.e., the housing deposit channel, which gives rise to a double-dip in housing prices: an initial decline upon impact, followed by a temporary rebound, and a subsequent second dip in the longer run. A general equilibrium model formalizes the theory behind this mechanism, and empirically, lag-augmented local projection estimation techniques, supported by extensive robustness checks, demonstrate that the patterns observed in the US data align with the theoretical model's predictions. Our study investigates the effects of monetary policy on the housing market and reciprocally, how the housing market influences the efficacy of monetary policy, particularly in achieving inflation targeting objectives.

Keywords: Monetary transmissions, Deposit channel, Housing market, Macroeconometrics
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*Corresponding author. Economics and Public Policy Professor, Department of Economics, Paris campus, ESCP Business School, email: hghiaie@escp.eu

†Ph.D. Researcher, University Paris Nanterre, EconomiX UMR 7235 CNRS, email: philipp.roderweis@parisnanterre.fr .

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1. Introduction

This paper addresses the following key questions: (i) How does contractionary monetary policy affect the housing market in the short, medium and in the longer run? and in turn, (ii) What is the impact of housing channels on the effectiveness of monetary policy? The existing literature suggests that interest rate hikes decrease housing demand, which consequently reduce housing prices. For instance, a meta-analysis by Ehrenbergerova et al. (2023), assessing vector autoregression (VAR) estimates, observes that on average a 1 percentage point increase in interest rates causes a 0.7 percent median decrease in housing prices at the one-year horizon and 0.9 percent at the two-year horizon. Figure 1 replicates their results using a US-specific sub-sample from this study[1], showing a significant decline in US housing prices following an interest rate increase.

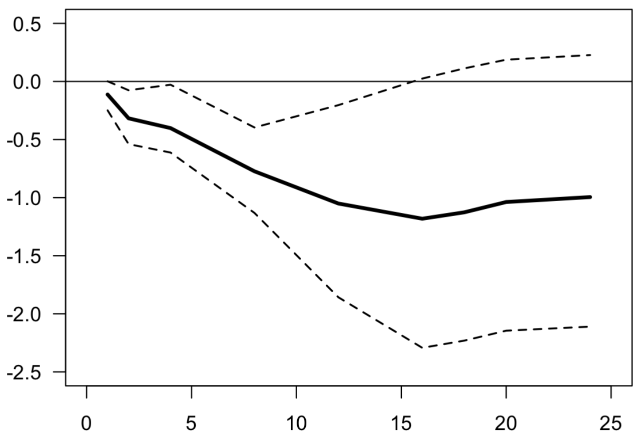

Figure 1: Mean response of US housing prices to interest rate shock. Solid line represents mean impulse response after 100bp increase in interest rates. The dashed lines indicate one standard deviation confidence intervals. Horizontal axis measures the number of quarters and vertical axis measures the percentage change.

Contrary to the literature, our paper indicates both theoretically and empirically that rising interest rates do not always lead to a persistent decline in housing demand and housing prices. Our paper is the first to unveil a "housing price double-dip" as a result of contractionary monetary policy and it brings these findings into line with a novel transmission channel, the "housing deposit channel of monetary policy". Both are explained below.

Building on the standard theoretical framework of Iacoviello (2005), our findings show that housing prices are influenced not only by the traditional mortgage relationship between banks and borrowers, but also by the financial sector's pass-through of interest rates to lenders. This introduces a non-monotonical feedback loop in three phases, i.e., a housing price double-dip, as follows. *i*) Initial dip: A rate hike reduces mortgage-driven housing demand, leading to a decline in housing prices (standard effect). *ii*) Rebound (the housing deposit channel in action):

[1] Ehrenbergerova et al. (2023) collect 1,447 estimates of the effect of changes in short-term interest rates on housing prices from 31 VAR studies. In Figure 1, IRFs are collected manually, with the responses and their confidence intervals measured using pixel coordinates, following Rusnák et al. (2013). From the studies mentioned in Ehrenbergerova et al. (2023) that focus solely on the US housing market, we collect the responses of housing prices to a change in the short-term interest rate after one, two, four, eight, twelve, and sixteen quarters, as well as the longest time period. For each observation, the change in the interest rate is standardized to an increase of 100 basis points. The confidence bands are set at ± 1SE. The nine studies used in this analysis are the following: Assenmacher-Wesche & Gerlach (2008), Calza et al. (2007), Coibion et al. (2017), Gupta, Jurgilas, Kabundi & Miller (2012), Gupta, Jurgilas, Miller, Van Wyk et al. (2012), Jarociński & Smets (2008), McDonald & Stokes (2013), Musso et al. (2011), Sousa (2014).

as banks are able to increase their deposit spread (see Drechsler et al. 2017), lender households redirect deposits into housing, creating a rebound in housing prices. *iii*) Second dip: eventually, banks adjust deposit rates to recover funding, drawing capital back from housing and causing a second delayed dip.

Although our theoretical framework outlines the housing deposit channel and the housing price double-dip, the existing empirical literature largely fails to capture these dynamics beyond the initial decline in housing prices. The reason is that the effects of monetary policy on housing prices are primarily analyzed by estimating structural VAR models (SVARs).[2] SVARs are often unable to capture transitory states and long-term fluctuations since they are inherently restricted in their dynamics and, by definition, intentionally over-optimistic with regard to the rate of decay of the impulse responses, assuming the VAR is stable (Jordà et al. 2023). This leaves the medium and longer-run behavior of housing prices mostly unexplored.

This paper fills this gap by employing lag-augmented local projection (LA-LP) techniques, using the same variables and time period as Jarociński & Smets (2008), while additional lags of the variables are included in the regression as controls. This paper follows Montiel Olea & Plagborg-Møller (2021) who demonstrate that LA-LP are particularly well suited to drawing robust inference with regard to impulse responses at long horizons. Consequently, these techniques mitigate the overparameterization challenges inherent in VAR models[3] and enable a more reliable analysis of housing price dynamics over longer horizons.[4] Our empirical findings reconfirm that a contractionary monetary policy shock induces a double-dip pattern in housing prices: an initial decline following the shock, a temporary rebound, and a subsequent long-run decline.

To confirm that our findings are not due to random sampling variation, we conduct several robustness checks. We, first, distinguish endogenous fluctuations in the FFR from exogenous monetary policy shocks similar to Romer & Romer (2004). The resulting IRFs closely align with the baseline estimates. Second, incorporating alternative variable choices and housing price indexes, as in Calza et al. (2007) and Calza et al. (2013), reaffirms the double-dip pattern in housing prices following interest rate hikes. Third, we re-estimate our baseline model using four standard alternatives to the real housing price index employed in the initial analysis. The results remain consistent and confirm our original findings. Lastly, we show that shocks triggering an initial decline in housing prices, similar to an interest rate hike, do not produce the same effect. For instance, credit risk and uncertainty shocks lead to a decline in housing prices but show no evidence of a second dip in the longer term.

The empirical identification in this paper is based on the observation that deposit spreads and short-term deposits respond immediately to changes in the policy rate. This helps to dis-

[2]Standard VAR models are used in the majority of the existing empirical work on monetary policy shocks and housing price dynamics, as they are widely considered to be standard for analyzing the propagation of shocks at business cycle frequencies.

[3]The issue of overparameterization occurs as the number of component series (variables or lags) is increased. This might bias the estimation results and compromise analysis derived from more distant impulse responses.

[4]Besides, LP techniques are the most appropriate for the goal of this paper as they are able to capture more pronounced up and down movements in a time series given that they do not impose the recursive structure that VARs do. Moreover, standard confidence intervals based on LA-LP are considered to have correct asymptotic coverage uniformly over the persistence in the data generating process and over a wide range of horizons providing good coverage/length properties. This means that confidence intervals remain valid even if the data exhibits unit roots, and even at horizons h that are allowed to grow with the sample size T.

tinguish between shocks transmitted through a housing deposit channel and those that are not. To do so, following Romer & Romer (2004) and Coibion et al. (2017), this paper uses unanticipated interest rate surprises around Federal Open Market Committee (FOMC) meeting days as a variable for a monetary policy shocks. Zero-maturity deposits are checked for changes in the week following the rate surprises. Interest rate changes that affect the housing market through a deposit channel are identified using the "poor man's" sign-restriction approach (Jarociński & Karadi 2020): Only interest rate surprises that are accompanied by opposite-sign deposit changes in the week following the FOMC are considered. The corresponding impulse responses show a two-dip dynamic of housing prices along the horizon, strongly indicating a housing deposit channel of monetary policy.

Additionally, empirical validation for the housing deposit channel is provided by demonstrating that the deposit channel of monetary policy, documented by Drechsler et al. (2017), extends to the housing market. We merge their branch-level banking data with county house-price indexes to build a panel with over 32,000 observations. The identification exploits cross-sectional variation in banking market concentration, whereby we show that housing prices respond more strongly to monetary tightening in counties with highly concentrated banking markets. This finding is consistent with banks in concentrated markets raising deposit spreads more aggressively, which in turn triggers larger deposit outflows and stronger reallocation of funds into housing. A comprehensive set of robustness checks – including county-specific linear trends, demographic controls, banking market structure controls, state-year fixed effects, and placebo tests – confirms the results are not driven by spurious correlations. Taken together, this evidence serves as a validation for the existence of a housing deposit channel.[5]

Lastly, our findings challenge the effectiveness of a "leaning against the wind" policy (as proposed by Borio & White 2004, Roubini 2006, Woodford 2012, Bank for International Settlements 2016, for instance), which involves actively using interest rates to curb financial imbalances in the housing market; housing price double-dip risks misleading policymakers into believing that the initial tightening was insufficient, potentially leading to premature or excessive rate hikes. This undermines the reliability of standard Taylor rule-based targeting and weakens its effectiveness in guiding monetary policy. In addition, since the channel operates via shifts in deposit allocations rather than mortgage credit, it may also bypass macroprudential controls. These findings highlight the need to extend inflation-targeting frameworks to account for delayed and non-linear housing market responses to interest rate changes.

Related literature and contribution

To the best of our knowledge, our paper is the first to empirically assess the response of housing prices to monetary policy over the medium to longer term using LA-LP methods. It is the first study to identify that housing prices fall twice, i.e., the housing price double-dip, after a contractionary monetary policy. Moreover, the paper introduces a novel transmission mechanism of monetary policy, the housing deposit channel, which highlights the role of housing markets in the effectiveness and dynamics of monetary policy. Finally, the general equilibrium model presented in this paper is the first to incorporate the housing deposit channel.

[5] Notably, this is consistent with Drechsler et al. (2017), who underline that the deposit channel can account for the entire transmission of monetary policy through bank balance sheets. Analogously, the housing deposit channel we document accounts for the monetary policy transmission mechanisms observed in the time series analysis.

Several transmission channels of interest rate policy to the housing market and thus the economy are proposed in the literature (see Mishkin 2007, for instance).[6] More recently, Drechsler et al. (2017) have added an additional channel to the relevant literature: the deposit channel of monetary policy. The closest paper to ours is Drechsler et al. (2022) who show that monetary tightening can fuel housing booms by shifting mortgage supply from banks to non-banks via the deposit channel.[7] Our paper extends the literature by identifying a novel channel operating through household portfolio reallocation. This mechanism highlights how deposit disintermediation alone can produce non-monotonic housing dynamics even in the absence of credit expansion, with important implications for inflation-targeting policy design.

Given the difficulties of VAR in dealing with longer horizons which was discussed earlier, the empirical strategy in our paper relies on well-established local projection techniques to analyze medium- and longer-term dynamics. A handful of papers analyze the impact of monetary policy on housing using LPs (see Hülsewig & Rottmann 2021, Adra & Menassa 2022, Miles & Zhu 2023, for instance), although this is mostly because these techniques are well suited to observing regime switching or country-specific responses. For instance, in a recent paper, Gorea et al. (2024) employ LP methods to provide evidence on the causal relationship between interest rates and US housing prices using listings data. Their empirical strategy is, in part, the closest to our methodology.

While Gorea et al. (2024) find that housing prices respond to a contractionary monetary policy surprise within two weeks, their long-run analysis points to the existence of a relationship over extended horizons. However, their focus is confined to a short-term horizon of up to one year. In contrast, our paper focuses on time series dynamics and explicitly explores the longer-term impact of monetary policy on housing prices, using LA-LP techniques as per Montiel Olea & Plagborg-Møller (2021). By including additional lags as controls in the LP regression, the standard confidence intervals can be assumed to have correct asymptotic coverage, avoiding a possible efficiency loss relative to VARs, even at more distant horizons. This is empirically confirmed by Buda et al. (2023) and Aruoba & Drechsel (2024), among others. Consequently, in our paper, the robust inference of LA-LP enables the identification of new dynamics between monetary policy and the housing market. We are able to show that housing prices fall not once but twice after a contractionary policy shock, indicating a double-dip behavior of prices in the long run.

Finally, our paper contributes to the literature on shock identification, such as Romer & Romer (2004), Gürkaynak et al. (2005), Jarociński & Karadi (2020). To analyze to what extent the housing deposit channel adds to the double-dip dynamics of housing prices, our paper uses unanticipated interest rate surprises around narrow windows on FOMC meeting days, while examining changes in zero maturity deposits in the week following the surprise interest rate changes. The "poor man's" sign restriction approach of Jarociński & Karadi (2020) is applied. Double-dip movements are more pronounced for shocks that account for the housing deposit

[6] Mishkin (2007) finds at least six channels: direct effects of interest rates on the user cost of capital, expectations of future housing price movements, and housing supply; and indirect through standard wealth effects of housing prices, balance sheet/credit channel effects on consumer spending, and balance sheet/credit channel effects on housing demand.

[7] Abadi et al. (2023), Choi & Rocheteau (2023) and Xiao (2020), among others, expand on the deposit channel, ignoring the housing market despite its significance as the largest asset on household balance sheets in developed countries.

channel of monetary policy than for those that do not.

In the remainder of this paper, section 2 theoretically identifies the key drivers of housing price dynamics following a tightening in monetary policy within a general equilibrium setup. Section 3 explains the fundamentals of LP techniques and introduces the lag-augmented LP process. Section 4 then empirically assessing the long-term effects of contractionary monetary policy. Section 5 provides robustness checks. Section 6 empirically analyses the housing deposit channel and assesses the monetary policy efficiency. Section 7 explores implications for monetary policy transmission. Finally, section 8 concludes.

2. Theoretical evidence

This section presents a general equilibrium model to elucidate the housing deposit channel and housing price double-dip. The model includes two types of households i.e., lender (patient, superscripts l) and borrower (impatient, superscripts b) in the same standard style as Iacoviello (2005). This modeling captures different reactions to interest rate hikes. Each type of household is represented by a unit measure of infinitely-lived agents. The model further includes a central bank and a financial sector which set the interest rates. The model is nominal, and all prices in the economy are relative, with the price of consumption serving as the numeraire.

2.1. Lender households

The households' problem is

$$\begin{aligned}
&\mathbb{E}_t \sum_{j=0}^{\infty} \beta_l^j \left[\log c_{t+j}^l + \chi_l^h \log h_{t+j}^l + \chi_l^d \log d_{t+j} \right] \\
&s.t \\
&c_t^l + d_t + p_t^h (h_t^l - (1-\delta_h) h_{t-1}^l) = w^l + r_{t-1}^d \frac{d_{t-1}}{\pi_t} \qquad (1)
\end{aligned}$$

where t represents time. $\beta_l < 1$ is the lender household discount factor. At every period t, the lender household engages in the following activities: consuming non-durable goods c_t^l, depositing in financial institutions d_t, buying houses h_t^l at the price p_t^h. δ_h is the housing depreciation rate and π_t is the inflation rate. The household receives w^l as endowment wage (for simplicity's sake, the wage is assumed fixed), r_{t-1}^d as the interest rate on the bank deposits of the last period. χ_l^h and χ_l^d are the coefficients which represent the relative importance of housing and liquidity in the utility function, respectively. Bank deposits are considered as liquid assets and they provide liquidity/utility to the household as per Drechsler et al. (2017).

The first-order conditions with respect to consumption, deposit and housing are

$$\lambda_t^l = \frac{1}{c_t^l} \rightarrow \Lambda_{t+1}^l = \beta_l \mathbb{E}_t \frac{\lambda_{t+1}^l}{\lambda_t^l} \tag{2}$$

$$1 = \frac{\chi_l^d}{\lambda_t^l} d_t^{-1} + \Lambda_{t+1}^l r_t^d / \pi_{t+1} \tag{3}$$

$$p_t^h = \frac{\chi_h}{\lambda_t^l} (h_t^l)^{-1} + \Lambda_{t+1}^l p_{t+1}^h (1 - \delta_h) \tag{4}$$

where λ_t^h is the Lagrange multiplier.

2.2. Borrower households

The problem of impatient households is

$$\begin{aligned}
&\mathbb{E}_t \sum_{j=0}^{\infty} \beta_b^j \left[\log c_{t+j}^b + \chi_b^h \log h_{t+j}^b\right] \\
&s.t. \\
&c_t^b + p_t^h (h_t^b - (1-\delta_h) h_{t-1}^b) + r_{t-1}^m \frac{m_{t-1}}{\pi_t} \leq w^b + m_t \\
&m_t \leq \theta p_t^h h_t^b
\end{aligned} \tag{5}$$

$\beta_b < 1$ is the discount factor of borrower households ($\beta_b < \beta_l$). Borrower households at time t consume c_t^b, accumulate housing h_t^b, request mortgages m_t at the rate r_t^m from the financial sector and receive total income w^b (for simplicity, the wage is assumed fixed).

The last equation in the borrower problem 5 is the borrowing constraint and standard in the literature, for example in Justiniano et al. (2015), Alpanda & Zubairy (2016), Ghiaie (2020) and Ghiaie (2023), among others. This constraint restricts the borrower household mortgage to a fraction of its housing value. θ is the Loan-to-Value ratio (LTV) in the mortgage market.

The first-order conditions with respect to consumption, borrower households and mortgage, respectively, are

$$\lambda_t^b = \frac{1}{c_t^b} \rightarrow \Lambda_{t+1}^b = \beta_b \mathbb{E}_t \frac{\lambda_{t+1}^b}{\lambda_t^b} \tag{6}$$

$$p_t^h - \frac{\lambda_t^m}{\lambda_t^b} \theta p_t^h = \frac{\chi_b^h}{\lambda_t^b} (h_t^b)^{-1} + \Lambda_{t+1}^b (1 - \delta_h) p_{t+1}^h \tag{7}$$

$$1 - \frac{\lambda_t^m}{\lambda_t^b} = \Lambda_{t+1}^b \frac{r_t^m}{\pi_{t+1}} \tag{8}$$

where λ_t^b is the Lagrange multiplier of the budget constraint and λ_t^m is the Lagrange multiplier of the borrowing constraint at time t.

2.3. Central bank and financial sector

As the aim of this section is to explore the housing deposit channel in more depth, for simplicity's sake, this paper assumes both r_t^d and r_t^m are exogenous.[8] r_t^m is set by the central bank and

[8] In a fully specified DSGE model, all variables, including interest rates, are determined endogenously. However, we intentionally simplify the framework by treating some variables as exogenous and do not calibrate the model

r_t^d by the financial sector. Following Drechsler et al. (2017), the financial sector sets the policy rate r^m and then sets their deposit rate r^d based on their market power where $r^m = r^d + s$ and $s > 0$. s is the spread and depends on the market power of the banking sector. We refer the readers to Drechsler et al. (2017) for more details on the bank market power.

2.4. Housing price equilibrium

From equation 3 and 4, the steady state[9] of the housing price from the lender side is:

$$p_l^h = \frac{\chi_l^h}{\lambda^l(1-(1-\delta_h)(1-\frac{\chi_l^d}{\lambda^l}d^{-1})\frac{1}{r^d})h^l}. \tag{9}$$

Combining equation 7 and 8, and without loss of generality assuming $\theta = 1$, and setting $\delta_h = 0$ for the sake of simplicity, give the steady state of the housing price from the borrower side:

$$p_b^h = \frac{\chi_b^h}{\lambda^b\beta_b(r^m-1)h^b}. \tag{10}$$

Following Iacoviello (2015), the housing supply is assumed constant and normalized to one i.e, $h_t^l + h_t^b = 1$ to focus on the demand side.[10] Given this normalization and the fact that at the equilibrium $p_l^h = p_b^h$, solving equation 9 and 10 for h^b implies

$$h^b = \frac{\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}{\frac{\chi_l^h}{\lambda^l(1-\beta_l)} + \frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}. \tag{11}$$

Substituting 11 in 10 reveals the housing price dynamics at the equilibrium:

$$p_E^h = \underbrace{\frac{\chi_l^h}{\lambda^l(1-\beta_l)}}_{\text{lender side}} + \underbrace{\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}_{\text{borrower side}} \tag{12}$$

The right-hand side of equation 12 represents the lender side (first term) and borrower side (second term). The following subsection describes the consequent housing price dynamics which emerge from a contractionary monetary policy.

2.5. What drives housing prices?

The answer to this question lies in the housing deposit channel of monetary policy, which drives the double-dip in housing prices. Given equation 12, which illustrates that both lenders and borrowers influence housing prices, the channel and resulting double-dip pattern unfold in three distinct phases, as follows.

or conduct standard IRF analysis. Our primary objective is to derive the housing price equilibrium in the next subsection and demonstrate the existence of the housing deposit channel, rather than to analyze the broader economy or produce a policy-oriented paper. This exogeneity assumption does not compromise our results, instead, it enhances the model's tractability and analytical clarity.

[9] We assume $\pi_t = \frac{p_t}{p_{t-1}}$ therefore at the steady state $\pi = 1$. This value does not change the results of our analysis. Detail calculations are provided in appendix E

[10] In Appendix F, we relax this assumption and solve this equation with flexible housing supply. The results indicate that a variable housing supply does not alter the conclusions of this paper.

First dip. We initially focus on the borrower side. As shown by Mian & Sufi (2009) and Mian & Sufi (2011), housing price cycles are generally considered to arise from significant exogenous shocks, typically related to the effective demand for housing. An initial interest rate hike reduces the effective demand for housing as borrower households decrease their mortgage demand. In turn, this causes a temporary bust in prices immediately after impact. This first bust is observed in most of the existing literature and is also captured by the empirical and theoretical models in our paper.

A change in the interest rate r^m has both direct and indirect effects on borrowers. When the interest rate rises, borrower households face higher costs, leading to a direct decrease in the demand for housing. In addition, there is an indirect negative impact through wealth effects, resulting in a decrease in the borrower's consumption c^b (note, $\lambda^b = \frac{1}{c^b}$). As a result, the borrower's side of equation 12 is always a decreasing function of the interest rate r^m.

Studies such as Morris & Palumbo (2001) and Krueger et al. (2024), among others, find a strong positive dynamic between wealth effects and household consumption, showing how changes in wealth, particularly housing wealth, influence consumption patterns. This relationship has been further explored in the context of monetary policy by Campbell & Cocco (2007) who find that housing wealth has a significant impact on consumption, particularly for credit-constrained households (in our model, borrowers). In addition, Coibion et al. (2017) study the distributional effects of monetary policy in the US, and find significant consumption inequality across different household quantiles. They show that borrower households reduce their consumption following an increase in the policy rate.

Housing deposit channel. We now focus on the lender side of equation 12. On the lender side, the response to interest rate changes is more nuanced. While the borrower side is always a negative function of the interest rate, the lender side depends on the pass-through of interest rates from banks to depositors, as follows. Drechsler et al. (2017) observe that households have a preference for liquidity, which they can obtain from cash and deposits. The Federal Funds Rate (FFR) is the cost of holding cash, while the difference between the FFR and the deposit rate (the deposit spread) is the cost of holding deposits. When the central bank raises the policy rate, as in the case of a contractionary monetary policy, cash becomes more expensive to hold.

Conversely, having market power in their local deposit markets, banks decide to increase their deposit spread s and keep the deposit rate r^d low.[11] Therefore, the opportunity costs of holding deposits for lender households increase, leading the utility for deposits χ_l^d to decline (see Polo 2021). Consequently, deposits are likely to flow into the housing market as housing represents the largest asset on household balance sheets in many developed economies (Piazzesi & Schneider 2016), while providing substantial utility χ_l^h. This pattern is evidenced in Figure 2, where lender households increasingly perceive the housing market as an investment opportunity following a rate hike, albeit with a lag.[12]

The housing deposit channel finances lender households' housing demand in response to lower prices, ultimately contributing to the recovery of housing prices[13] through the first term

[11] For more details, see section 4.2 and Drechsler et al. (2017).

[12] Seasonal housing serves a proxy for second homes. This is because data on second homes is not available for a frequent time period. The National Association of Home Builders (NAHB) bases its estimate of the number of second homes, i.e., non-rental property not classified as the taxpayer's principal residence, on, among other things, seasonal or vacation homes.

[13] Case & Shiller (2003) and Mikhed & Zemčík (2009) discuss a similar situation where the sharp increase in

Figure 2: Seasonal homes and interest rate growth. Seasonal housing serves a proxy for second homes. Left vertical axis indicates year-over-year growth of seasonal housing units in %. Right vertical axis indicates year-over-year growth of FFR in %. Data is provided by the US Census Bureau and the Federal Reserve System. A positive relationship between the FFR and the number of seasonal housing units is observed. This suggests that the demand for second homes as an investment opportunity for lender households increases with a lag after a rate hike.

of equation 12. Therefore, if lenders' effect is greater than borrowers' negative wealth effects, such that $\frac{\chi_l^h}{\lambda^l(1-\beta_l)} > \frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}$, the housing price will converge to pre-shock levels. This shift can lead to a partial recovery in housing prices after the initial dip caused by the interest rate hike, as observed in the empirical analysis in section 6.

Second dip. In response to deposit outflows, banks attempt to attract more deposits to meet mortgage demand and regulatory obligations[14] by raising r^d. This marks the beginning of the second dip. The rise in deposit spreads prior to the recovery period, which led to large deposit outflows, adds to the already high liquidity needs of lender households, thereby driving up demand for bank deposits. As lender households start to prioritize bank deposits, their demand for housing in the markets declines, which subsequently exerts downward pressure on housing prices again, although not to the same degree as in the first dip.

Additionally, the earlier surge in deposit spreads, which had triggered significant deposit outflows, now intensifies the liquidity constraints of lender households, increasing χ_l^d. These two dynamics which put downward pressure on housing prices, see equation 9, mark the onset of the second dip in housing prices. In this situation, bank deposits become attractive again which prompts lender households to shift their preference toward rebuilding deposits. As a result, housing demand weakens, leading to a decline in prices. However, this second decline is generally less significant than the initial drop, as financial conditions stabilize and the market adapts to the changing liquidity environment.

Moreover, the impact of other factors, such as regulatory changes, financial innovation, and shifts in market expectations, can further influence this dynamic. For example, the introduction of tighter lending standards (see θ in equation 5) can amplify the negative impact of interest rate increases on borrower demand, while innovations in mortgage products may mitigate this effect by making borrowing more accessible even in a high-interest-rate environment.

housing prices after a period of low prices is due to stock market investors switching to the housing market as a result of poor stock market conditions. An increase in demand for housing created by these investors pushes housing prices up.

[14]For example the capital requirement ratio (CRR) in Basel III and other obligations.

3. Empirical methodology

Our theoretical findings demonstrate that the key driver of housing price dynamics following a monetary policy shock is not only the response of borrowers but also the complex dynamics between banks and lenders through both the deposit and housing deposit channels of monetary policy. Now that we have established this theoretical framework, the next step is to examine whether this pattern is observable in empirical data. This requires testing the model's implications using real-world evidence, and determining the extent to which the housing deposit channel influences housing price fluctuations. This section presents the underlying empirical methodology of lag-augmented local projections.

3.1. VAR and local projection

Suppose a VAR process can be written as,

$$y_t = \sum_{j=1}^{\infty} A_j y_{t-j}; \quad j = 1, 2, ... \tag{13}$$

Under standard regularity assumptions, a VAR(p) process provides consistent estimates of the autoregressive matrices $A_1, ..., A_p$, so that $\|\hat{A}_j - A_j\| \xrightarrow{\text{p}} 0$, with $p, T \to \infty$ as long as p grows at rate $p^2/T \to 0$ (as per Lewis & Reinsel 1985). However, as shown by Jordà et al. (2023), in a finite sample, inconsistent estimates of the impulse response function arise if (1) the truncation lag is too short ($k < p$); and (2) if the truncation lag is appropriate, but the impulse response is calculated for periods that extend beyond the truncation lag. Furthermore, even if one decides to specify the VAR truncation lag, k, to be as large as the impulse response horizon (as long as $k^2/T \to 0$, as seen in Lewis & Reinsel 1985), issues of parametric load and overparameterization would still persist (Kuersteiner 2005). As a result, even though long lags are chosen, the task of analyzing gets more difficult or even impossible (Jordà et al. 2023).

To overcome these issues, Jordà (2005) proposes computing impulse responses using local projections instead of VARs. For the sake of clarity and consistency throughout the paper, consider the $AR(1)$ model for the data, y_t,

$$y_t = \rho y_{t-1} + u_t, \quad t = 1, 2, ..., T, \quad y_0 = 0. \tag{14}$$

The parameter of interest is a nonlinear transformation of ρ, namely, the impulse response coefficient at horizon $h \in \mathbb{N}$. This parameter is denoted by $\beta(\rho, h) \equiv \rho^h$. Furthermore, it is assumed that u_t is strictly stationary and satisfies $E(u_t|\{u_s\}_{s\neq t}) = 0$. The assumption requires the innovations to be mean independent relative to past and future innovations.

For conducting inference with regard to the impulse response $\beta(\rho, h)$, it is worth taking the benchmark (i.e., non-augmented) local projection approach of Jordà (2005) into consideration. A common motivation for this approach is that the $AR(1)$ model implies

$$y_{t+h} = \beta(\rho, h) y_t + \xi_t(\rho, h), \tag{15}$$

where the regression residual (or *multi-step forecast error)*,

$$\xi_t(\rho, h) \equiv \sum_{j=1}^{h} \rho^{h-j} u_{t+j}, \tag{16}$$

is generally serially correlated, even if the innovation u_t is independent and identically distributed (i.i.d.).

As can be seen, (non-augmented) local projections are basically direct estimates of the impulse response (moving average) coefficients, which straightforward regress y_{t+h} on y_t. Truncating the lag structure, even when $h > k$, has asymptotically vanishing effects on the consistency of the estimator. Recent work by Xu (2023) shows that in settings where the true lag order is unknown and possibly infinite, LPs are semiparametrically efficient as long as controlled lags are allowed to grow with the sample size. This means that the efficiency loss of LPs relative to VARs (i.e., bias-variance trade-off) diminishes the more lags one includes, and it effectively vanishes at the limit (Jordà 2023). In contrast, truncated VARs must be inverted in order to construct the impulse response. The impulse response therefore depends on the entire dynamic specification of the VAR. The cumulation of small sample inconsistencies over increasing horizons can accumulate and turn into non-negligible distortions of the impulse response, especially at long horizons (Jordà et al. 2023).

In this context, a Monte Carlo experiment by Jordà et al. (2023) compares cumulative response estimates of a simple AR model with three, six, nine, and twelve lags to LPs with only two lags. They find that an AR process with less than twelve lags produces cumulative effects that are relatively short-lived and far removed from the true impulse when analyzing long-run dynamics, completely missing the unwinding of the dynamics of periods 1-12 that follows in periods 13-24. Only the early stages of the impulse response are captured. In contrast, local projections, even when truncated at short lags, provide a fairly close estimate of the true responses, especially at long horizons.

However, as shown by Montiel Olea & Plagborg-Møller (2021), the validity of this non-augmented LP approach, as well as of standard VAR processes, is sensitive to the persistence of the data. Specifically, it may lead to a non-normal limiting distribution for the impulse response estimator when $\rho \approx 1$, since the regressor y_t exhibits near-unit-root behavior in this case. Hence, inference based on normal critical values will not be valid uniformly over all values of $\rho \in [-1, 1]$, even for fixed forecast horizons h. Only when ρ is safely within a stationary region, is the LP estimator considered to be asymptotically normal. Yet, standard LP inference generally requires the use of HAC/HAR standard errors to account for serial correlation in the residual $\xi_t(\rho, h)$, which could be challenging when dealing with the small sample sizes available in macroeconomics.

3.2. Lag-augmented local projection

To robustify and simplify inference, by solving the issues of data persistence and the interest in long impulse response horizons, Montiel Olea & Plagborg-Møller (2021) propose a *lag-augmented* local projection, which adds y_{t-1} as an additional control variable and provides asymptotically valid inference for both stationary and non-stationary data over a wide range of response horizons.

Let's define the covariate vector $x_t \equiv (y_t, y_{t-1})'$.[15] Given any horizon $h \in \mathbb{N}$, the lag-augmented LP estimator $\hat{\beta}(h)$ of $\beta(\rho, h)$ is specified by the coefficient on y_t in a regression of y_{t+h} on y_t and y_{t-1}:

$$\begin{pmatrix} \hat{\beta}(h) \\ \hat{\gamma}(h) \end{pmatrix} \equiv \left(\sum_{t=1}^{T-h} x_t x_t' \right)^{-1} \sum_{t=1}^{T-h} x_t y_{t+h}, \quad x_t \equiv (y_t, y_{t-1})'. \tag{17}$$

Here $\hat{\beta}(h)$ is the impulse response estimator of interest, while $\hat{\gamma}(h)$ is a nuisance coefficient. The purpose of the lag augmentation is to make the effective regressors of interest stationary even when the data y_t have a unit root. Note that one would obtain the same $\hat{\beta}(h)$ estimate, if regressing instead on (u_t, y_{t-1}), since u_t is simply a linear transformation of y_t and y_{t-1}, in that $u_t = y_t - \rho y_{t-1}$. Note further that the equations 15-16 imply

$$y_{t+h} = \beta(\rho, h) u_t + \beta(\rho, h+1) y_{t-1} + \xi_t(\rho, h). \tag{18}$$

If u_t were observed, the above equation suggests regressing y_{t+h} on u_t, while controlling for y_{t-1}. Intuitively, this will lead to an asymptotically normal estimator of $\beta(\rho, h)$ since the regressor of interest u_t is stationary by assumption, and since the term that involves a possible non-stationary regressor, y_{t-1}, is controlled for. The coefficient $\hat{\beta}$ converges to the coefficient β. In other words, u_t being a stationary variable, no matter the persistence (i.e, ρ) and no matter the horizon, one will always be regressing on a stationary regressor, leading to a uniformly normal limit distribution.[16]

Moreover, lag augmentation has the additional benefit of simplifying the computation of standard errors, as shown by Montiel Olea & Plagborg-Møller (2021). As equation 16 indicates, the residuals of a local projection generally have a moving average structure. Because they are dated t to $t+j$, they do not affect the consistency of the local projection estimate $\hat{\beta}(\rho, h)$. However, the residual correlation affects the construction of standard errors (Jordà 2023). As already mentioned above, Montiel Olea & Plagborg-Møller (2021) show that, contrary to the proposition by Jordà (2005) or Ramey (2016) of using Newey-West heteroscedasticity and autocorrelation consistent/robust estimators, HAC/HAR standard errors are not necessarily needed to conduct inference on *lag-augmented* LP. This is true despite the fact that the regression residual $\xi_t(\rho, h)$ might be serially correlated. Instead, Montiel Olea & Plagborg-Møller (2021) propose that it is sufficient to use usual heteroscedasticity-robust Eicker-Huber-White standard error of $\hat{\beta}(h)$, $\hat{s}(h)$ (see Appendix A).

Relying on the Eicker-Huber-White standard errors, $\hat{s}(h)$, one can define the nominal

[15]This paper only provides a brief overview of the LA-LP theory in the context of a simple univariate $AR(1)$ model. The discussion merely intends to illustrate the main points and can easily be extended to a multivariate $VAR(p)$ model. However, as the formal uniformity result for a general $VAR(p)$ model would be too extensive in the context of our paper, and the application in an AR(1) is sufficient to capture the main idea of LA-LP, the reader is referred to Montiel Olea & Plagborg-Møller (2021) for further details and proof of the inference procedure for lag-augmented LPs in a $VAR(p)$ setting.

[16]This argument for why lag-augmented LP can be expected to have a uniformly normal limit distribution, even when $\rho \approx 1$, is analogous to the reasoning for using lag augmentation in AR inference, see Sims et al. (1990), Toda & Yamamoto (1995), Dolado & Lütkepohl (1996), Inoue & Kilian (2002,0).

$100(1-\alpha)\%$ lag-augmented LP confidence interval for impulse response at horizon h as,

$$\hat{C}(h,\alpha) \equiv \left[\hat{\beta}(h) - z_{1-\alpha/2}\hat{s}(h), \hat{\beta}(h) + z_{1-\alpha/2}\hat{s}(h)\right], \tag{19}$$

where $z_{1-\alpha/2}$ is the $(1-\alpha/2)$ quantile of the standard normal distribution. The main result shown by Montiel Olea & Plagborg-Møller (2021) is that the lag-augmented LP confidence interval above is uniformly valid regardless of the persistence of the data, i.e., whether or not the data have a unit root. Crucially for our paper, this result does not break down at moderately long horizons h, and the inference is valid even under the *worst-case choices* of parameter $\rho \in [-1, 1]$ and horizon $h \in [1, \bar{h}_T]$ (see Appendix B).

The above outlines that a simple way to obtain correct inference for the local projection is to add an additional lag as a regressor and then select a heteroscedasticity-robust estimator to compute the standard errors, as there is no longer a need to correct for serial correlation. For the empirical application of lag-augmented LP, Montiel Olea & Plagborg-Møller (2021) propose a parametric wild bootstrap procedure where data are simulated from a VAR and then local projections are fitted to the stimulated data to construct percentile t-confidence intervals. In the IRF analysis below, both standard delta methods and the parametric wild bootstrap method proposed by Montiel Olea & Plagborg-Møller (2021) to calculate confidence intervals are applied.

With regard to the empirical literature, most analyses of housing price dynamics and monetary policy rely on standard VAR techniques, (see Iacoviello & Minetti 2008, Goodhart & Hofmann 2008, Jarociński & Smets 2008, Calza et al. 2013, McDonald & Stokes 2013, for instance). As most of them do not explicitly account for the longer-run responses of housing prices, they observe the typical dip after interest rate hikes in the short run. However, as our paper examines longer-term dynamics, the use of VAR is problematic, as it is limited in that the use of a short lag length is required,[17] while being overly optimistic about the rate of impulse response decay (given the stability of the VAR). As a result, the literature faces major challenges in analyzing impulse responses at longer horizons.

For instance, Antolin-Diaz & Surico (2025) show that by employing Bayesian shrinkage and a sufficiently large sample size, it might be possible to uncover impulse responses at horizons that are usually overlooked in business cycle analysis.[18] Similar methods are employed in Carriero et al. (2023) to analyze the long-run effects of uncertainty shocks on economic output,finding shocks to produce two dips in output over the long horizon. Inoue & Kilian (2020) address some of the above issues by suggesting lag-augmentation in the AR context. However, as shown in Montiel Olea & Plagborg-Møller (2021), when the data exhibit near-unit-root behavior, the lag-augmented AR estimator of the impulse responses could be criticized as being inconsistent at any horizon growing at a rate that is faster than the square root of the sample size, causing the confidence intervals to explode with length.

[17] A short lag length is essential in VARs to avoid the problem of overfitting and running into the so-called "curse of dimensionality," i.e., too many variables and/or too many lags in the model lead to overparameterization and imprecise estimates. In addition, autoregression (AR) inference methods that rely on the delta method break down, among other things, when suffering from unit roots or when looking at long horizons.

[18] Using a Bayesian VAR (BVAR), characterized by a very high-order lag polynomial, they provide evidence that unexpected increases in government spending are capable of boosting economic activity twice over time. However, they also show that their choice of lag length brings the impulse responses obtained by the BVAR close to what would have been obtained with lag-augmented LPs.

4. Empirical results

This section presents the baseline model evaluating the effects of monetary policy on the housing market using lag-augmented local projections. LPs are generally well-suited to capturing housing price movements, as they avoid the recursive structure imposed by VARs. However, as discussed in section 3, this flexibility in non-augmented LPs typically comes at the cost of higher variance than in VAR-based methods. Thus, our paper uses the lag-augmented approach which mitigates this trade-off and delivers more reliable long-horizon impulse responses with valid and reasonably tight confidence intervals across a broad range of data-generating processes.

4.1. Data

To be able to compare impulse responses based on LA-LP with those based on standard VARs, this paper adapts the empirical set-up described in Jarociński & Smets (2008) (JS, hereafter). JS assess the role of the housing market and monetary policy in the US business cycles from the second half of the 1980s to June 2007. We use the same variables and the same time period as JS.[19] The primary distinction lies in our adoption of an LA-LP approach to inference. Yet, our paper explicitly accommodates valid IRFs at distant horizons, offering a more conservative outlook on the rate of decay. Simultaneously, we address the issue of excessive regressors in the model.

Following JS, the propagation of a restrictive monetary policy shock in a system of nine US variables including real GDP, the GDP Deflator, commodity prices, the FFR, the money stock M2, as well as real consumption, real housing investment, real house prices, and the long-term interest rate spread is studied. These variables are included at a monthly frequency, which enables a more detailed analysis of housing market developments.[20] Moreover, a higher number of observations is naturally obtained, permitting the extension of the impulse response horizon, while accounting for the short sample bias in LP estimation pointed out by Herbst & Johannsen (2024). All variables are in logs, with the exception of the interest rates and the housing investment share, implicitly allowing for long-run relationships (Calza et al. 2007). To measure housing prices, this paper uses the nationwide Case-Shiller house price index.[21] For additional information regarding the variables, see JS.

Monetary shocks in JS are identified recursively by zero restrictions. They are assumed to affect economic activity and prices with a lag, while having an immediate effect on the term spread and money stock. The original VAR is estimated using a sample running from January 1987 to June 2007.[22]

[19]Given the prolonged period of expansionary monetary policy following the financial crisis up to recent years, extending the sample to include a more recent period is not pertinent to the objective of this paper. Nonetheless, we have conducted the same analysis for the 2008-2020 period. Unsurprisingly, the results reveal a less pronounced dynamic regarding a double dip in housing prices, as contractionary monetary policy played an insignificant role after 2008 compared to earlier periods.

[20]Monthly values of the quarterly Real GDP are retrieved through interpolation with the industrial production index. Monthly values of the quarterly GDP Deflator are retrieved trough interpolation with the Consumer Price Index and Producer Price Index. Interpolation follows the procedure described in Chow & Lin (1971).

[21]The use of alternative house price indices produces qualitatively similar results, see Appendix 5.3.

[22]The VAR in levels of JS uses standard Minnesota priors. However, no specific priors were included to capture long-run behavior in order to examine dynamics at longer horizons.

4.2. Baseline

Figure 3a plots the IRFs of housing prices in response to a monetary policy shock, as seen in JS. Housing prices begin to fall immediately after a contractionary monetary policy shock, bottoming out below baseline after approximately two and a half years.

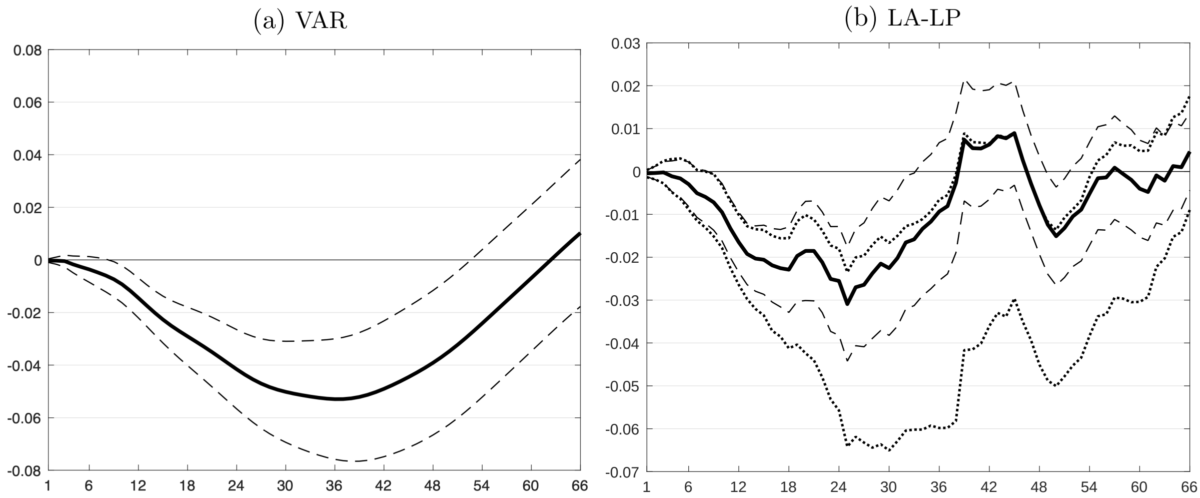

Figure 3: Impulse response functions of housing prices to monetary policy shock using: (a) VAR and (b) LA-LP. Time (horizontal axis) is in months. The solid black lines represent the IRFs. The dashed and dotted lines indicate one standard deviation delta-method and percentile-t bootstrap confidence interval, respectively.

A somewhat different picture can be seen when looking at the IRFs produced by LA-LPs in Figure 3b.[23] Following Jordà et al. (2023) local projection techniques provide close estimates of the true responses at long horizons,[24] even when truncated at a low lag length. In this context, the LA-LPs in particular provide asymptotically valid inference over a wide range of response horizons (Montiel Olea & Plagborg-Møller 2021). Both standard delta methods (in Figure 3b, dashed lines) as well as the parametric wild bootstrap methods (in Figure 3b, dotted lines) are used to calculate confidence intervals. We implement bootstrap procedures following Montiel Olea & Plagborg-Møller (2021) since LP estimation, similar to VAR estimation, can suffer from small sample bias (Herbst & Johannsen 2024).

The bootstrap method more accurately captures finite sample variability, resulting in confidence intervals that, while wider than those produced by delta methods, more accurately represent the true parameter uncertainty. Notably, in our case, the expanded confidence intervals extend primarily downward, suggesting that the true magnitude of the house price declines may be even more pronounced than our point estimates suggest. Similar to the VAR responses, real house prices immediately fall after impact. However, they revert to their pre-shock levels after roughly three years. Following this recovery period, a second recessionary wave at a 4 year horizon is evident. The second contraction is clearly visible and significant, while being less

[23] A lag length of $p = 5$ is chosen to capture relevant information. We check for robustness using a lag length of $p = 2$ based on the Schwarz information criterion for monthly data. However, as shown by Jordà et al. (2023), the Schwartz criterion tends to select lag lengths that are too small. Accordingly, we also consider lag lengths of $p = 3$, $p = 4$, and $p = 6$. The estimated IRFs do not change significantly when the lag length is changed.

[24] Following Xu (2023), together with the lag length of $p = 5$, we chose a horizon, h, which is small enough so that $n \geq 3h + p - 3$. Here, we use a horizon of $h = 66$, binding $n \geq 200$, which is the case for used observations from 1987m1 to 2007m6 ($n = 246$).

strong.

The above dynamics confirm the theoretical mechanism of the housing deposit channel of monetary policy as described in section 2.5: an initial positive shock to the FFR triggers an immediate decline in housing prices as effective demand for housing falls, with the IRF being significantly negative between 9 and 33 or 9 and 40 months, depending on the calculation of the confidence interval. In turn, a sudden increase in the policy rate by the central bank makes holding cash more expensive. Banks have the effective market power to raise the deposit spread. As a result, lender households withdraw their bank deposits, causing deposits to flow out of the banking system (for more details, see also Drechsler et al. 2017).

This outflow finds its way into concentrated markets. Since housing is the primary asset on household balance sheets in many advanced economies and provides substantial utility, these displaced funds often flow into the housing market. Lower housing prices create an incentive for lender households to reallocate their funds and finance purchases through the housing deposit channel. This shift plays a critical role in the recovery of housing prices, as indicated by the increase in the IRF between 24 and 40 months.

As prices recover, collateral constraints ease and the demand for mortgages rises. This increases banks' demand for deposits, which had previously been withdrawn in significant amounts. However, the high demand for deposits after the initial recovery reduces the demand for housing in the markets and pushes the impulse response of housing prices down significantly a second time, although not as low as in the initial decline.

In summary, a contractionary monetary policy shock is empirically found to trigger a double-dip effect in housing prices: an initial decline immediately after the shock's impact, followed by a second decline in the long run after a preceding period of increase. Further analysis of the housing deposit channel and monetary policy efficiency is provided in the next section.

5. Robustness checks

The following sections carry out several robustness checks on the baseline analysis to ensure that the pattern of housing prices identified in section 4 is not simply the result of random sampling variation.

5.1. Alternative monetary policy shocks

Since interest rate changes may be anticipated by markets, potentially distorting the effect of real interest rate hikes on prices, our paper follows Romer & Romer (2004) (RR, hereafter) in identifying monetary policy innovations that are cleansed of anticipatory effects related to economic conditions. RR first construct a historical measure of changes in the target FFR at each Federal Open Market Committee (FOMC) meeting from 1969 to 1996. Using the real-time Fed staff forecasts presented in the Greenbooks prior to each FOMC meeting, they construct a measure of monetary policy shocks from the component of policy changes at each meeting that is orthogonal to the Fed's information set. Following Coibion et al. (2017), the RR policy shock is extended to December 2008.

The IRFs shown in Figure 4, are qualitatively similar to those in Figure 3b. A drop in the housing price is observed within two years, followed by a gradual recovery to almost pre-shock levels. Finally, a second dip in housing prices is discernible following the initial shock. The use of exogenous monetary policy shocks confirms the robustness of the findings in section 4.2 and underscores the reliability and generalisability of the analysis, providing additional confidence in the conclusions drawn from the study.

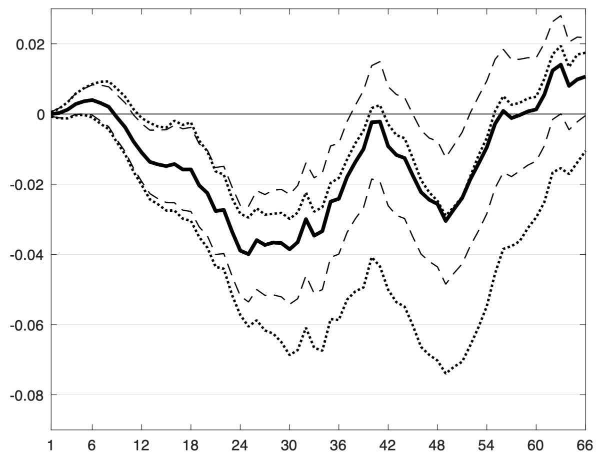

Figure 4: Impulse response functions of housing prices to a monetary policy shock following Romer & Romer (2004). Time (horizontal axis) is in months. The solid black lines represent the IRFs. The dashed and dotted lines indicate one standard deviation delta-method and percentile-t bootstrap confidence interval, respectively.

5.2. Alternative specification

The aforementioned characteristics should also be evident when examining other specifications. Indeed, when assessing the propagation of monetary shocks within a set of endogenous variables used by Calza et al. (2013) and adopting their identification scheme, comparable conclusions to the baseline results emerge. Figure 5 shows the IRFs of real house prices estimated with LA-LPs, including, in this order, private consumption, residential investment, the consumer price index, the real house price index, a three-month interbank interest rate, and the real effective exchange rate.[25]

It should be noted that, instead of using a shock to the FFR as a contractionary monetary policy change, Calza et al. (2013) apply an innovation to the three-month interbank interest rate. This may lead to slightly different results as transmission does not necessarily work the same way or is less pronounced when considering interest rates other than the FFR.[26] Eventually, although the IRFs show a significant post-shock decline followed by a steady recovery to pre-shock levels, the recovery period is less pronounced than in the baseline model. Nevertheless, a second drop can be observed after the recovery period.

5.3. Alternative housing price variables

Figure 6 shows the responses of alternatives to the real housing price index used in the paper to a monetary policy shock. The nominal nationwide Case-Shiller house price index (Figure 6a)

[25] All variables are in logs except for the interest rates. A lag length of two is chosen by Calza et al. (2013), which also seems appropriate for a model with monthly frequency data, following the Schwarz information criterion.

[26] We also employ the variables used in Calza et al. (2007) as robustness, whereby residential investment is excluded from the aforementioned data set. Similar IRFs are obtained.

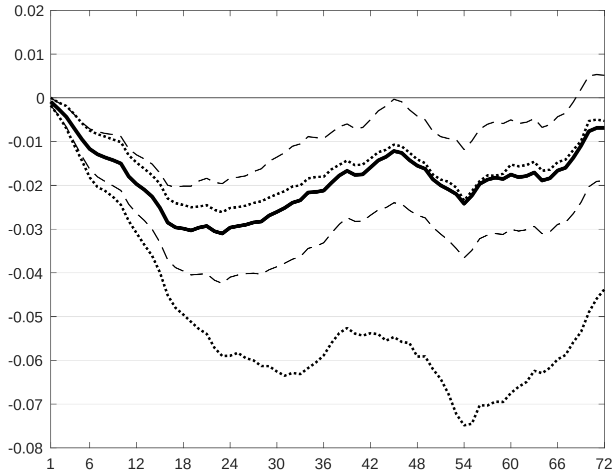

Figure 5: Impulse response functions of housing prices to monetary policy shock following the specification of Calza et al. (2013). Time (horizontal axis) is in months. The solid black lines represent the IRFs. The dashed and dotted lines indicate one standard deviation delta-method and percentile-t bootstrap confidence interval, respectively.

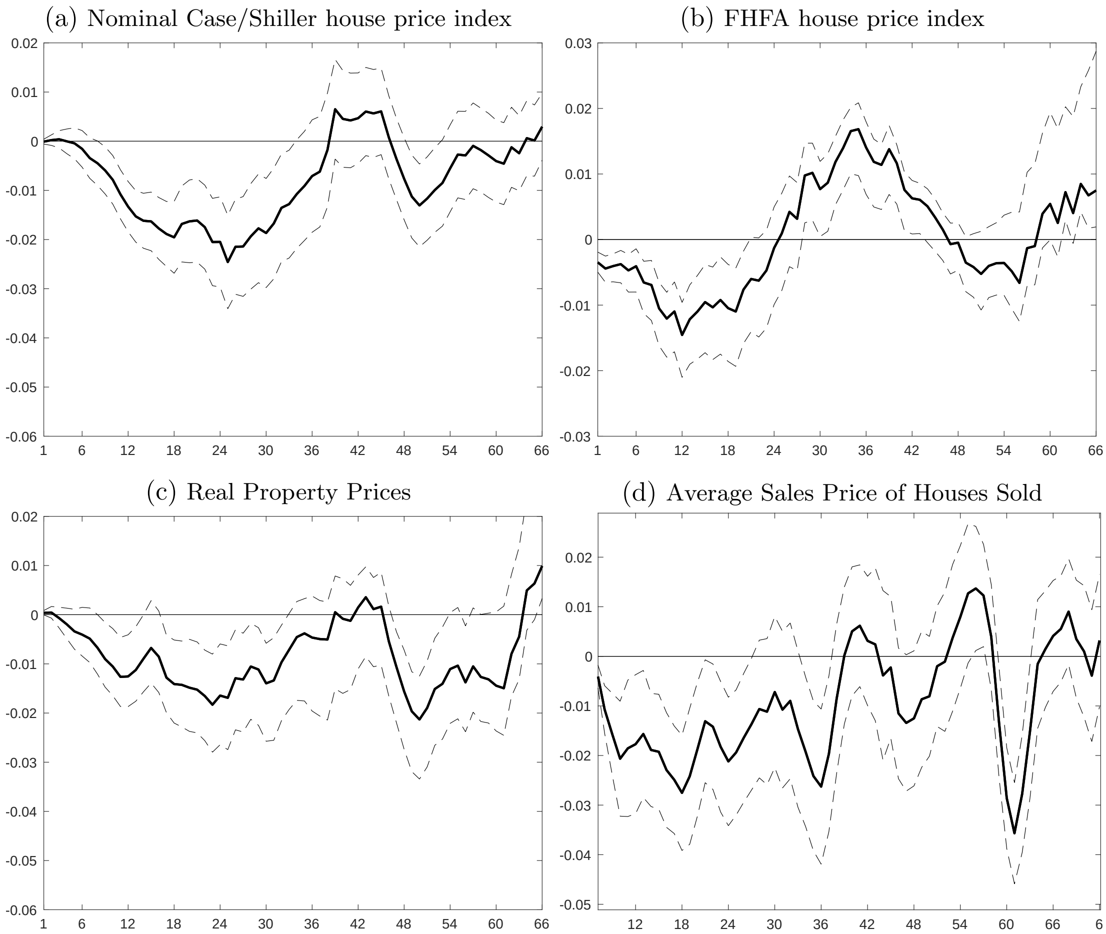

Figure 6: Impulse response functions of housing prices to monetary policy shock. Time (horizontal axis) is in months. The solid black lines represent the IRFs. The dashed lines indicate one standard deviation confidence interval.

as well as the US house price index data taken from the US Federal Housing Finance Agency (FHFA) (Figure 6b) produce IRFs showing a clear double-dip behavior. Same is true for the responses of real residential property prices (Figure 6c) and the average sales price for houses sold in the US (Figure 6d).[27]

5.4. Do other shocks produce housing price double-dips?

Finally, our paper considers whether shocks other than in interest rates also leads to the double-dip dynamics seen in the baseline model. The literature finds that shocks to uncertainty or financial risk, among others, can cause housing prices to fall (see, for instance El-Montasser et al. 2016, Gertler & Gilchrist 2019, Balcilar et al. 2021, Becard & Gauthier 2023). However, the transmission channels are different, and it is questionable whether these types of innovations also lead to a second decline, as in the case of responses to a monetary policy shock.

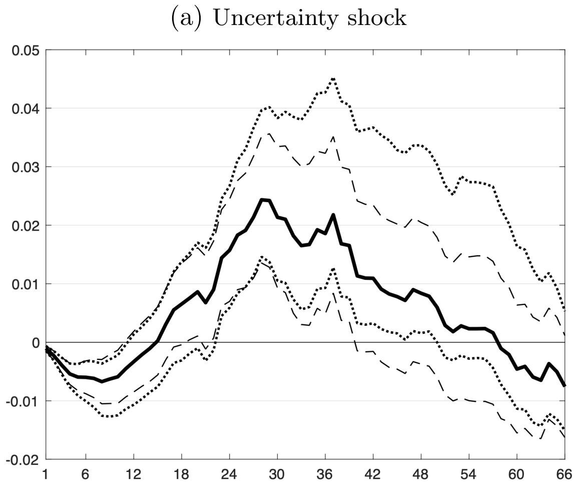

Figure 7: Impulse response functions of housing prices to uncertainty and credit spread shock: (a) uncertainty shock and (b) credit spread shock. Time (horizontal axis) is in months. The solid black lines represent the IRFs. The dashed and dotted lines indicate one standard deviation delta-method and percentile-t bootstrap confidence interval, respectively.

To measure the tightness of financial market conditions, our papers relies on corporate bond spreads. Specifically, the excess bond premium (EBP) is included in the data set[28] from Gilchrist & Zakrajšek (2012). This is an estimate of the extra compensation that bond investors demand for bearing the credit risk of US non-financial corporations. According to Gilchrist & Zakrajšek (2012), the EBP has predictive power for future economic activity, with shocks to the excess bond premium that are orthogonal to the current state of the economy leading to declines in economic activity and asset prices. An increase in the EBP appears to reflect a reduction in the risk-bearing capacity of the financial sector, leading to a contraction in the supply of credit, a deterioration in macroeconomic conditions and a collapse in housing prices.

Similarly, uncertainty events can affect the dynamics of the housing market. For example, under uncertainty, consumers tend to reduce their consumption and investors tend to delay their investments (Bloom 2009) due to precautionary motives, thereby depressing both the demand and supply in the housing market. Higher risk premium for financing projects in the presence of uncertainty increases the cost of debt financing (Christiano et al. 2014). To measure uncertainty,

[27]Monthly values of the quarterly real residential property prices and average sales price for houses sold are obtained by interpolation with the Case-Shiller real house price index, similar as seen in Rahal (2016). The interpolation follows the Chow & Lin (1971) procedure.
[28]Data provided by the US Federal Board System (Giovanni et al. 2016).

the Economic Policy Uncertainty (EPU) index constructed by Baker et al. (2016) is used. The EPU is an index based on newspaper articles about policy uncertainty. It counts the number of newspaper articles containing the terms uncertain or uncertainty, economic or economy, and one or more policy-related terms.

Figures 7a and 7b show the IRFs of real house prices to an uncertainty (EPU) and credit spread (EBP) shock, respectively, using LA-LPs with control variables from JS. As suggested by classical economic theory, both impulse responses show a negative reaction after the respective shock, before recovering in the long run. In contrast to a monetary policy shock, however, there is no double-dip in housing prices.

6. Housing deposit channel

As section 4.2 displays a general overview of housing price dynamics to monetary policy shock, focusing on longer run behavior, this section explicitly examines the housing deposit channel as a monetary transmission mechanism and offers additional empirical validation for the housing deposit channel.

6.1. Specific identification of the housing deposit channel

The process starts via the deposit channel according to Drechsler et al. (2017): banks have a certain degree of market power that allows them to increase the deposit spread, the difference between the FFR and the deposit rate, following an increase in the FFR. Households face a higher cost of holding deposits as opposed to cash or other investments and consequently withdraw deposits from the bank.

(a) Checking deposits (b) Savings deposits

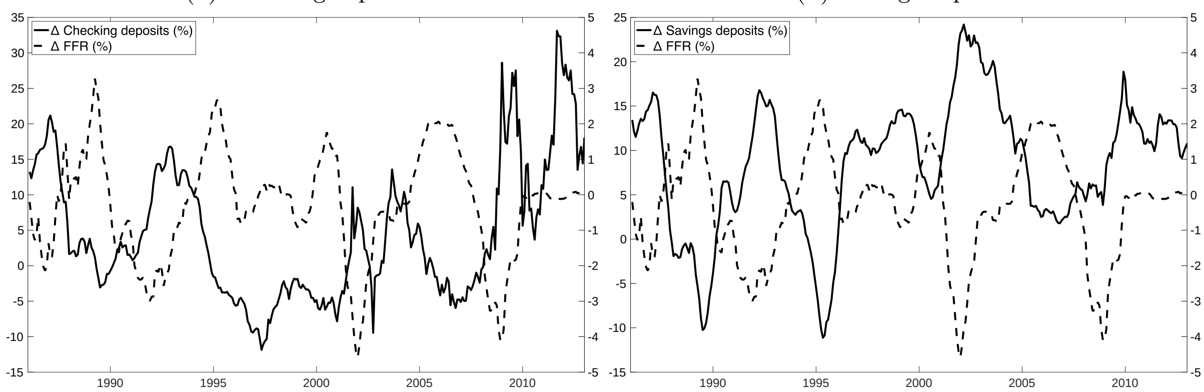

Figure 8: Deposit and interest rate growth: (a) checking deposits and (b) savings deposits. Left vertical axis indicates year-over-year growth of deposits in %. Right vertical axis indicates year-over-year growth of federal funds rate in %. Data is provided by the Federal Reserve System.

In this context, Drechsler et al. (2017) find that deposit spreads and zero maturity deposits immediately respond to rate changes in the FFR. Figure 8 plots the year-over-year change in the FFR against the percentage growth rate in the aggregate amounts of checking deposits (Figure 8a) and savings deposits (Figure 8b). These empirical insights reveal clear relationships. Figure 8a depicts a significant negative correlation of -35% between the growth rate of checking deposits and fluctuations in the FFR. Figure 8b reinforces the findings, revealing an even more pronounced correlation of -59% between changes in the FFR and the growth rates of liquid savings deposits.

Consequently, the reaction of zero maturity deposits to an interest rate change can help distinguish between shocks transmitted through a deposit channel and those that are not. To distinguish monetary policy shocks that operate through a housing deposit channel of monetary policy from those that do not, our paper uses unanticipated interest rate surprises around narrow windows on FOMC meeting days as a variable for a monetary policy shock, as per Romer & Romer (2004) and Coibion et al. (2017). We then check for changes in deposits in the week following the surprise rate changes.[29]

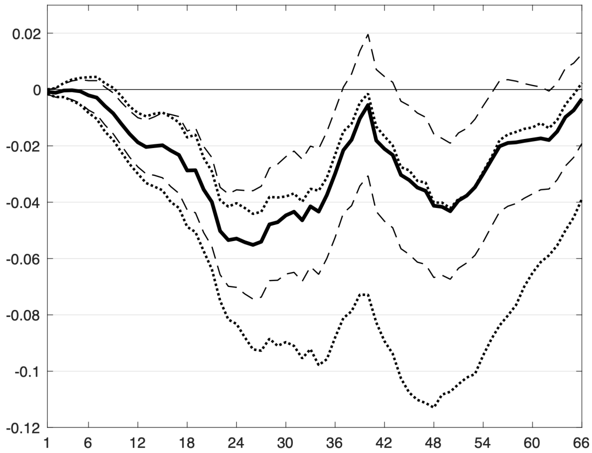

Figure 9: Impulse response function of housing prices to monetary policy shocks transmitted through housing deposit channel. Time (horizontal axis) is in months. The solid black line represents the IRF. The dashed and dotted lines indicate one standard deviation delta-method and percentile-t bootstrap confidence interval, respectively.

Interest rate changes that affect the economy through the deposit channel are identified using the "poor man's" sign restriction approach of Jarociński & Karadi (2020): Only interest rate surprises that are accompanied by opposite sign deposit changes in the week following FOMC meetings are considered.

The one-week window following unanticipated interest rate changes allows for effective isolation of immediate transmission channel effects while minimizing potential confounding influences. The one-week window is particularly appropriate because deposit withdrawals typically do not occur immediately on the day of an interest rate increase, but unfold gradually over the following days as households and firms adjust their portfolios in response to widened deposit spreads. The observation period ensures that observed deposit movements can be causally attributed to monetary policy. A higher-frequency identification approach, e.g. using daily data, would be unsuitable for capturing this full response lag in the transmission of monetary policy.

The responses of housing prices to these shocks are depicted in Figure 10. The results show a similar dynamic as in Figure 4 and as will be theoretically shown in section 2. An immediate dip in housing prices after impact is followed by a recovery period to pre-shock levels, and finally a second dip. This proves that monetary policy is transmitted to the housing market through a deposit channel. In addition, one observes that the two dips are of greater magnitude than those

[29] Changes in other zero maturity deposits, such as savings deposits, were also considered. They generate similar IRFs.

observed after a "normal" interest rate shock in the previous section by comparing Figures 3b and 4.[30]

6.2. Deposit and housing deposit channels

In this section, we provide additional empirical validation for the housing deposit channel. Drechsler et al. (2017) show that deposit supply is more responsive to monetary policy in markets with higher deposit concentration: when the FFR rises, banks in high-concentration counties increase deposit spreads and experience larger deposit outflows compared to those in low-concentration areas. If the housing deposit channel proposed in our paper holds, these stronger outflows should be associated with greater substitution into housing assets, i.e., this leads to a stronger rebound in house prices following monetary tightening in high-concentration counties. This identification strategy provides a direct test of whether there is a housing deposit channel of monetary policy.

To do so, we follow the standard idea of Drechsler et al. (2017). We first merge the their dataset with county-level housing price indices from the FHFA. We then analyze housing price dynamics with the same geographic granularity as deposit market concentration measures in the base dateset. The original dataset contains information on individual bank branches, including deposits, locations, and other branch characteristics. However, we replace their dependent variables, namely changes in deposit spreads or log changes in total deposits, with the annual growth rate of county level house prices. Since the housing prices are only available at the county level, we aggregate the original branch-level data to construct a county-year panel. The final dataset covers the period 1994-2007[31], i.e., 32,263 county-year observations, thereby providing substantial statistical power and enabling robust inference for our analysis.

To test whether the same cross-sectional variation in market concentration that drives differential deposit responses to monetary policy also leads to differential housing market reactions, we estimate the following regression:

$$\Delta HPI_{c,t} = \beta \Delta FFR_t \times \mathrm{HHI}_c + \zeta_c + \lambda_t + \varepsilon_{c,t}, \tag{20}$$

where ΔHPI_{ct} is the annual change in the house price index in county c and ΔFFR_t is the contemporaneous change in the Fed funds target rate. HHI_c is the Herfindahl-Hirschman index measuring market power over deposits in county c. In the baseline estimation ζ_c and λ_t are county and year-fixed effects, respectively and standard errors are clustered at the county level. Table 1 reports the results of this baseline estimation (Column 1) as well as the corresponding robustness tests (Columns 2-7).

[30] We also analyzed shocks that do not pass through the deposit channel, i.e., changes in the federal funds rate followed by changes in deposits with the same sign. The IRFs show a quite different pattern, as can be seen in Appendix C.

[31] As in the main empirical section, the sample is restricted to 2007.

Table 1: Effect of FFR changes on annual housing price growth.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta FFR \times HHI$	**0.7041******	**0.7041***	**0.7043******	**0.6917******	**0.4922******	**0.4663******	
	(0.1452)	**(0.3658)**	**(0.1452)**	**(0.1540)**	**(0.1745)**	**(0.1330)**	
$\Delta FFR \times Income$				-0.7675***			
				(0.1153)			
$\Delta FFR \times Education$				2.2592***			
				(0.2768)			
$\Delta FFR \times Large\ County$					-0.1468***		
					(0.0428)		
$\Delta FFR \times Branches\ (p.c.)$					0.0208		
					(0.0167)		
$\Delta FFR \times HHI^{placebo}$							**0.0200**
							(0.1220)
County FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	N	Y
State × Year FE	N	N	N	N	N	Y	N
County trends	N	N	Y	N	N	N	N
Two-way clustering	N	Y	N	N	N	N	N
Observations	31,516	31,516	31,516	31,510	31,510	31,516	31,516
R^2	0.238	0.238	0.238	0.239	0.238	0.525	0.237

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table estimates the effect of FFR changes on annual housing price growth. The data are from Drechsler et al. (2017) and the FHFA. Standard errors are clustered at county level (except column 2: two-way clustering by county and year). Columns 2-7 test robustness of baseline specification in Column 1. Column 7 uses randomly assigned HHI values as placebo test.

The results demonstrate that monetary policy transmission through deposit markets generates differential housing market responses across counties with varying levels of banks concentration. Column 1 in Table 1 shows that a one percentage point increase in the FFR is associated with a significant 0.704 percentage point increase in housing price growth in high-concentration banking markets relative to low-concentration markets. This result directly supports our proposed transmission mechanism: when the policy rate rises, banks increase deposit spreads by more and experience greater deposit outflows. These deposits flow into alternative investments, particularly housing, generating stronger price responses in counties where the deposit channel is most pronounced.

We subject these findings to extensive robustness testing. Column 2 employs a two-way clustering that accounts for correlation both within counties over time and across counties within the same year, addressing the fact that monetary policy shocks simultaneously affect all counties while local conditions persist over time. Column 3 controls for county-specific linear trends to account for systemic growth patters unrelated to monetary policy, such as the persistent appreciation in Silicon Valley counties driven by the technology sector expansion. Column 4 includes demographic controls by interacting monetary policy changes with county income and education levels. Column 5 incorporates banking market structure controls, interacting monetary policy changes with market size and branch density to control for other features of local banking markets that might independently affect monetary policy transmission.

Column 6 includes state-year fixed effects, controlling for all time-varying state-level factors that could confound our results, such as state-specific economic shocks, housing regulations, or regional policy implementation. This specification compares only counties within the same state and year, eliminating concerns that the results reflect broader regional trends rather than local banking competition. The coefficient of interest remains significant under this identification strategy, while R^2 increases substantially from 0.238 to 0.525, indicating that state-year variation explains much of the housing price movements in the data. Finally, Column 7 presents a placebo test that replaces actual HHI measures with randomly assigned values. If our identification strategy is sound, these random competition measures should show no relationship with housing prices. The placebo regression yields a small, statistically insignificant coefficient. This confirms that our results are not driven by spurious correlations or omitted variables correlated with bank market structure.

Further robustness checks, reported in Table 2, test whether the results are driven by outliers or extreme values by winsorizing housing price changes at the 1st and 99th percentiles (Column 1), excluding counties with very low or high bank concentration (Column 2), and replacing the continuous HHI measures with tercile dummies (Column 3) to allow for non-linear effects.

These findings demonstrate that the deposit channel operates through the housing market, with deposits withdrawn from branches in high-concentration counties flowing into local housing markets. The dynamics captured in this simple regression framework align closely with the local projection estimates, confirming that our empirical approach fully captures these transmission mechanisms. This result is consistent with Drechsler et al. (2017), who show that the deposit channel can account for the entire transmission of monetary policy through bank balance sheets. Similarly, the housing deposit channel we document accounts for the monetary policy transmission mechanisms observed in sections 4 and 6.1.

Table 2: Supplementary robustness checks.

	(1)	(2)	(3)
$\Delta FFR \times HHI$	**0.701*****	**0.470*****	
	(0.126)	**(0.146)**	
$\Delta FFR \times HHI_{tercile} = 2$			0.060
			(0.040)
$\Delta FFR \times HHI_{tercile} = 3$			0.170***
			(0.044)
County FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	31,516	30,876	31,516
R^2	0.244	0.236	0.237

*** p<0.01, ** p<0.05, * p<0.1

Notes: The data are from Drechsler et al. (2017) and the FHFA. Standard errors are clustered at county level.

7. Policy implications: monetary policy efficiency and inflation targeting

Our findings contribute to the ongoing debate on the role of housing prices in inflation targeting and the overall effectiveness of monetary policy (see, e.g., Bernanke & Gertler 2001, Cecchetti et al. 2003). While most central banks do not explicitly target housing prices or house price inflation (Ingves 2007), rising housing prices can influence macroeconomic conditions through financial channels. As Iacoviello & Minetti (2003) emphasize, higher housing prices increase collateral values, enhancing borrowers' access to credit. This, in turn, can amplify aggregate demand and signal future inflationary pressures. These dynamics have prompted discussions on whether housing prices should be incorporated into monetary policy frameworks, including modified Taylor rules (see Käfer 2014, for a comprehensive review).

This divergence has given rise to a range of perspectives, particularly following the recent surge in U.S. housing prices, see for example Bhar et al. (2024). In light of these emerging developments on inflation-targeting monetary policy, our paper provides new evidence on the long-run transmission of monetary policy through the housing market. For instance, one aspect is the forecast horizon. Most inflation-targeting central banks operate with forecast horizons of two to three years. Benati (2021), for example, provides evidence suggesting that the trade-offs between housing prices and GDP are largely a short-term phenomenon. Our findings indicate that that the housing market absorb and then re-release monetary pressure with a lag, functioning more like a buffer than a terminal endpoint in the transmission mechanism. Standard Taylor-rule frameworks, which assume relatively smooth and persistent transmission, may therefore misguide rate-setting decisions. The double-dip dynamic implies that short-term inflation moderation via housing may be partially reversed, then amplified again, over longer horizons. As a result, monetary policy should not focus solely on the immediate effects of house and asset prices on inflation and the real economy. Instead, it is crucial to consider the longer-term consequences of these dynamics.

On the other hand, there is support for an alternative monetary policy approach known as the "leaning against the wind" theory. This theory advocates policies that systematically react to signs of "excessive" credit growth or "disequilibria" in asset prices by slightly raising interest rates above the levels required solely to control inflation and real economic activity (Bank for International Settlements 2016). Proponents argue that such a strategy could mitigate the build-up of financial imbalances and reduce the risk of future economic downturns by allowing asset prices to be taken into account in monetary policy (i.e., extending the Taylor rule to include housing prices).

Our results show that a policy of "leaning against the wind", which involves further increases in interest rates to cool the housing market, can be counterproductive. Our empirical model suggests that housing prices recover in the medium term after a contractionary monetary policy shock. Consequently, policymakers may misread a housing price rebound as evidence that the initial tightening was inadequate, leading them to tighten policy further.

Lastly, since this channel operates through deposit reallocation rather than credit expansion, it bypasses many macroprudential tools designed for mortgage regulation (e.g., LTV caps). This limits the effectiveness of non-interest-rate interventions. These findings suggest that monetary policy models must explicitly account for this channel to avoid mistimed interventions and to improve the forecasting of inflationary pressures tied to housing market dynamics.

8. Conclusion

This paper shows that interest rate hikes trigger a double-dip in housing prices via a novel transmission mechanism, the housing deposit channel. Using a general equilibrium model, it explains how borrower and lender households respond differently to monetary tightening. These theoretical insights are empirically validated using local projection methods and confirmed through extensive robustness checks and an accurate identification strategy.

Although the results of our paper illustrate a distinct behavior of housing prices and propose a novel transmission channel of monetary policy, further studies could be conducted to extend its scope. One avenue for future research is to consider the varying exposure of individual banks and their customers, similar to Drechsler et al. (2022), or in different regions of the US, similar to Albuquerque et al. (2024). Moreover, given the post-COVID-19 tightening cycle in the US, it would be interesting to examine whether similar effects on housing prices emerge during that period, in line with Burgert et al. (2024). However, extending the empirical approach to a post-COVID-19 period seems more challenging, given the potential for biased estimates due to the sequence of extreme observations and the limited number of observations available.

Finally, extending this analytical framework to non-US economies is a promising but methodologically complex direction for future research. The methods of identifying monetary shocks, the optimal criteria for selecting variables, the structural characteristics of the housing market, and the architecture of the banking system differ substantially in European countries or Canada from those in the United States. As a result, direct application of the present model specification may prove inadequate without careful recalibration to account for country-specific institutional arrangements and market dynamics. Further theoretical and empirical work is needed to develop appropriate frameworks that can account for these cross-country differences while maintaining comparability of results.

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Appendix A Standard errors

The heteroscedasticity-robust Eicker-Huber-White standard error of $\hat{\beta}(h)$, as proposed by Montiel Olea & Plagborg-Møller (2021), is given by,

$$\hat{s}(h) \equiv \frac{\left(\sum_{t=1}^{T-h} \hat{\xi}_t(h)^2 \hat{u}_t(h)^2\right)^{1/2}}{\sum_{t=1}^{T-h} \hat{u}_t(h)^2}, \tag{A1}$$

where the lag-augmented LP residuals are defined as follows:

$$\hat{\xi}_t(h) \equiv y_{t+h} - \hat{\beta}(h)y_t - \hat{\gamma}(h)y_{t-1}, \quad t = 1, 2, ..., T-h, \tag{A2}$$

and the realized regressor of interest being

$$\hat{u}_t(h) \equiv y_t - \hat{\rho}y_{t-1}, \quad t = 1, 2, ..., T-h, \quad \hat{\rho}(h) \equiv \frac{\sum_{t=1}^{T-h} y_t y_{t-1}}{\sum_{t=1}^{T-h} y_{t-1}^2}. \tag{A3}$$

The reason why the approach of Montiel Olea & Plagborg-Møller (2021) works is, that under the assumption made on u_t, the term $\xi_t(\rho, h)u_t$ is serially uncorrelated even if $\xi_t(\rho, h)$ itself is serially correlated. Notice that this result crucially relies on (i) lag-augmenting the local projections and (ii) the strengthening in the assumption of u_t being strictly stationary with $E(u_t|\{u_s\}_{s\neq t}) = 0$ of the usual martingale difference assumption on u_t.[32] As mentioned by Jordà (2023), in practical settings, it is important to ensure that enough lags are included to ensure that this condition is met.

Appendix B LA-LP inference

Consider any upper bound $\bar{h}_T$ on the horizon which satisfies $\bar{h}_T/T \to 0$. This implies that,

$$\underset{\rho\in[-1,1]}{inf} \quad \underset{1\leq h\leq \bar{h}_t}{inf} \quad P_\rho\left(\beta(\rho, h) \in \hat{C}(h, \alpha)\right) \to 1 - \alpha \quad as\; T \to \infty, \tag{B1}$$

where P_ρ denotes the distribution of the data, y_t, under the $AR(1)$ model in equation 16 with parameter ρ. This gives the probability that the confidence interval covers the impulse response for that specific parameter, ρ, and at any horizon, h.

Equation B1 states that, for sufficiently large sample sizes, LP inference is valid even under the *worst-case choices* of parameter $\rho \in [-1, 1]$ and horizon $h \in [1, \bar{h}_T]$. Such *uniform* validity is a much stronger result than *point-wise* validity for fixed ρ and h. In fact, if one restricts attention to only the stationary region $\rho \in [-1 + \alpha, 1 - \alpha], \alpha \in (0, 1)$, then the statement in equation B1 is true with the upper bound $h = (1 - \alpha)\bar{h}_T$ on the horizon. That is, if one knows the time series is not close to a unit root, then local projection inference is valid even at long

[32] The strengthening still allows for conditional heteroscedasticity and other plausible features of economic shocks, see Montiel Olea & Plagborg-Møller (2021).

horizons h that are non-negligible fractions of the sample size T.

Appendix C IRF: Poor man's approach - same sign

Figure 10 shows the response of housing prices to an interest rate shock, where only interest rate surprises that are accompanied by the same sign deposit changes in the week following FOMC meetings are considered.

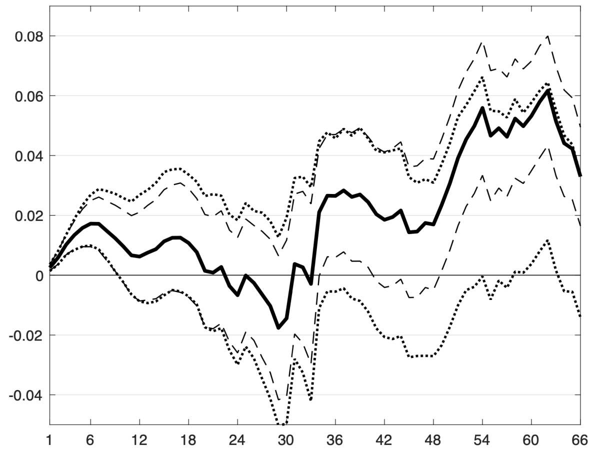

Figure 10: Impulse response function of housing prices to monetary policy shocks not transmitted through housing deposit channel. Time (horizontal axis) is in months. The solid black line represents the IRF. The dashed and dotted lines indicate one standard deviation delta-method and percentile-t bootstrap confidence interval, respectively.

Appendix D Controlling for customers' shift in liquidity preference

As Figure 11 shows, illiquid small time deposits are positively related to the FFR, which is the opposite of the relationship between more liquid savings and checking deposits shwon in Figure 8). Thus, as the FFR rises and liquid deposits become relatively more expensive, households partly substitute towards less liquid deposits. To control for the shift in liquidity preferences - that is the possibility that customers shift their funds from short-term deposits to longer-term deposits instead of investing in the housing sector - we add a measure of time deposits to the model specification estimated in section 6.[33]

Figure 12 shows the response of the housing price to a shock as defined in section 6, while controlling for possible liquidity shifts to longer-term deposits. The paper finds a similar dynamic to that in Figure 10.

[33]The variable is defined as small time deposits divided by core deposits. Core deposits are thereby the sum of checking, savings, and small time deposits and are considered to be a bank's most dependable source of funding (Drechsler et al. 2017).

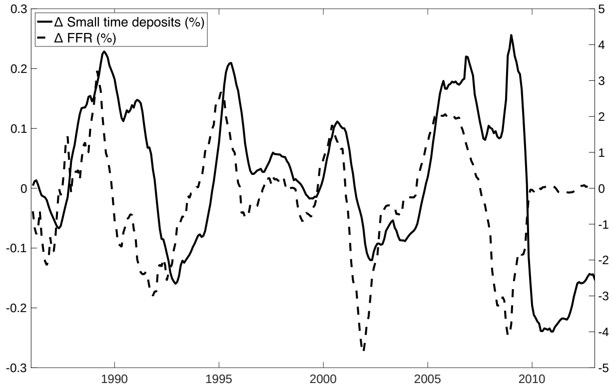

Figure 11: Small time deposit and interest rate growth. Left vertical axis indicates year-over-year growth of small time deposits in %. Right vertical axis indicates year-over-year growth of federal funds rate in %. Data is provided by the Federal Reserve System.

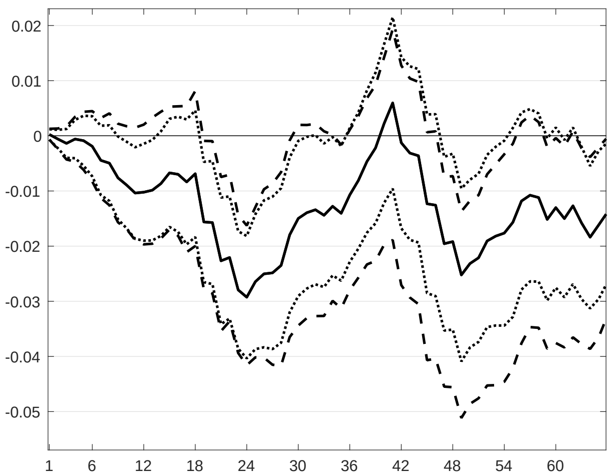

Figure 12: Impulse response function of housing prices to monetary policy shocks transmitted through housing deposit channel. Time (horizontal axis) is in months. The solid black line represents the IRF. The dashed and dotted lines indicate one standard deviation delta-method and percentile-t bootstrap confidence interval, respectively. In this specification it is specifically controlled for a possible customers' shift in liquidity preference.

Appendix E Housing price equilibrium (step-by-step)

E.1 Housing price (lender side)

The housing price p^h, emerging from the lender side, in equation 9 is derived from equation 3 and 4. Equation 3 can be solved for Λ^l_{t+1}, so that,

$$\Lambda^l_{t+1} = (1 - \frac{\chi^d_l}{\lambda^l_t} d^{-1}_t) \frac{\pi_{t+1}}{r^d_t}. \tag{E1}$$

Substituting Λ^l_{t+1} in equation 4 implies at the steady state:

$$p^h_t = \frac{\chi_h}{\lambda^l} (h^l)^{-1} + \left[(1 - \frac{\chi^d_l}{\lambda^l} d^{-1}) \frac{\pi}{r^d} \right] p^h (1 - \delta_h). \tag{E2}$$

Subtracting the term $\{ \left[(1 - \frac{\chi^d_l}{\lambda^l} d^{-1}) \frac{\pi}{r^d} \right] p^h (1 - \delta_h) \}$ from the right-hand-side and factoring out p^h, one obtains:

$$\frac{\chi_l^h}{\lambda^l}(h^l)^{-1} = p^h(1-(1-\delta_h)(1-\frac{\chi_l^d}{\lambda^l}d^{-1})\frac{1}{r^d}). \tag{E3}$$

By solving for p^h, it emerges the housing price from the lender side, as seen in equation 9:

$$p^h = \frac{\chi_l^h}{\lambda^l(1-(1-\delta_h)(1-\frac{\chi_l^d}{\lambda^l}d^{-1})\frac{1}{r^d})h^l}. \tag{E4}$$

E.2 Housing price (borrower side)

The housing price p^h, emerging from the borrower side, in equation 10 is derived from equation 7 and , assuming $\theta = 1$. First, equation 8 is solved for $\frac{\lambda_t^m}{\lambda_t^b}$, so that,

$$\frac{\lambda_t^m}{\lambda_t^b} = 1 - \Lambda_{t+1}^b \frac{r_t^m}{\pi_{t+1}}. \tag{E5}$$

Substituting then $\frac{\lambda_t^m}{\lambda_t^b}$ in 7 implies at steady state:

$$p^h - \left[1 - \Lambda^b r^m\right] p^h = \frac{\chi_b^h}{\lambda^b}(h^b)^{-1} + \Lambda^b(1-\delta_h)p^h. \tag{E6}$$

Factoring out p^h at the left-hand-side implies,

$$p^h\Lambda^b r^m = \frac{\chi_b^h}{\lambda_t^b}(h_t^b)^{-1} + \Lambda^b(1-\delta_h)p^h; \tag{E7}$$

$$\frac{\chi_b^h}{\lambda^b}(h^b)^{-1} = p^h\Lambda^b r^m - \Lambda^b(1-\delta_h)p^h; \tag{E8}$$

$$\frac{\chi_b^h}{\lambda^b}(h^b)^{-1} = p^h\beta_b(r^m - (1-\delta_h)). \tag{E9}$$

Solving for p^h gives the housing price emerging from the borrower side, as seen in equation 10:

$$p^h = \frac{\chi_b^h}{\lambda^b\beta_b(r^m-(1-\delta_h))h^b}. \tag{E10}$$

E.3 Housing price (equilibrium)

Combining equation 9 and 10, since, in the equilibrium, $p_l^h = p_b^h$, implies:

$$\frac{\chi_b^h}{\lambda^b(\beta_b(r^m-1)h^b} = \frac{\chi_l^h}{\lambda^l(1-(1-\delta_h)(1-\frac{\chi_l^d}{\lambda^l}d^{-1})\frac{1}{r^d})h^l}. \tag{E11}$$

Following equation E1 and the first-order condition 6 of the lender side, $\beta_l = \Lambda^l = (1 - \frac{\chi_l^d}{\lambda^l}d^{-1})\frac{1}{r^d}$. Together with setting $\delta_h = 0$ (for the sake of simplicity) and factoring in β_b, this implies:

$$\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)h^b} = \frac{\chi_l^h}{\lambda^l(1-\beta_l)h^l}. \tag{E12}$$

Following Iacoviello (2015), the housing supply is assumed constant to one, so that $h_t^l + h_t^b = 1$. Consequently, by definition, $h^l = 1 - h^b$, which implies,

$$\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)h^b} = \frac{\chi_l^h}{\lambda^l(1-\beta_l)(1-h^b)}. \tag{E13}$$

When solving for h^b, one multiplies by $(1-h^b)$, so that,

$$\frac{(1-h^b)}{h^b}\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)} = \frac{\chi_l^h}{\lambda^l(1-\beta_l)}; \tag{E14}$$

$$(\frac{1}{h^b} - 1)\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)} = \frac{\chi_l^h}{\lambda^l(1-\beta_l)}; \tag{E15}$$

$$\frac{1}{h^b}\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)} - \frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)} = \frac{\chi_l^h}{\lambda^l(1-\beta_l).} \tag{E16}$$

From the latter equation one can easily find h^b (as seen in equation 11):

$$h^b = \frac{\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}{\frac{\chi_l^h}{\lambda^l(1-\beta_l)} + \frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}. \tag{E17}$$

Substituting h^b in equation 10 reveals the housing price dynamics at the equilibrium:

$$p^h = \frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)} \frac{\frac{\chi_l^h}{\lambda^l(1-\beta_l)} + \frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}{\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}; \tag{E18}$$

$$p_E^h = \underbrace{\frac{\chi_l^h}{\lambda^l(1-\beta_l)}}_{\text{lender side}} + \underbrace{\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}_{\text{borrower side}}. \tag{E19}$$

Appendix F Housing price (equilibrium) - with a non-constant housing supply

Let's suppose the housing supply is not constant, but rather a function of the interest rate, set by the central bank: $h^l + h^b = f(r^m)$. Raising interest rates can significantly impact housing construction by increasing the overall cost of construction projects. Higher interest rates make borrowing more expensive, leading to reduced investment in new housing developments. This, in turn, can exacerbate existing supply chain issues, driving up prices for building materials as demand decreases but costs rise. As construction becomes more expensive, fewer projects may be initiated, further tightening housing supply. Consequently, housing supply can be viewed as a function of interest rates, as fluctuations in rates directly influence the feasibility and cost of construction.

Equation 38 changes as follows:

$$\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)h^b} = \frac{\chi_l^h}{\lambda^l(1-\beta_l)(f(r^m)-h^b)}. \tag{F1}$$

When solving for h^b, one multiplies by $1 - f(r^m)$, so that,

$$\frac{(f(r^m)-h^b))}{h^b}\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)} = \frac{\chi_l^h}{\lambda^l(1-\beta_l)}; \tag{F2}$$

$$(\frac{f(r^m)}{h^b}-1)\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)} = \frac{\chi_l^h}{\lambda^l(1-\beta_l)}; \tag{F3}$$

$$\frac{f(r^m)}{h^b}\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)} - \frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)} = \frac{\chi_l^h}{\lambda^l(1-\beta_l).} \tag{F4}$$

From the latter equation one can easily find h^b (as seen in equation 11):

$$h^b = f(r^m)\frac{\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}{\frac{\chi_l^h}{\lambda^l(1-\beta_l)} + \frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}. \tag{F5}$$

Substituting h^b in equation 10 reveals the housing price dynamics at the equilibrium:

$$p^h = \frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}\frac{\frac{\chi_l^h}{\lambda^l(1-\beta_l)} + \frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}{f(r^m)\frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}}; \tag{F6}$$

$$p_E^h = \frac{1}{f(r^m)}(\frac{\chi_l^h}{\lambda^l(1-\beta_l)} + \frac{\chi_b^h}{\lambda^b(\beta_b r^m - \beta_b)}). \tag{F7}$$

Since $f(r^m)$ is always a positive function, increasing $f(r^m)$ only reduces the speed, not the direction of the price dynamics found in Section 2. Moreover, since r^m is bounded, the assumption that $\frac{1}{f(r^m)}$, and thus housing supply, is constant, following Iacoviello (2015), is valid. Consequently, it is correct to focus only on the price movements resulting from the demand for housing, as we've done so far, since accounting for a non-constant housing supply does not significantly change the conclusions of this paper.