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Housing demand shocks and households' balance sheets

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Housing Demand Shocks and Households' Balance Sheets

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February 8, 2021

Abstract

We examine the dynamic effects of housing demand shocks on a large set of U.S. macroeconomic series and detailed household balance sheet components for four wealth percentile groups. The results show that a positive housing shock translates into a large and persistent boom of economic activity, an expansion of credit and an increase of interest rates. While households of all wealth percentile groups make heavy use of home equity-based borrowing, we find a larger consumer spending sensitivity for weaker balance sheet households. This is supported by the elasticities of consumption with respect to house prices implied by our structural dynamic factor model. A historical decomposition suggests that housing demand shocks have largely contributed to the pronounced drop in poorer households' consumption during the Great Recession. Variance decompositions indicate that the identified housing shock has high explanatory power for key economic indicators, housing indices and household balance sheet series.

JEL Code: D31, E21, E32, E44, R31

Keywords: Housing demand shocks, Household balance sheets, Bayesian dynamic factor model

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1 Introduction

The financial crisis of 2007-2008 was closely related to the collapse of the U.S. housing market. Accordingly, a growing literature suggests that housing demand shocks are significant drivers of business cycle fluctuations ([Iacoviello and Neri, 2010](#), [Liu et al., 2013](#)).

The tight connection between economic activity and housing is often ascribed to three main channels. The first one stems from Tobin's q effect, which indicates that rising house prices lead to an increase in real estate values over construction costs, thereby stimulating residential investment which can be a key component of GDP growth ([Leamer, 2007](#)). A second transmission channel works via the credit market. A positive housing demand shock increases homeowners assets and thus the value of collateral, mitigating households' and firms' credit constraints ([Iacoviello, 2005](#), [Mian and Sufi, 2011](#), [Liu et al., 2013](#)). The same balance sheet mechanism applies to the lending side, as financial intermediaries expand credit supply along with the increase of assets held ([Adrian et al., 2010](#)). The third channel is an implication of consumption smoothing in life-cycle models. An unexpected and permanent increase of wealth leads households to borrow more and increase consumption. The dynamic interdependence between household balance sheets, the credit market and the housing market is thus able to amplify each channel, possibly making it a powerful driver of real economic activity.

The experience of the Great Recession indicated that the strength of such feedback loops also depends on the heterogeneity of households' balance sheets. While traditional macroeconomic models assume a representative agent framework in which households are insured against individual wealth shocks, recent empirical evidence points at the importance of modelling housing, credit and consumption using heterogeneous agent models ([Bostic et al., 2009](#), [Mian and Sufi, 2011](#), [Aladangady, 2017](#)). Of particular interest has been the relationship between a shock to housing wealth and the cross-sectional response of consumption, as housing market spillovers are suggested to be largely concentrated on consumption ([Iacoviello and Neri, 2010](#), see also channel 2 and 3 above). A prominent example is [Mian et al. \(2013\)](#), who show that an increase of housing wealth implies markedly different consumption responses depending on households' initial net wealth. [Berger et al. \(2017\)](#) develop a quantitative model that stresses the importance of individual households' borrowing constraints in explaining the large reaction of aggregate consumption.

A proper understanding of the joint dynamics of the real economy, the financial sector and households' balance sheets is thus crucial in forming more preemptive policy measures, be it fiscal or monetary. Given the many variables involved, a comprehensive empirical analysis requires an econometric framework that is able to sufficiently model such rich joint dynamics. This article reexamines the empirical evidence concerning housing demand shocks and its propagation mechanisms in a dynamic environment consisting of a broad range of macroeconomic and financial series. To show robustness of the results, we use a smaller dataset consisting of 73 variables and a larger one with 160 series. Both datasets comprise various balance sheet components for households belonging to four different wealth percentile groups. We estimate dynamic factor models (DFMs), which allow to extract a few latent common factors from a

large panel of economic series, thus capturing the underlying information without running into degrees of freedom problems. This is especially important in the case considered here, as the impact of a housing shock on household balance sheet components is less likely to be homogeneous across wealth groups. The dynamic effects of a housing demand shock are then obtained by imposing a set of theoretically motivated sign restrictions on the contemporaneous response of a few selected economic indicators and a large number of housing variables.

The paper's main contributions to the literature are the following. First, the identification of the housing demand shock is arguably sharper than in the existing literature. The vast majority of studies impose potentially strong identifying assumptions by employing a temporal ordering to the impact matrix while using quarterly data (Jarocinski and Smets, 2008, Cardarelli et al., 2009, Bagliano and Morana, 2012, Cesa-Bianchi, 2013, Buch et al., 2014). Based on the transmission channels described above, however, it seems likely that all economic indicators react within one quarter when the housing market is disrupted. While Furlanetto et al. (2019) identify a housing shock using only sign restrictions, it is not possible to analyze the effects on the housing market due to the use of a six-variable vector autoregression (VAR). Our identification scheme relaxes the possibly contaminated zero restrictions, while the model environment allows to restrict and analyze the response of a broad set of housing series. Second, for four different wealth percentile groups, we assess the reactions of balance sheet components when faced with a housing demand shock. This allows to analyze not only if the dynamic consumption and credit response differs with respect to the initial level of net wealth, but also whether the distribution of net wealth gains is uniformly distributed across wealth segments. A historical decomposition enables to crosscheck the popular narrative that negative housing demand shocks have caused poorer households to cut consumption sharply during the Great Recession, while households at the top of the wealth distribution were unaffected. Finally, we compute the elasticity of consumption with respect to house prices for each wealth group and compare it to the literature on wealth effects. To the best of our knowledge, this is the first study to analyze these effects in a widely data-driven and dynamic environment. It is thus highly complementary to the empirical literature on the heterogeneous effects of housing shocks using microdata (Bostic et al., 2009, Mian and Sufi, 2011, Mian et al., 2013, Aladangady, 2017), which often relies on cross-regional regressions to obtain partial equilibrium estimates of the consumption or credit response. While we are concerned with the general equilibrium effects of a housing demand shock, our DFM imposes little structure a priori in contrast to studies on the wealth effect of housing using DSGE models (for example, Berger et al., 2017, Guren et al., 2020b).

Our results show that an unexpected positive housing demand shock causes a large and persistent boom of real economic activity and a brightening of labor market conditions, despite an immediate increase of interest rates. The expansion of credit and consumption aggregates along with house prices suggests that both the credit mechanism and the wealth effect are important transmission channels of housing shocks. The strong positive response of all unrestricted housing start series and residential investment provide some comfort to the identifying assumptions. The second part of our analysis provides evidence that housing demand shocks

are key to understand household balance sheet dynamics across the wealth distribution. In particular, impulse responses suggest that the reaction of durable consumption is a decreasing function of net wealth. Variance decompositions assign a bulk of the variation found in consumption to the housing shock, especially for the bottom 50% of households. The historical decomposition shows that the cumulative effects of housing demand shocks have significantly affected consumption of the poorest during the Great Recession. However, we also find evidence that part of the cutback in top 1% consumption is explained by housing demand shocks in that period. Elasticities of consumption with respect to house prices, which are a byproduct of our structural model, suggest a larger spending sensitivity for weaker balance sheet households. Our results are highly robust across both datasets.

The rest of the paper is organized as follows. Section 2 discusses the econometric framework and structural identification of the housing demand shock. The data are outlined in Section 3. Impulse response functions and variance decompositions are analyzed in Section 4. Section 5 concludes. The Appendix provides additional results with alternative model specifications and gives a detailed overview of the data.

2 Econometric Framework

Structural macroeconomic shocks are often identified using small-scale VAR models in order to conserve degrees of freedom. The inclusion of only a couple of series, however, is likely to cause omitted variable problems that may affect impulse responses and variance decompositions alike (see [Bernanke et al., 2005](#) for a thorough discussion). Moreover, economic concepts such as "real activity" are hard to capture using only a specific data series. This issue is especially pronounced in the case considered here. Using only one or two housing series to identify a housing shock introduces an arguably large degree of arbitrariness. Finally, VARs allow to compute impulse responses only for the included variables, which is often a subset of what the researcher or policy-maker is interested about.

To take advantage of the information contained in large panel datasets we employ a dynamic factor model (see [Stock and Watson, 2016](#) for an overview). Intuitively, the DFM approach boils down to extracting a small number of latent common factors that summarize the information from a much richer dataset. Consider the following dynamic factor model

$$y_t = \sum_{l=0}^s \lambda_l f_{t-l} + e_t \quad \text{with } e_t \sim iid.N(0, R) \quad (1a)$$

$$f_t = \sum_{p=1}^h \phi_p f_{t-p} + \epsilon_t \quad \text{with } \epsilon_t \sim iid.N(0, Q) \quad (1b)$$

where y_t is a $(k \times 1)$ vector of observed variables and f_t is a $(m \times 1)$ vector of latent factors. The number of factors is typically much smaller than the length of the cross-section, $m \ll k$. The idiosyncratic disturbances e_t are uncorrelated at all leads and lags with f_t and ϵ_t and are assumed to have a diagonal covariance matrix R . The $(k \times m)$ loading matrices λ_l relate the factors to all economic and financial indicators. Note that if $s > 0$ then the factor lags are

allowed to directly affect the series in y_t . Finally, ϕ_p are coefficient matrices, each of dimension $(m \times m)$, governing the dynamics in the state equation (1b). Clearly, the state equation follows the common VAR structure. The factor model can also be expressed in static form (see [Stock and Watson, 2016](#)) if we let $h \geq s + 1$, $F_t = (f'_t, \dots, f'_{t-h+1})'$ and $\Lambda^* = (\lambda_0, \dots, \lambda_s)$:

$$y_t = \Lambda F_t + e_t \quad (2a)$$

$$F_t = \Phi F_{t-1} + u_t \quad (2b)$$

where $\Lambda = \begin{pmatrix} \Lambda^* & 0_{k \times m(h-s-1)} \end{pmatrix}$, $\Phi = \begin{pmatrix} \phi_1 & \cdots & \phi_h \\ I_{m(h-1)} & & 0_{m(h-1) \times m} \end{pmatrix}$ and $u_t = \begin{pmatrix} \epsilon_t \\ 0_{m(h-1) \times 1} \end{pmatrix}$.

Note that in contrast to studies using factor-augmented VAR (FAVAR) models, we do not impose that any factor be observed (for example, [Bernanke et al. \(2005\)](#) impose a short-term interest rate as observed factor and use this assumption for identification of the structural shock). For our purposes, it is also not necessary to provide an economic interpretation to the latent factors as in [Belviso and Milani \(2006\)](#).

2.1 Estimation

We rely on now standard Bayesian methods to estimate the model in (2a-2b). The likelihood-based approach is able to explicitly exploit the structure of the state equation in the estimation of the factors (see [Bernanke et al., 2005](#)). As a byproduct, it also delivers full posterior distributions naturally quantifying the extent of uncertainty. The estimation procedure consists of a multimove Gibbs sampler ([Carter and Kohn, 1994](#), see [Kim and Nelson, 1999](#) for an overview) in which the parameters are sampled conditional on the most recent draws of the factors, and the factors are drawn conditional on the most recent parameter estimates. Following [Bai and Wang \(2015\)](#), we employ the Jeffreys prior to account for the lack of a priori information about the model parameters. The Bayesian framework considered here is thus able to perform estimation and inference of large dynamic factor models with a dynamic structure in both the observation and the state equation.

It is well known that due to indeterminacy the factor model is not identified without further restrictions (see [Stock and Watson, 2016](#)). The unobserved factors can always be rotated into an observationally equivalent representation. To achieve identification, we rely on the minimal restriction conditions derived in [Bai and Wang \(2015\)](#). More exactly, we assume that the upper $(m \times m)$ block of λ_0 is an identity matrix. Since the identifying restrictions concern only the contemporary loadings, the VAR(h) dynamics of the factors are left completely unrestricted. In other words, it is not necessary to impose the conventional practice that the covariance matrix of the dynamic factors f_t is an identity matrix. A disturbance arising from the state equation is thus able to affect all macroeconomic and financial indicators in y_t with no lags. The use of this minimal restriction strategy allows to impose contemporaneous sign restrictions on any series to identify our structural housing demand shock.

2.2 Structural Identification

We assume that the reduced-form vector of state-equation shocks ϵ_t is a linear combination of structural shocks w_t , such that $\epsilon_t = A_0 w_t$. Under the assumption that $\mathbb{E}[w_t w_t'] = I_m$, we can decompose the covariance matrix $Q = \mathbb{E}[\epsilon_t \epsilon_t'] = \mathbb{E}[A_0 w_t w_t' A_0'] = A_0 A_0'$. One popular approach to fully identify the system is to choose A_0 to be the Cholesky factor of the VAR covariance matrix as in [Sims \(1980\)](#). It is well known that the triangular nature of the Cholesky factor implicitly imposes a temporal ordering (see, for example, the discussion in [Canova and De Nicolo, 2002](#)). In the context of housing shocks, this identification scheme has been followed by [Cesa-Bianchi \(2013\)](#) and [Bagliano and Morana \(2012\)](#). In contrast, [Buch et al. \(2014\)](#), [Cardarelli et al. \(2009\)](#) and [Jarocinski and Smets \(2008\)](#) impose a mixture of sign and zero restrictions, assuming that output or prices react to housing shocks only with a lag. Given the many channels through which the housing market may affect the economy, such zero restrictions are arguably imposing strong identifying assumptions. For that reason, we adopt the agnostic identification strategy by [Uhlig \(2005\)](#) and, for the factor model framework, [Ahmadi and Uhlig \(2015\)](#), and only restrict the sign of selected variables.

All sign restrictions are theoretically motivated and are keeping with a large literature summarized in [Justiniano et al. \(2015\)](#), [Christiano et al. \(2014\)](#) and [Furlanetto et al. \(2019\)](#). More specifically, we identify the housing demand shock by imposing that real GDP, core prices of personal consumption expenditures (PCE) and the three month treasury bill rate react positively upon impact. This rules out that the identified shock is contaminated with supply or monetary shocks. It is, however, more challenging to disentangle the housing demand shock from investment shocks (see [Justiniano et al., 2010](#)) and other demand shocks (for example discount factor or fiscal shocks). Our strategy follows [Furlanetto et al. \(2019\)](#), who suggest that traditional demand shocks can be excluded by imposing a positive sign restriction on the response of the ratio of (real gross private domestic) investment over output.¹ Investment and housing shocks are thus assumed to create investment booms. To further separate housing from investment shocks we restrict stock prices as measured by the S&P 500 to react positively.² Note that up to now, it is still not possible to distinguish a positive housing shock from a shock originating in the credit markets. Keeping with [Furlanetto et al. \(2019\)](#) and the literature in [Justiniano et al. \(2015\)](#), we restrict the loan-to-value (LTV) ratio to react negatively. This allows total credit to increase under the restriction that the value of real estate does so by more.³ Finally, a positive housing demand shock increases real estate loans as well as quantity and prices of housing ([Iacoviello and Neri, 2010](#)). We therefore use our detailed dataset to impose positive sign restrictions on aggregate real estate loans as well as on building permits and house prices in all four Census regions⁴. Since a shock is unexpected by nature, it is arguably more appropriate to constrain permits instead of housing starts, which are left unrestricted. In contrast to small-scale VAR studies also using sign restrictions ([André et al., 2012](#), [Furlanetto](#)

¹Restricting the ratio allows investment to increase when faced with a demand shock but less so than the remaining part of aggregate demand.

²A positive investment shock increases the supply of capital and lowers its price. Since the price of capital is taken as a proxy of the stock market value for firms, an investment shock negatively impacts the value of equity (see the discussion in [Furlanetto et al., 2019](#) and [Christiano et al., 2014](#)).

³More exactly, total credit amounts to total loans to the non-financial private sector, while housing value is given by real estate at market value of households and non-profit organisations.

⁴The US Census Bureau splits the U.S. into four regions: the Northeast, the Midwest, the South, and the West.

et al., 2019), our factor model allows testing whether the identified housing shock actually leads to new housing units being built.

To incorporate the sign restrictions we employ the procedure described in Rubio-Ramirez et al. (2010). For each draw from the reduced-form posterior, the algorithm works as follows. First, we produce A_0^{chol} using the Cholesky decomposition of the covariance matrix Q to obtain uncorrelated shocks as in a recursively identified model. Then we compute the QR decomposition of $W = QR$, where W is a $(m \times m)$ matrix filled with independent standard normally distributed variables. Post-multiplying A_0^{chol} by Q forms a candidate structural impact matrix $A_0^{cand} = A_0^{chol}Q$. Contemporaneous impulse responses are then generated according to $y_0^{irf} = \Lambda^* A_0^{cand}$, which allows to check the sign restrictions. If this is not the case we draw a new W and repeat the procedure until the sign restrictions are satisfied. Note that we follow the recommendations of Canova and Paustian (2011) in two ways. First, we restrict only impact responses to avoid the often questionable dynamic constraints. Second, the factor model framework allows us to impose a large number of sign restrictions to identify the structural shock. Moreover, all sign restrictions are motivated by the dynamic stochastic general equilibrium (DSGE) literature as advised by Musso et al. (2011).

3 Data

We estimate the dynamic factor model on two quarterly datasets, one containing 73 and the other 160 indicators. As suggested by Bai and Ng (2008a) and Boivin and Ng (2006), a larger cross-section may not necessarily improve estimation accuracy in factor models. It thus seems appropriate to use both a relatively small dataset consisting of only key series and a large one to check the robustness of the results. The sample starts in 1989Q3 and ends in 2019Q3. All indicators are transformed to induce stationarity, see the Appendix for a detailed description. The large dataset is an augmented version of the FRED-QD database (see McCracken and Ng, 2020) with the main difference that household balance sheet data has been added. The smaller dataset builds on the same database but focuses on key economic indicators, the housing and credit market and household balance sheet data.

To evaluate whether a housing demand shock has heterogeneous effects on households' balance sheets we draw on the Distributional Financial Accounts (DFAs) provided by the Board of Governors (see Batty et al., 2019). The relatively new DFAs contain detailed time series on the assets and liabilities held by four different wealth percentile groups (bottom 50%, 50th to 90th percentiles, 90th to 99th percentiles, and the top 1%). Figure 1 shows the evolution of real net wealth for all wealth percentile groups. The greatest wealth losses are found between 2007Q3 and 2009Q1 and are especially concentrated on households belonging to the top decile. The subsequent recovery is associated with an unprecedented wealth level, however unequally distributed among the population. While net worth of the bottom 50% is close to zero for the entire sample, the top 1% accounts for a substantial fraction of U.S. wealth. In 2019Q3, around 70% of wealth is held by the top decile. The heterogeneous evolution among wealth groups is clearly related to individual composition effects. Wealthier households have traditionally been

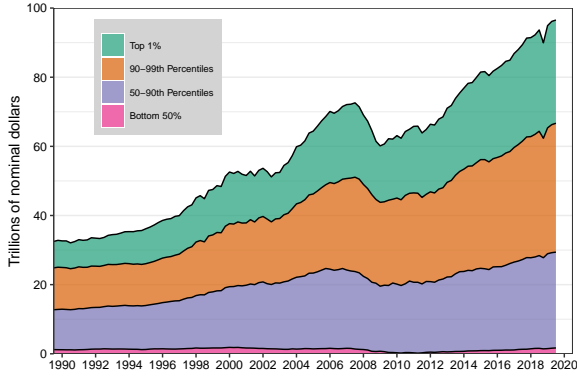


Figure 1: Evolution of Net Worth

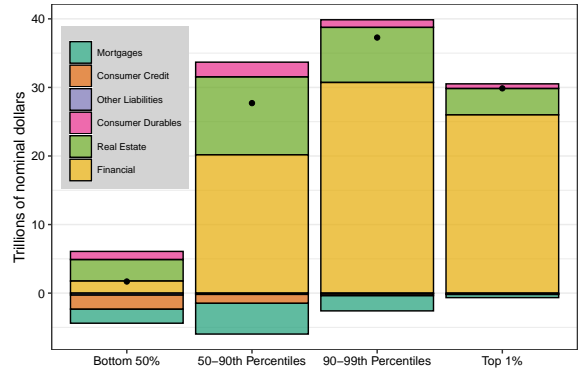


Figure 2: Balance Sheet Composition 2019Q3

exposed more to cyclical assets like equity, as the largest fraction of wealth is of financial nature (see Figure 2 for 2019Q3). Real estate is the principal asset component for households belonging to the bottom 50%. In contrast to other percentile groups, financial assets account for only a minor share of total assets. The liability side shows the poorest households' dependence on consumer credit, as they hold over half of total consumer credit.

In order to ensure that results are not driven by population differences from the different-sized wealth groups, we scale the series of each group by the respective number of percentiles.⁵ Moreover, all series enter the estimation procedure in standardized form.

4 Results

In this section, we present empirical results from our dynamic factor model with both datasets. To determine the number of unobserved factors, m , we compute the information criteria IC_{p2} and BIC_3 by Bai and Ng (2002) (see also the discussion in Bai and Ng, 2008b), the ER and GR criteria by Ahn and Horenstein (2013) and the $IC_{1,c,n}^{T*}$ and $IC_{2,c,n}^{T*}$ criteria by Alessi et al. (2010). For the smaller dataset, all criteria suggest five factors except for $ER = 2$ and $IC_{p2} = 8$. The same two criteria are estimated to be $ER = 2$ and $IC_{p2} = 6$ with the rich dataset, while all other suggest four factors. We follow the majority and set $m = 5$ for the narrow and $m = 4$ for the more extensive database, but report results for a range of alternative specifications in the Appendix. We set $s = 1$ in observation equation (1a), thus allowing a dynamic relationship between the latent states and the variables. According to the Bayesian information criterion (BIC), the factor dynamics in (1b) are characterized by a VAR(1) for the smaller and a VAR(2) for the larger dataset. We follow Uhlig (2005) and report the pointwise median together with 68% posterior bands. The y_t vector has been ordered such that the first m series are given by leading indicators of different data groups.⁶ All results are based on 90'000 draws from the Gibbs sampler, from which the first 87'000 are discarded as burn-in.

The presentation of our empirical results is organized around our two research questions. We

⁵For example, credit held by the bottom 50% is divided by 50.

⁶More specifically, the first five series consist of real GDP, the industrial production index, the total number of nonfarm employees, total housing starts, and the S&P 500. See the Appendix for a detailed list of the groups and series. Random permutations of the observation vector had negligible effects on our results.

begin with the question of how the housing demand shock is transmitted to the aggregate US economy before analyzing the responses of households' balance sheets.

4.1 How Are Housing Demand Shocks Transmitted to the Aggregate Economy?

4.1.1 Impulse Responses

Figure 3 plots the impulse responses, estimated on the smaller sample, of the level of key indicators to a one standard deviation housing demand shock. The black line reports the median response. Results from the large dataset are vastly similar and therefore relegated to the Appendix (see figure 8).

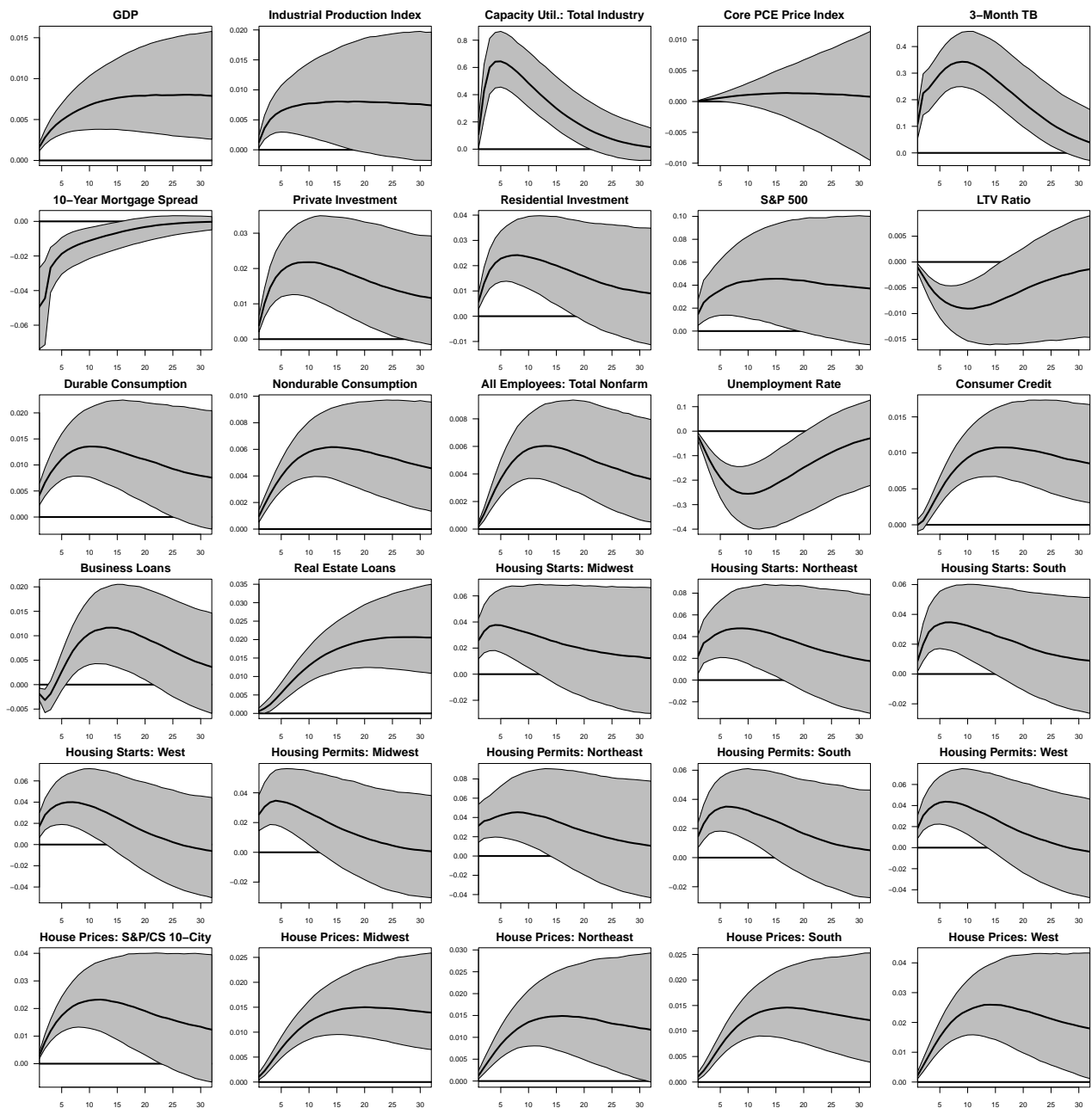


Figure 3: Dynamic responses of variables to housing demand shock using the small dataset

Notes: The figure plots the impulse responses of the level of key variables to the identified housing demand shock. The gray areas indicate the 68% posterior probability regions. The straight black line indicates the posterior median at each horizon.

In line with the transmission channels discussed above, a housing demand shock generates a significant and persistent economic boom. Real GDP, industrial production, and capacity utilization increase between 0.5 and 0.6% within one year. Residential investment, a subcomponent of GDP measuring the purchase of newly built residential structures, rises disproportionately by 2% after four quarters. The economic expansion is reflected in the labour market indicators, as the unemployment rate decreases while the total number of nonfarm employees grows. On the credit side, real estate loans and consumer credit increase persistently over the impulse horizon, which conforms to the collateral channel of a housing demand shock. The fact that business loans grow only slightly and return to their initial level stands in contrast to studies identifying credit shocks (for example, [Boivin et al., 2018](#)), thus pointing towards a successful disentanglement of credit and housing shocks. The LTV ratio is restricted to be negative on impact but stays so for at least four years. Conforming to consumption smoothing arguments from life-cycle models, both durable and nondurable consumption rise. Importantly, the response of durable consumption is more pronounced in magnitude than for nondurable consumption. Financial variables mirror the boom of real economic indicators. The 3-month treasury bill rate is hump-shaped, suggesting that the Fed increases its benchmark rate as a reaction to the initial rise of GDP growth and the capacity utilization index. The median response of the S&P 500 stock market index increases by around 4% over the horizon. Interestingly, the reaction of the consumption price index is relatively muted despite the economic expansion, confirming the empirical results in [Furlanetto et al. \(2019\)](#). More exactly, the core PCE price index is slightly positive for only a few quarters, after which the posterior distribution centers around the zero line. In contrast, house price indices of all four Census regions react strongly positive to the housing demand shock over the entire horizon. The S&P/Case-Shiller 10-City home price index, which was left unrestricted also on impact, confirms the price hike. In line with Tobin’s q effect, rising prices for housing are associated with a general increase of building permits for at least three years. The fact that the unrestricted housing starts rise in all four geographic areas provides further comfort to our identifying assumptions.

All impulse responses discussed are robust to the choice of the dataset, even though the model specification differs and the extensive dataset contains more than twice as much variables as the smaller one.⁷ Among these additional series are sectoral employment indicators, which provide further evidence that a housing shock has in fact been identified. Figure 9 in the Appendix plots the respective impulse responses and shows that the construction sector features the most pronounced reaction among all sectors.

4.1.2 Variance Decompositions

Table 1 shows the importance of housing demand shocks in explaining economic fluctuations during our 1989-2019 sample. While variance decompositions are calculated for each draw that satisfies the sign restrictions, the table presents median values at a 32-quarter horizon. The second column reports the fraction of the common component of the series explained by the housing demand shock. The third column shows the contribution of the common component to the overall variance of the indicators. The fourth column is simply the product of the previous

⁷Further robustness tests are reported in Appendix figures 11 and 12, covering a wide range of alternative model specifications.

two and represents the fraction of the total variability explained by the housing demand shock. The next three columns show the results for the large dataset.

In line with the literature, our variance decompositions show that housing demand shocks are significant drivers of business cycle fluctuations. The housing shock explains between 24 and 44% of the variance of the common component of real economic indicators such as GDP, the industrial production index and the capacity utilization measure. Labor market indicators, credit series and the 3-month TB rate are also well explained. Importantly, the housing demand shock has high explanatory power for housing starts, housing permits and house price variation for all four Census regions. Column four and seven indicate that our structural model explains around 20% of total variation in house price series. Column three and six of Table 1 show that five and four unobserved factors are able to capture a large fraction of fluctuations in key economic indicators.

Table 1: Variance Decompositions and R^2

Series	Small Dataset			Large Dataset		
	VD	R^2	Total	VD	R^2	Total
GDP	0.33	0.66	0.22	0.43	0.68	0.29
Industrial Production Index	0.13	0.74	0.10	0.33	0.82	0.27
Capacity Util.: Total Industry	0.36	0.93	0.33	0.44	0.91	0.40
Core PCE Price Index	0.09	0.19	0.02	0.11	0.27	0.03
3-Month TB	0.47	0.97	0.45	0.56	0.94	0.53
10-Year Mortgage Spread	0.22	0.53	0.11	0.26	0.52	0.14
Private Investment	0.18	0.64	0.11	0.26	0.64	0.17
Residential Investment	0.18	0.75	0.13	0.36	0.63	0.22
S&P 500	0.16	0.72	0.12	0.25	0.45	0.11
LTV Ratio	0.17	0.70	0.12	0.27	0.61	0.17
Durable Consumption	0.20	0.46	0.09	0.37	0.46	0.17
Nondurable Consumption	0.30	0.42	0.12	0.41	0.47	0.19
All Employees: Total Nonfarm	0.23	0.94	0.22	0.26	0.93	0.25
Unemployment Rate	0.20	0.82	0.16	-	-	-
Unemployment Rate: Women	-	-	-	0.30	0.70	0.21
Consumer Credit	0.27	0.41	0.11	0.42	0.37	0.16
Business Loans	0.14	0.62	0.09	0.23	0.53	0.12
Real Estate Loans	0.23	0.52	0.12	0.39	0.41	0.16
Housing Starts: Midwest	0.17	0.32	0.05	0.29	0.22	0.06
Housing Starts: Northeast	0.10	0.46	0.05	0.21	0.35	0.07
Housing Starts: South	0.13	0.50	0.07	0.31	0.43	0.13
Housing Starts: West	0.16	0.46	0.07	0.35	0.34	0.12
Housing Permits: Midwest	0.16	0.70	0.11	0.35	0.50	0.17
Housing Permits: Northeast	0.13	0.40	0.05	0.26	0.27	0.07
Housing Permits: South	0.14	0.74	0.10	0.33	0.54	0.18
Housing Permits: West	0.17	0.52	0.09	0.34	0.39	0.13
House Prices: S&P/CS 10-City	0.23	0.81	0.19	0.36	0.74	0.27
House Prices: Midwest	0.29	0.67	0.20	0.43	0.60	0.26
House Prices: Northeast	0.18	0.75	0.13	0.28	0.66	0.19
House Prices: South	0.26	0.77	0.20	0.38	0.65	0.25
House Prices: West	0.26	0.85	0.22	0.37	0.71	0.26

Notes: The second column reports the fraction of the common component of the series explained by the housing demand shock at a 32-quarter horizon. The third column shows the contribution of the common component to the overall variance of the indicators. The fourth column is simply the product of the previous two and represents the fraction of the total variability explained by the housing demand shock. The next three columns show the results for the large dataset.

4.2 Do Households Respond Differently to the Housing Demand Shock Depending on Net Wealth?

The substantial aggregate effects of a housing demand shock demonstrate the importance of understanding the underlying transmission channels. Of particular interest after the financial crisis has been the relationship between fluctuations in housing wealth and the response of consumption. In fact, housing market spillovers are suggested to be largely concentrated on consumption ([Iacoviello and Neri, 2010](#)). As outlined above, an increase of housing wealth may a) raise collateral and therefore mitigate credit constraints and b) increase consumption due to the wealth effect. Both channels are arguably sensitive to the cross-sectional distribution of wealth and the composition of households' balance sheets. For example, richer households are less likely to face credit constraints and may give the precautionary savings motive a small role. This translates into a smaller elasticity to consume out of wealth compared to the poor. As a consequence, the aggregate consequences of a housing shock might largely be driven by the consumption response of poorer households, although housing is a substantial balance sheet component for all wealth percentile groups.

Given the economic importance, an extensive number of studies have analyzed whether and to what extent (housing) wealth shocks cause heterogeneous responses among households. The hypothesis of a representative agent is typically rejected and economically significant wealth effects are reported (see, for example, [Mian and Sufi, 2011](#), [Mian et al., 2013](#), [Guren et al., 2020b](#), [Aladangady, 2017](#), [Berger et al., 2017](#)). To isolate the housing wealth effect, empirical studies frequently rely on cross-regional regressions using exogenous sources of housing variation as instruments. This strategy delivers partial equilibrium estimates, as aggregate general equilibrium effects are absorbed by the constant or the time fixed effect in a panel regression.⁸ In contrast and highly complementary to this strand of literature, we are interested in the general equilibrium effects of housing shocks. Looking again at the consumption response of different wealth percentile groups, it is interesting to see whether the implications of partial equilibrium estimates still hold. For example, it is well possible that the financial wealth effect associated with booming stock markets ignites consumption of the rich, thus leveling the cross-sectional consumption response. To understand the aggregate general equilibrium dynamics in the last section we thus analyze the general equilibrium behavior of households' balance sheets. In contrast to studies using DSGE models ([Berger et al., 2017](#), [Guren et al., 2020b](#), among others), our DFM imposes little structure a priori, thus mitigating the possibility that results are driven by a potentially misspecified model structure. Clearly, this comes at the cost of not being able to obtain "deep" structural parameters, for example the wealth effect of housing values conditional on household characteristics. It is also important to note a drawback concerning the disaggregated consumption measures used in this study. The use of household balance sheet data implies that nondurable consumption is not available, so that only the reaction of durable consumption can be estimated. However, comparing both aggregate consumption responses in the last section shows a relatively muted reaction for nondurable consumption in terms of magnitude. Durable consumption and (residential) investment are the primary forces driv-

⁸As [Guren et al. \(2020a\)](#) point out, the clear theoretical interpretation of cross-regional partial equilibrium estimates might be contaminated by local general equilibrium effects. They suggest to divide cross-regional estimates by an estimate of the local fiscal multiplier to adjust for local general equilibrium effects.

ing the pronounced GDP response. The literature also suggests that increased spending due to housing wealth is largely concentrated on durable goods (Mian et al., 2013, Andersen and Leth-Petersen, 2019).

4.2.1 Impulse Responses

Estimated on the small sample, figure 4 plots impulse responses of the level of real household balance sheet components to the housing demand shock. The first five columns show assets and liabilities, while the last column plots the response of total net wealth. Rows list the four wealth percentile groups. Results from the large dataset are almost identical,⁹ see Appendix figure 10. Note that responses are highly data-driven, as all balance sheet series are left completely unrestricted.

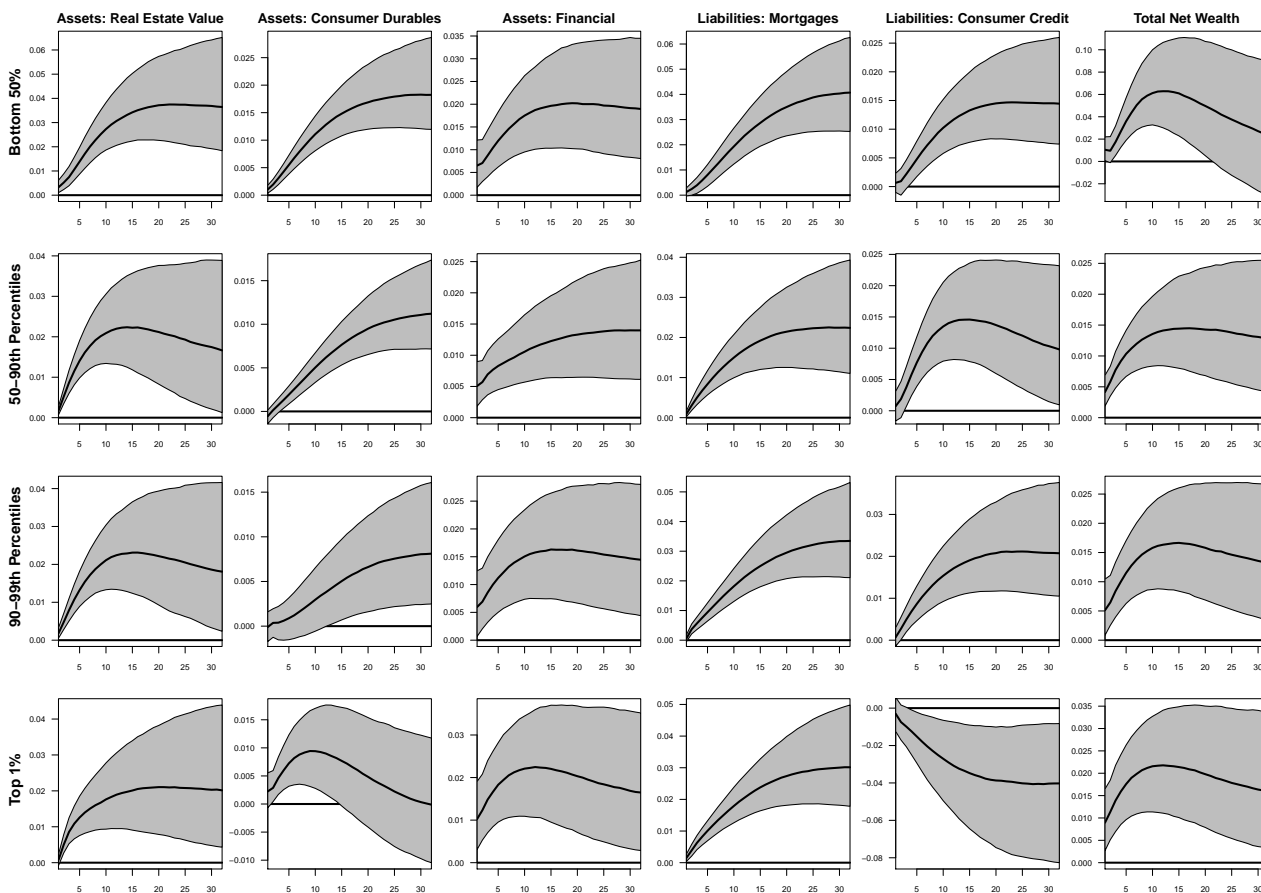


Figure 4: Dynamic responses of household balance sheet variables to housing demand shock using the small dataset

Notes: The figure plots the impulse responses of the level of households' balance sheet components to the identified housing demand shock. The gray areas indicate the 68% posterior probability regions. The straight black line indicates the posterior median at each horizon.

A quick glance is enough to observe that a housing demand shock is associated with a general expansion of balance sheets across all wealth segments. The increase of assets generally dominates the higher debt burden, although net wealth for households belonging to the bottom 50% slowly revert to the initial state. All groups participate in the newly built structures,

⁹Most impulse responses are slightly more pronounced with the large dataset. Appendix figures 13 and 14 confirm the benchmark results for a wide range of alternative model specifications.

as the real estate value held by each segment rises somewhat more than house price indices in the last section. However, the median response is most pronounced for households in the bottom 50% with a final growth of around 3.5%. In line with the stock market boom, financial assets held by all wealth segments increase. For both groups in the top decile, the response of financial assets clearly drives total net wealth dynamics (in 2019Q3, 85% and 77% of total assets are of financial nature for the top 1% and the 90-99th percentile group, respectively). On the credit side, we would expect a stronger tendency to borrow among poorer households, as net wealth is likely to proxy for credit constraints. In fact, [Mian and Sufi \(2011\)](#) provide evidence that only households at the top of the credit score distribution do not increase total debt leverage when faced with a housing wealth shock. Our impulse responses imply a significant and persistent expansion of mortgages across the wealth spectrum. Heterogeneity is not especially accentuated, although median mortgage expansion is largest for the bottom 50%. Comparing the evolution of mortgages and credit, we find equity extracted from housing to be more pronounced than non-housing related consumer credit for all groups (note that home equity lines of credit are also included in the mortgage category). Our findings support the evidence that home equity-based borrowing is not used to pay down expensive consumer credit balances ([Mian and Sufi, 2011](#)), as only the top 1% chooses to deleverage.

The real consequences of even a broad credit growth, however, ultimately depend on how households use their new liquidity. If most households just keep new money on the bank account, we would arguably observe little change in real outcomes. Apart from residential construction, the reaction of consumption is key to understand the strong linkage of housing shocks and business cycle fluctuations. The obtained impulse responses for durable consumption suggest that household balance sheet strength plays an important role in determining aggregate demand. The estimated long-term increase for the bottom 50% of households centers around 1.75%, while the effect on the next 40% is in the range of 1%. Households in the 90th to 99th percentiles increase durable consumer spending by about 0.75%, although the posterior mass concentrates above the zero line only 3 years after the shock. For the richest percentile of households, the housing demand shock first raises durable consumption before reverting back to the initial value. Conditional on the stock market boom and the remarkable holdings of financial assets of the top 1%, the muted reaction of consumption suggests a small role for financial wealth in determining consumption fluctuations. This conforms to the literature estimating financial wealth effects, which are reported to be substantially smaller than housing wealth effects ([Carroll et al., 2011](#), [Bostic et al., 2009](#), [Slacalek, 2009](#), [Muellbauer, 2008](#)). In summary, the response of aggregate durable consumption to a housing demand shock is estimated to be a decreasing function of net wealth. The evidence provided by the literature that spending of the rich does not react much to a housing wealth shock thus carries over to the factor general equilibrium case. However, given the notable net wealth of 50th to 90th wealth percentile households, one may wonder why the respective response of durable consumption is pronounced in the first place. Following [Kaplan et al. \(2014\)](#), a possible explanation is that a fraction of households belonging to this wealth segment are "wealthy hand-to-mouth". Despite owning sizable amounts of assets, these households hold balance sheets that carry little liquid wealth. As a result, they are more

susceptible to wealth shocks than non hand-to-mouth households.¹⁰

4.2.2 Variance Decompositions

Table 2 shows the importance of the housing demand shock in explaining the variance of balance sheet components for each wealth group.

Table 2: Variance Decompositions and R^2 for Balance Sheet Components

Series	Small Dataset			Large Dataset		
	VD	R ²	Total	VD	R ²	Total
Bottom 50%						
Total Net Wealth	0.19	0.29	0.06	0.24	0.30	0.07
<i>Assets</i>						
Real Estate Value	0.25	0.47	0.12	0.41	0.36	0.15
Consumer Durables	0.41	0.52	0.21	0.56	0.45	0.25
Financial	0.15	0.76	0.11	0.30	0.26	0.08
<i>Liabilities</i>						
Mortgages	0.31	0.50	0.15	0.53	0.43	0.22
Consumer Credit	0.23	0.30	0.07	0.39	0.22	0.08
50-90th Percentiles						
Total Net Wealth	0.23	0.52	0.12	0.42	0.33	0.14
<i>Assets</i>						
Real Estate Value	0.27	0.67	0.18	0.39	0.65	0.26
Consumer Durables	0.34	0.62	0.21	0.54	0.50	0.27
Financial	0.17	0.49	0.08	0.39	0.20	0.08
<i>Liabilities</i>						
Mortgages	0.29	0.64	0.19	0.45	0.65	0.29
Consumer Credit	0.22	0.33	0.07	0.39	0.265	0.10
90-99th Percentiles						
Total Net Wealth	0.14	0.91	0.13	0.41	0.29	0.12
<i>Assets</i>						
Real Estate Value	0.24	0.77	0.19	0.37	0.67	0.24
Consumer Durables	0.13	0.23	0.03	0.28	0.18	0.05
Financial	0.11	0.92	0.10	0.35	0.24	0.08
<i>Liabilities</i>						
Mortgages	0.38	0.49	0.19	0.59	0.40	0.24
Consumer Credit	0.27	0.26	0.07	0.46	0.21	0.10
Top 1%						
Total Net Wealth	0.15	0.92	0.14	0.35	0.36	0.12
<i>Assets</i>						
Real Estate Value	0.20	0.43	0.09	0.33	0.39	0.13
Consumer Durables	0.15	0.28	0.04	0.29	0.18	0.05
Financial	0.14	0.91	0.13	0.33	0.32	0.11
<i>Liabilities</i>						
Mortgages	0.37	0.59	0.22	0.59	0.55	0.33
Consumer Credit	0.13	0.20	0.03	0.22	0.13	0.03

Notes: The second column reports the fraction of the common component of the series explained by the housing demand shock at a 32-quarter horizon. The third column shows the contribution of the common component to the overall variance of the indicators. The fourth column is simply the product of the previous two and represents the fraction of the total variability explained by the housing demand shock. The next three columns show the results for the large dataset.

Irrespective of the dataset, the housing shock is a significant driver of the common component

¹⁰Households in the 50th to 90th wealth percentiles held 64% of total assets in either real estate or pension funds in 2019Q3, which is the highest share among all groups (Batty et al., 2019).

of all balance sheet indicators. The variance explained of total net wealth is sizeable, depending on wealth group and dataset between 21 and 42%. The housing demand shock not only has high explanatory power for fluctuations of real estate and mortgage components, i.e. two indicators intimately related to a housing shock, but also for the variation in financial assets. The variance decompositions for consumer durables confirms the heterogeneous pattern found in our graphical analysis. For the bottom 50% of households, the housing shock explains 44% (56%) of the common component of durable consumption using the small (large) dataset. Also for the poorest group, column four and seven show that the structural model explains between 20 and 25% of total variation in durable consumption. Although still considerable, the shock only explains about 20% (29%) of the common component and about 5% of total consumption variation for the richest percentile. Our variance decomposition thus confirms that housing shocks are a vital component to model balance sheet dynamics in general and consumption dynamics of poorer households in particular. Table 2 also shows that common disturbances are overall able to capture a large fraction of fluctuations in balance sheet series.

4.2.3 Historical Decompositions

It is widely believed that the housing market has played a significant role in explaining the outbreak and strength of the Great Recession (Mian and Sufi, 2011, Mian and Sufi, 2014). According to this narrative, negative house price shocks had a large effect on the economy via consumption spending. The aggregate collapse of consumption, so the argument, was mainly driven by poorer households, who cut spending disproportionately sharp as a result of declining housing wealth. In this section, we show historical decompositions to quantify how much the identified housing demand shock explains of the historically observed consumption patterns.

Figure 5 attributes the historical variation in demeaned consumption of each wealth group to housing demand shocks. The shaded area marks the period of the Great Recession. Results from the large dataset are slightly more pronounced and relegated to the Appendix (see figure 15). The bottom 50% of households cut durable consumption sharply during the crisis and stayed below the mean growth rate until 2017. The historical decomposition provides evidence that a large fraction of this contraction can be explained by housing demand shocks, both during and in the aftermath of the Great Recession. Although less pronounced, the cumulative effects of housing shocks also explain part of the cutback in durable consumption by the next 40%. In line with the variance decompositions, our structural model in general does not deliver much explanatory power for the evolution of consumption growth of the richest decile. During the Great Recession, however, the housing demand shock does explain about one percent of the contraction in consumption of the richest percentile. This results may seem contrasting to the findings of Mian and Sufi (2014), which suggest a muted reaction of the richest households' consumption when faced with negative housing wealth shocks. The apparent discrepancy is no contradiction, but just highlights the methodological difference: A housing demand shock is a housing wealth shock, but not exclusively. Consumption of each wealth group is arguably determined by distinct channels, and a housing demand shock impacts on all. A result that carries over from the partial to the general equilibrium setting, however, is that households belonging to the bottom 50% have strongly reduced consumption due to negative housing shocks.

Importantly, these adverse effects have pushed growth below mean rates until only recently.

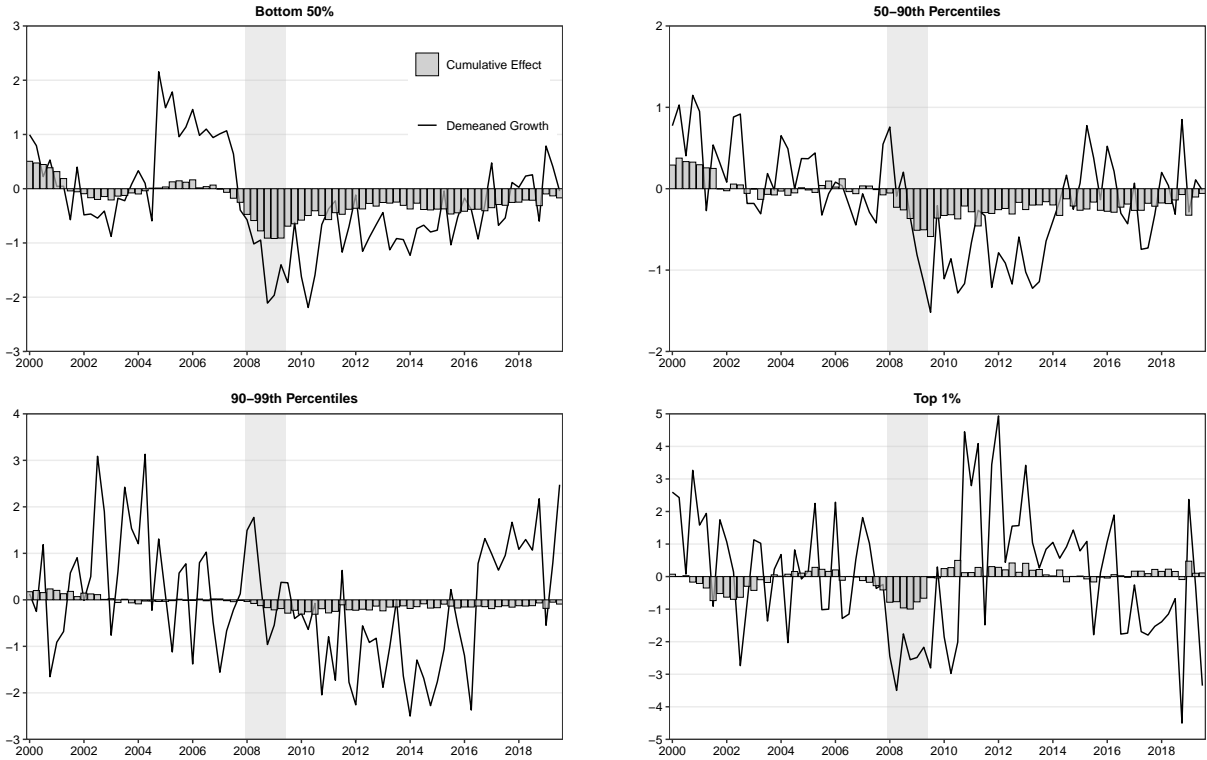


Figure 5: Historical contribution of housing demand shocks to durable consumption using the small dataset
Notes: Estimated on the small dataset, the historical decompositions show the median cumulative effect of housing demand shocks to demeaned growth of durable consumption for each wealth segment. The shaded area marks the period of the Great Recession according to the National Bureau’s (NBER) business cycle dating committee.

4.2.4 Long-term Elasticity of Consumption

The literature on wealth and collateral effects of housing frequently calculates the elasticity of consumption with respect to house price shocks. For example, [Carroll et al. \(2011\)](#) find a medium-term elasticity of 0.21 for total consumption and a one percent increase in house prices,¹¹ while [Mian et al. \(2013\)](#) report estimates between 0.11 and 0.29.¹² Based on their sensitivity instrument, [Guren et al. \(2020b\)](#) arrive at somewhat lower estimates between 0.06 and 0.13. Impulse responses from the estimated DSGE model in [Iacoviello and Neri \(2010\)](#) translate into a first-year elasticity of total per capita consumption of around 0.07. Durable consumption estimates can be found in the online Appendix of [Mian et al. \(2013\)](#) and range from 0.2 to 0.43. Regarding heterogeneity across the wealth distribution, they provide evidence that elasticities of consumption are smaller for richer households. We compare these results to the long-term elasticities implied by our impulse responses for durable consumption and house prices. To obtain one aggregate price index, we take the population-weighted average over the responses of the four (Census region) house price indices for each draw. Figure 6 shows the implied elasticities for all wealth groups based on the small dataset after 32 quarters. For each

¹¹Since they calculate marginal propensities to consume (MPCs) in 2007 dollars, estimates have to be multiplied by the ratio of housing assets to personal consumption expenditures for 2007.

¹²Their estimates need to be scaled by the mean ratio of housing to total wealth in order to be comparable. The mean ratio in their data is between 0.25 and 0.33.

boxplot, the bold horizontal line indicates the posterior median. The first and third quartile is given by the upper and lower end of the box, respectively. The lower whisker shows the 16th percentile, while the upper whisker shows the 84th percentile of the posterior distribution. Figure 7 shows the results for the large dataset.

The reported long-term median elasticities cover a wide range between 0.1 and 1.1. In line with the literature, we find estimates to be decreasing with household balance sheet strength. A one percent persistent increase of aggregate house prices is associated with a moderate 0.1% increase of durable consumption for the richest percentile. In contrast, consumption of the poorest 50% is estimated to match the rise in house prices one-to-one in the long-term. Median elasticities for households in the 50th to 90th wealth percentiles are between 0.6 and 0.7, which is close to the 0.5 estimates of the next 9%. The fact that median elasticities decline relatively slowly with wealth confirms the empirical results in Berger et al. (2017) and is at the center of recent work by Kaplan et al. (2014) on wealthy-hand-to-mouth households. Except for the richest percentile, the obtained elasticities are on the upper range when compared to the literature on wealth effects. Clearly, our median estimates need to be interpreted with caution, as posterior masses are wide for each boxplot. However, the location of the posterior distributions indicate the presence of heterogeneous elasticities across the wealth distribution.

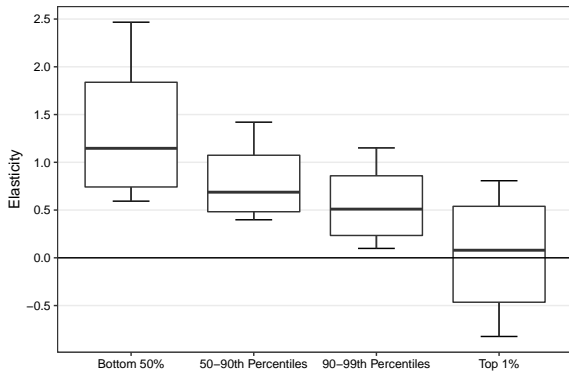


Figure 6: Small Dataset

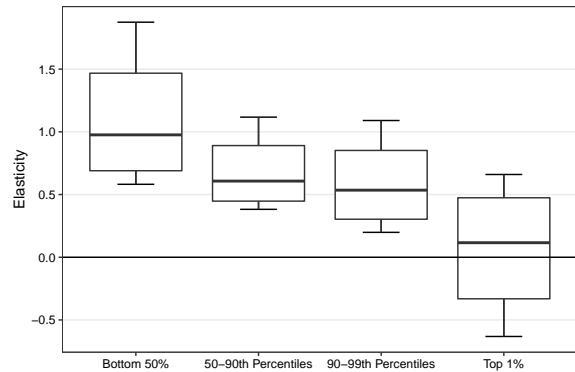


Figure 7: Large Dataset

Notes: The figure shows boxplots for the elasticity of consumption with respect to the average house price response based on the small and the large dataset. Boxplots are based on impulse responses after 32 quarters from the identified housing demand shock. For each boxplot, the bold horizontal line indicates the posterior median. The first and third quartile is given by the upper and lower end of the box, respectively. The lower whisker shows the 16% posterior percentile, while the upper whisker shows the 84% percentile.

5 Conclusion

In this article, we have reexamined the evidence on the propagation mechanism of housing demand shocks to aggregate economic activity and provide new evidence on the empirical link between aggregate outcomes and household balance sheet dynamics. Using a dynamic factor model and two different datasets, we identified shocks by imposing theoretically motivated sign restrictions on a few selected economic indicators and a large number of housing series.

The results show that a positive housing demand shock generates a substantial and persis-

tent economic boom. In line with the outlined transmission channels, we find a large increase in residential investment, aggregate mortgage loans and aggregate consumption. Real economic indicators such as GDP, the industry capacity utilization rate, and the industrial production index increase despite an immediate rise of interest rates. Variance decompositions reveal that housing demand shocks explain a large fraction of business cycle fluctuations in general and house price variation in particular. The common factors are shown to adequately capture the movements in observable variables.

The second part of our analysis provides evidence that housing demand shocks are key to understand household balance sheet dynamics. Based on detailed time series for four different wealth percentile groups, our results support the finding that heterogeneity across the wealth distribution matters. While this is true especially for durable consumption, we also find important cross-sectional similarities: All wealth segments profit from a positive housing demand shock in terms of net wealth. Also, each wealth group extracts a significant amount of equity from housing, although the response is most pronounced for the poorest 50% of households. Given this groups' substantial holdings of consumer credit, we might expect that the new liquidity is used to pay down the more expensive consumer credit balances. In line with the literature, we do not find such an effect. Consumer credit increases for all groups but the richest percentile, which holds a negligible amount of consumer credit and is likely not to be drained from the associated costs. Importantly, the response of durable consumption is a decreasing function of net wealth. Variance decompositions attribute a substantial fraction of durable consumption variation to the housing demand shock, especially for the bottom 50% of households. The structural model is in general well suited to explain household balance sheet variation. A historical decomposition of durable consumption confirms the narrative that housing shocks have caused a significant part of the fall in durable consumption for the poor during the Great Recession. However, while the cumulative effects in general are negligible for the richest percentile of households, we find evidence that the shock has negatively affected their consumption in that period. Finally, we translate impulse responses into elasticities of consumption with respect to house prices. Although uncertainty regarding these estimates is high, results suggest a larger spending sensitivity for weaker balance sheet households. Altogether, our findings indicate that household balance sheets play a significant role in determining aggregate outcomes. All results are robust to two different datasets and model specifications.

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6 Appendix

6.1 Technical Details

Conditional on the factors, we assume the parameters of the state equation to follow Jeffreys prior. In the observation equation the covariance matrix R is assumed to be diagonal with the loadings and R following a normal-inverse gamma prior. So given the $((T-s) \times m(s+1))$ matrix F and Y containing the factors and the data, each row of Λ^* and the associated diagonal entry of R is drawn equation-by-equation. If we denote the i th row of the loadings matrix Λ^* by Λ_i^* , y_i the $((T-s) \times 1)$ vector consisting of the i th observation variable, and σ_i^2 the i th diagonal entry in R , then the priors are specified as $\pi(\sigma_i^2) = IG(v_0, s_0)$ and $\pi(\Lambda_i^* | \sigma_i^2) = N(\Lambda_{i,0}^*, \sigma_i^2 \Sigma_{\lambda,0}^{-1})$. In this case the posterior is characterized as follows

$$\begin{aligned}
& \Lambda_i^* | \sigma_i^2, y_i, F \sim N(\Lambda_{i,T}^*, \sigma_i^2 (F'F + \Sigma_{\lambda,0})^{-1}) \\
& \text{where } \Lambda_{i,T}^* = (F'F + \Sigma_{\lambda,0})^{-1} (F'F \hat{\Lambda}_i^* + \Sigma_{\lambda,0} \Lambda_{i,0}^*) \\
& \text{and } \hat{\Lambda}_i^* = (F'F)^{-1} F' y_i \\
& \sigma_i^2 | y_i, F \sim IG(v_T, s_T) \\
& \text{where } v_T = \frac{T-s+v_0}{2} \\
& \text{and } s_T = \frac{(y_i - F \Lambda_{i,T}^*)' (y_i - F \Lambda_{i,T}^*) + (\Lambda_{i,T}^* - \Lambda_{i,0}^*)' \Lambda_{i,0}^* (\Lambda_{i,T}^* - \Lambda_{i,0}^*) + s_0}{2}
\end{aligned} \tag{3}$$

Following [Bai and Wang \(2015\)](#) the upper left $(m \times m)$ block of Λ^* is restricted to be an identity matrix. The state equation can be written in matrix form as

$$\xi = X \Phi^* + U \tag{4}$$

where ξ is a $((T-h) \times m)$ matrix containing the factors, X is a $((T-h) \times mh)$ matrix containing the lagged factors, and Φ^* is equal to the upper m rows of Φ . Defining $\phi = \text{vec}(\Phi^*)$ and employing a diffuse prior $\pi(Q, \phi) \propto \pi(Q) \propto |Q|^{-(m+1)/2}$ gives us a posterior in the form of

$$\begin{aligned}
& \phi | Q, \xi, X \sim N(\hat{\phi}, Q \otimes (X'X)^{-1}) \\
& \text{where } \hat{\phi} = \text{vec}((X'X)^{-1} X' \xi) \\
& Q | \xi, X \sim IW(\hat{U}' \hat{U}, T - mh) \\
& \text{where } \hat{U} = \xi - X (X'X)^{-1} X' \xi
\end{aligned} \tag{5}$$

The priors for the observation equation are set to be $v_0 = m + 3$, $s_0 = 0.1$, $\lambda_0^* = 0_{m(s+1) \times 1}$, while $\Sigma_{\lambda,0} = I_{m(s+1)}$. The factors are provided by the Kalman filter and subsequent backward sampling. The Gibbs sampler iterates between drawing the factors and drawing the parameters, such that the joint posterior is numerically approximated.

6.2 Impulse Responses

6.2.1 Benchmark Model

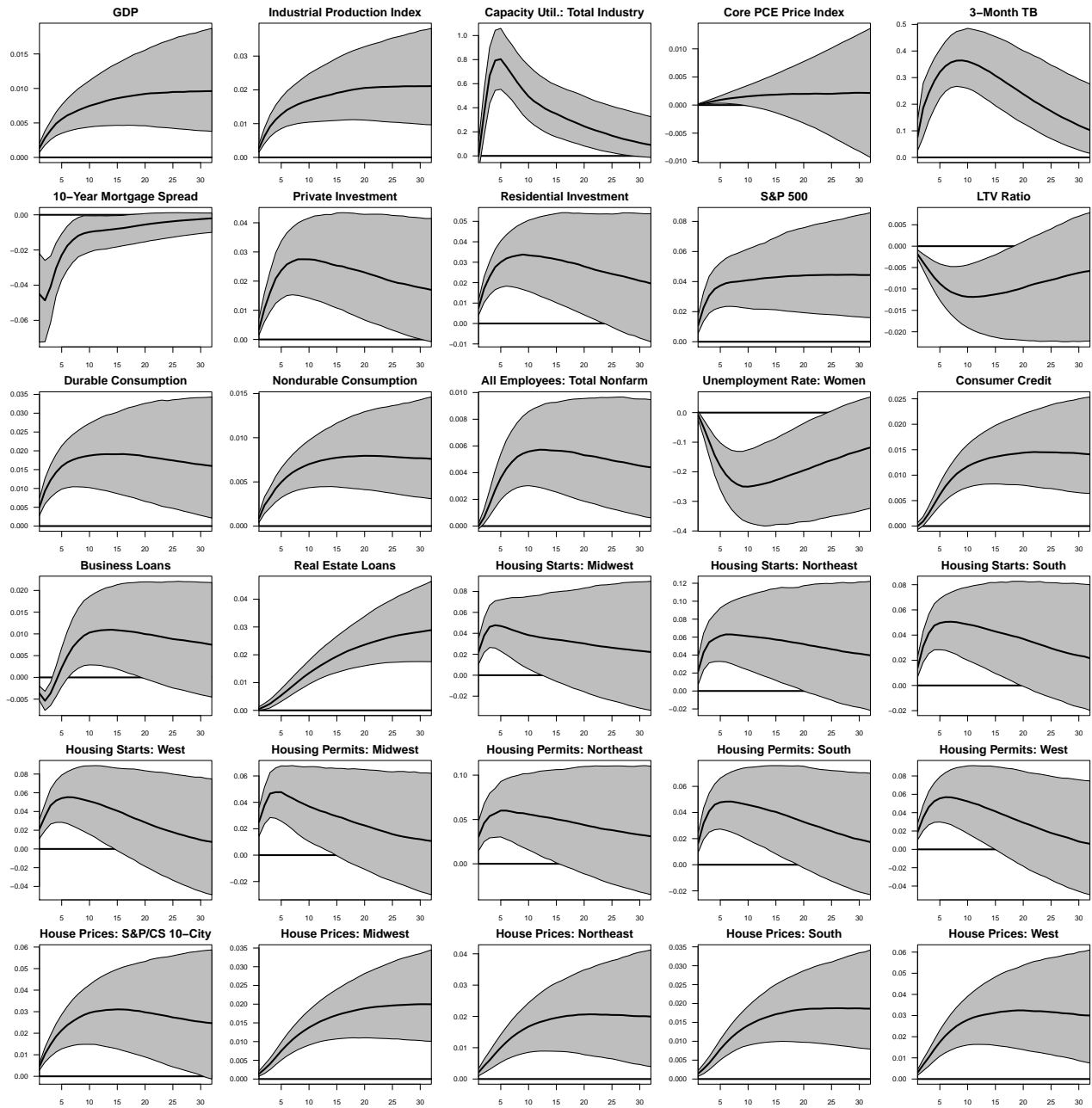


Figure 8: Dynamic responses of variables to housing demand shock using the large dataset

Notes: The figure plots the impulse responses of the level of key variables to the identified housing demand shock. The gray areas indicate the 68% posterior probability regions. The straight black line indicates the posterior median at each horizon.

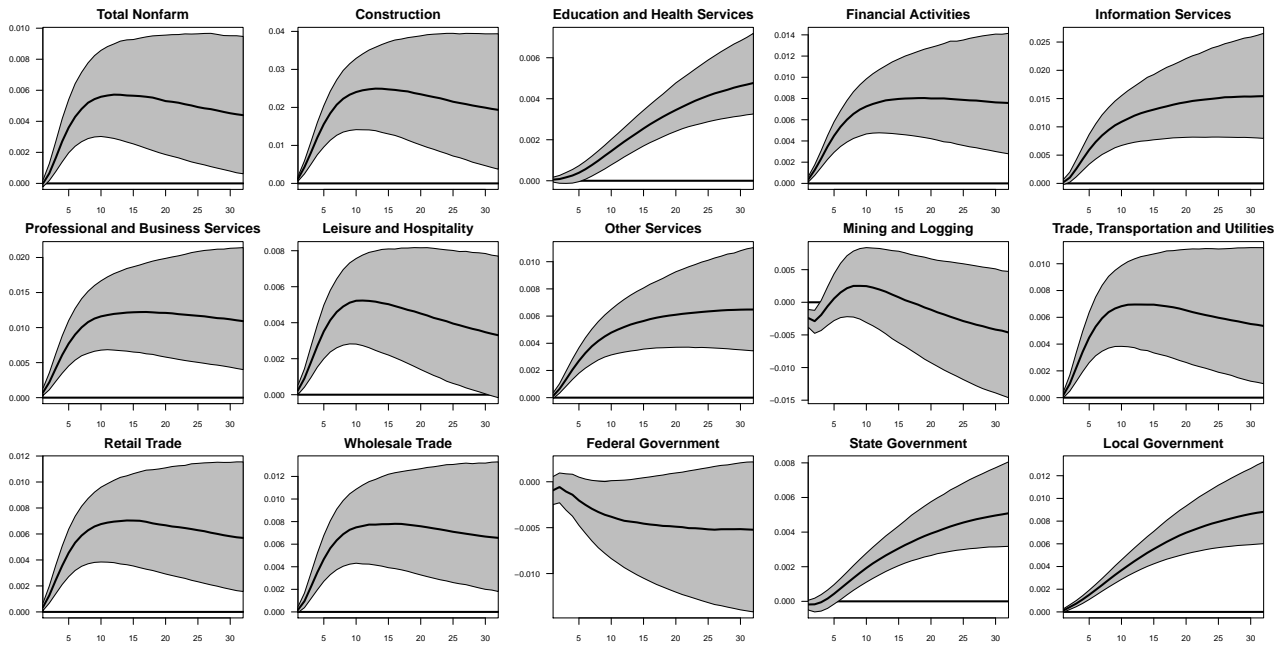


Figure 9: Dynamic responses of sectoral employment variables to housing demand shock using the large dataset
Notes: The figure plots the impulse responses of the level of sectoral employment variables to the identified housing demand shock. The gray areas indicate the 68% posterior probability regions. The straight black line indicates the posterior median at each horizon.

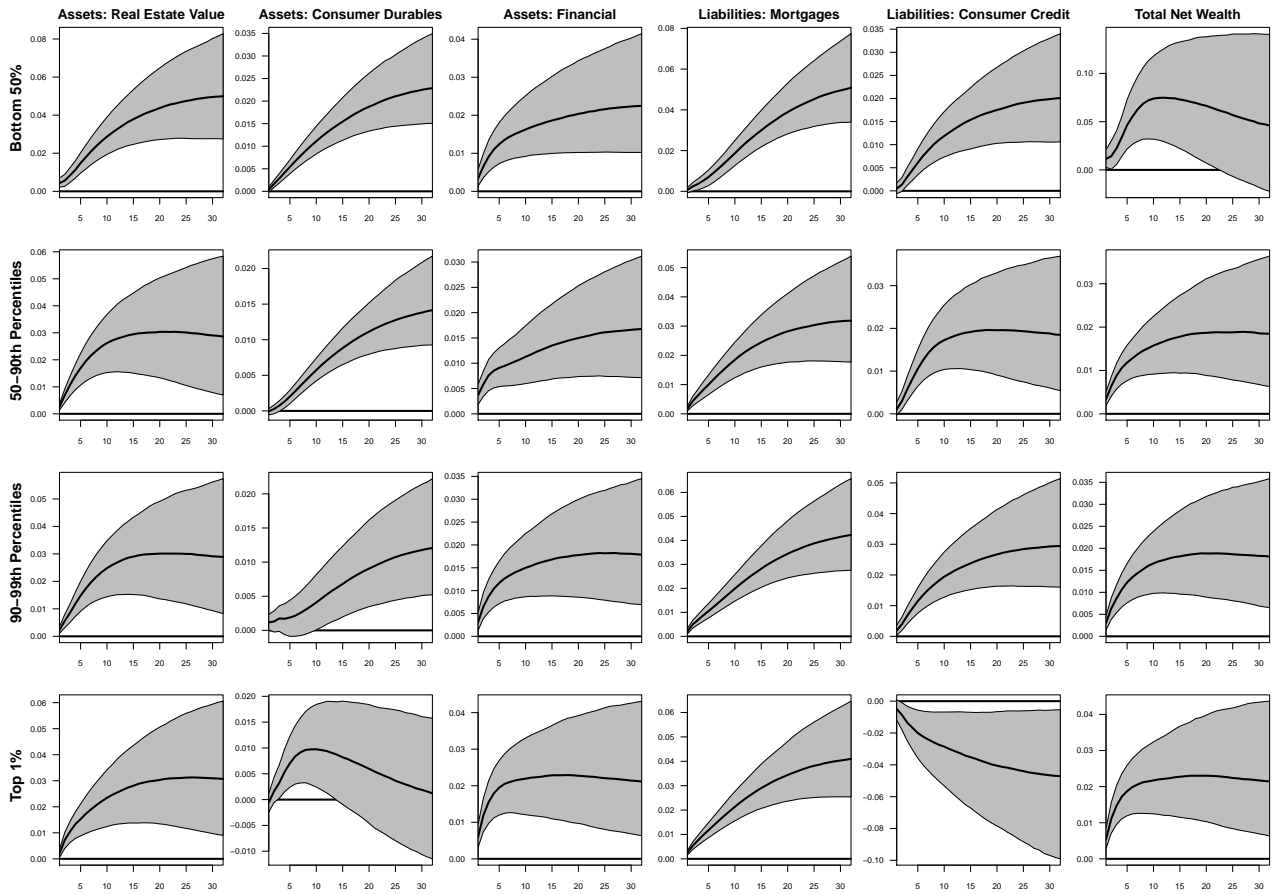


Figure 10: Dynamic responses of household balance sheet variables to housing demand shock using the large dataset

Notes: The figure plots the impulse responses of the level of households' balance sheet components to the identified housing demand shock. The gray areas indicate the 68% posterior probability regions. The straight black line indicates the posterior median at each horizon.

6.2.2 Robustness of Results across Model Specifications

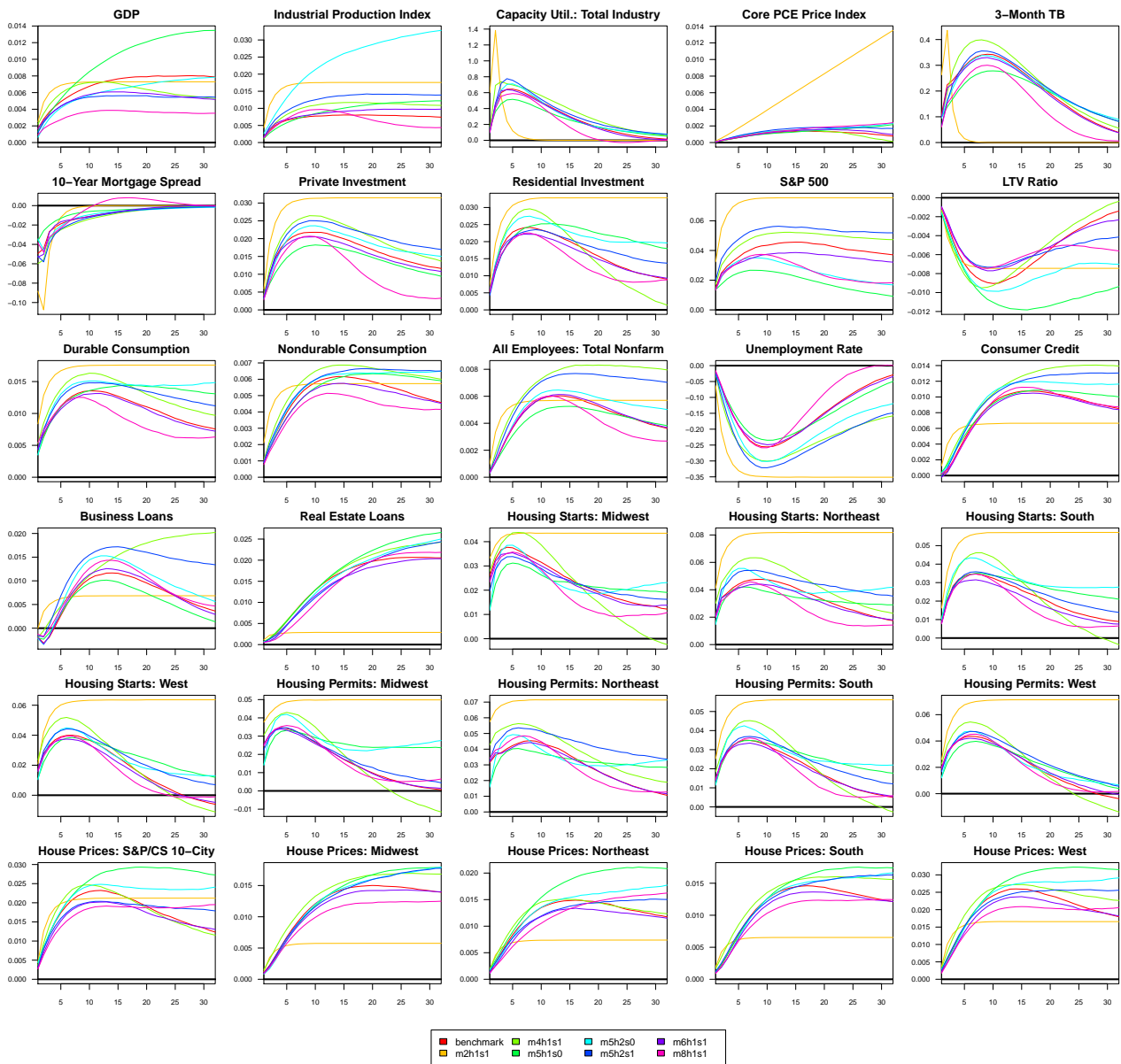


Figure 11: Dynamic median responses of variables to housing demand shock using the small dataset and various model specifications

Notes: The figure plots the median impulse responses of the level of key variables to the identified housing demand shock for a wide range of model specifications.

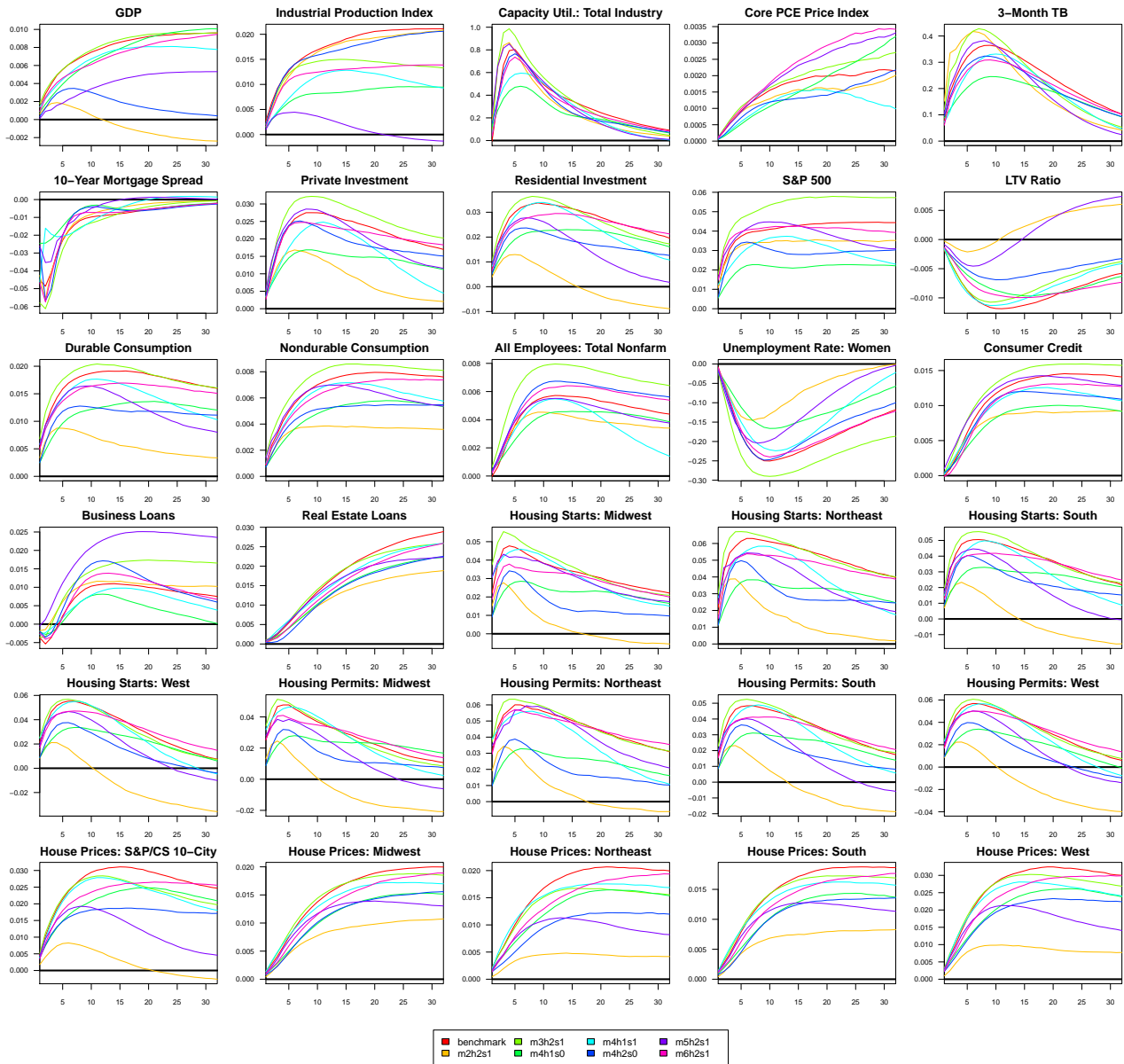


Figure 12: Dynamic median responses of variables to housing demand shock using the large dataset and various model specifications

Notes: The figure plots the median impulse responses of the level of key variables to the identified housing demand shock for a wide range of model specifications.

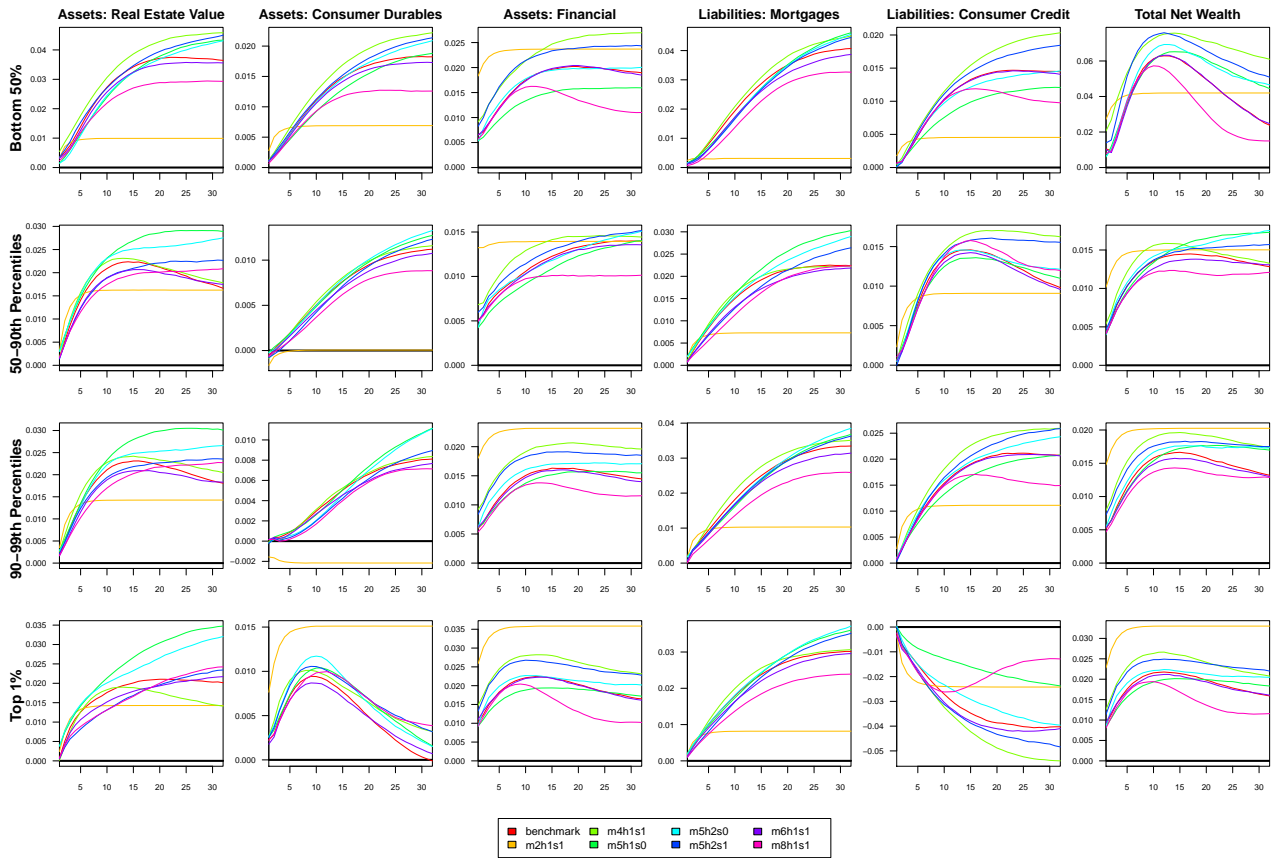


Figure 13: Dynamic median responses of household balance sheet variables to housing demand shock using the small dataset and various model specifications

Notes: The figure plots the median impulse responses of the level of households' balance sheet components to the identified housing demand shock for a wide range of model specifications.

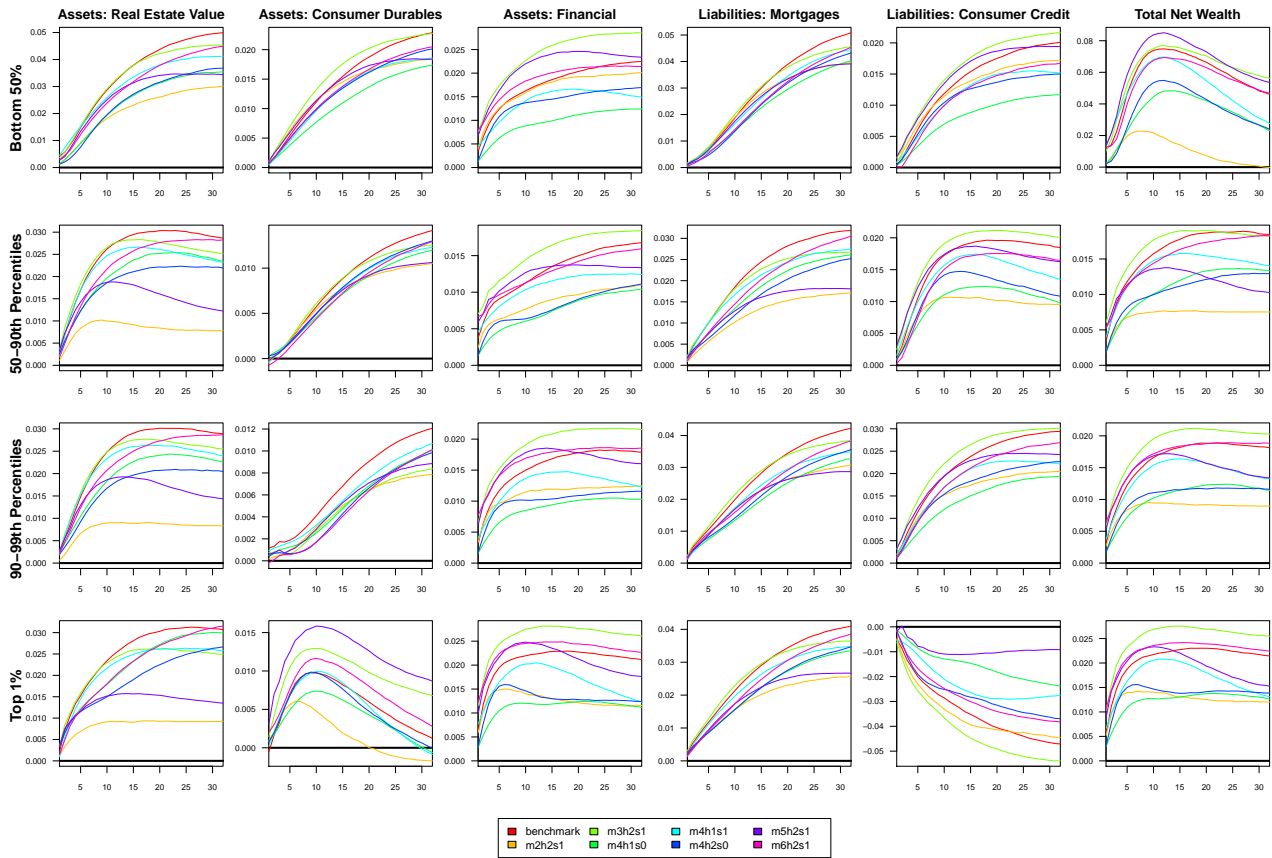


Figure 14: Dynamic median responses of household balance sheet variables to housing demand shock using the large dataset and various model specifications

Notes: The figure plots the median impulse responses of the level of households' balance sheet components to the identified housing demand shock for a wide range of model specifications.

6.3 Historical Decompositions

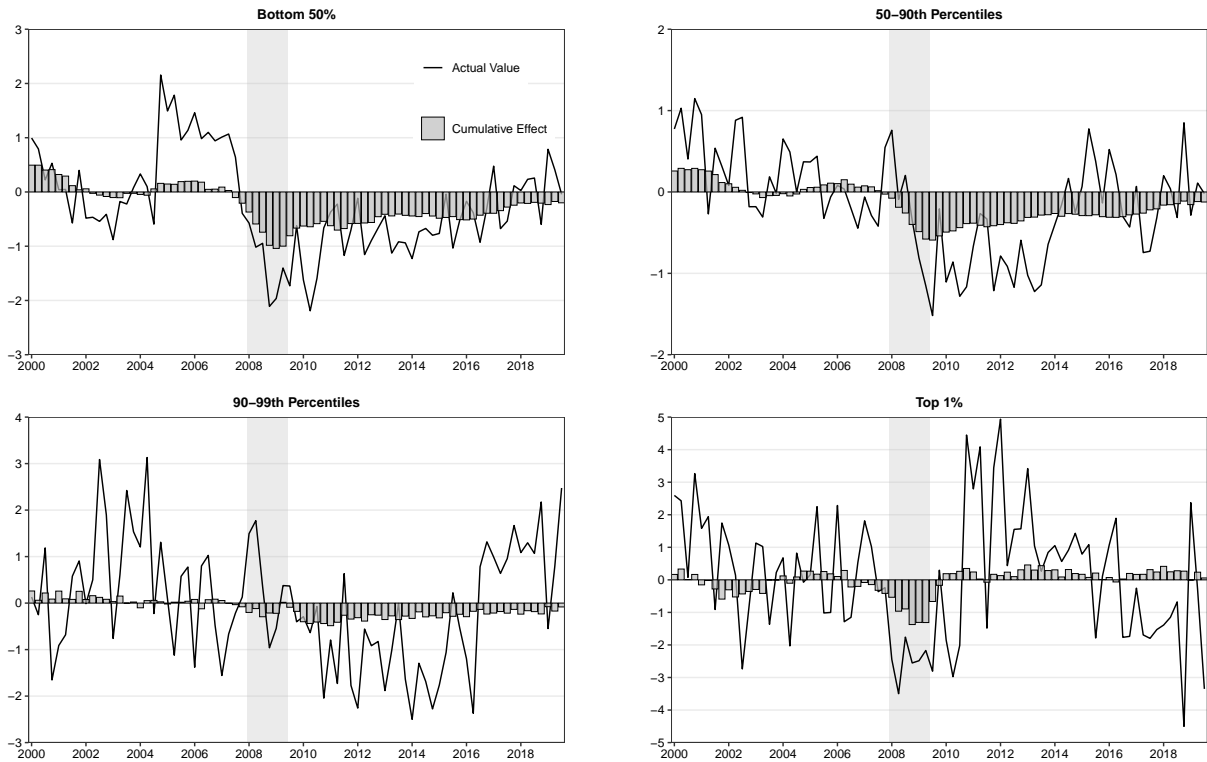


Figure 15: Historical contribution of housing demand shocks to durable consumption using the large dataset
Notes: Estimated on the large dataset, the historical decompositions show the median cumulative effect of housing demand shocks to demeaned growth of durable consumption for each wealth segment. The shaded area marks the period of the Great Recession according to the National Bureau’s (NBER) business cycle dating committee.

6.4 Data

The first column gives the variable names from the FRED-QD database (see [McCracken and Ng, 2020](#)), except for the series ending with *. For these cases see the description in the second column. The third column gives the code of how each series y_i is transformed to stationarity. Here, (1) means no transformation, (2) is Δy_{it} , (5) is $\Delta \log(y_{it})$, and (6) is $\Delta^2 \log(y_{it})$. The fourth column indicates whether the series is part of the large dataset (0), small and large dataset (1), or only the small dataset (2).

Data Group 1: NIPA

Variable	Description	Transformation	Dataset
GDPC1	Real GDP	5	1
PCECC96	Real Consumption	5	1
PCDGx	Real Durable Consumption	5	1
PCESVx	Real Service Consumption	5	1
PCNDx	Real Nondurable Consumption	5	1
GPDIC1	Real Gross Private Domestic Investment	5	1
Y033RC1Q027SBEAx	Real Gross Private Domestic Fixed Investment: Equipment	5	1
PNFIx	Real Private Fixed Investment: Nonresidential	5	1
PRFIx	Real Private Fixed Investment: Residential	5	1
A014RE1Q156NBEA	Shares of GDP: Gross Private Domestic Investment: Private Inventories (Percent)	1	1
A823RL1Q225SBEA	Real Federal Government Consumption and Gross Investment (Percent Change)	1	1
FGRECPTx	Real Federal Government Current Receipts	5	0
SLCEx	Real State and Local Government Consumption	5	0
EXPGSC1	Real Exports	5	0
IMPGSC1	Real Imports	5	0

Data Group 2: Industrial Production

Variable	Description	Transformation	Dataset
INDPRO	Industrial Production Index	5	1
IPDMAT	Industrial Production Index: Durable Materials	5	0
IPNMAT	Industrial Production Index: Nondurable Materials	5	0
IPDCONGD	Industrial Production Index: Durable Consumer Goods	5	0
IPB51110SQ	Industrial Production Index: Durable Automotive Products	5	0
IPNCONGD	Nondurable Consumer Goods	5	0
IPBUSEQ	Business Equipment	5	0
IPB51220SQ	Consumer Energy Products	5	0
TCU	Capacity Utilization: Total Industry (Percent)	1	1
CUMFNS	Capacity Utilization: Manufacturing (Percent)	1	1

Data Group 3: Employment and Unemployment

Variable	Description	Transformation	Dataset
PAYEMS	All Employees: Total Nonfarm	5	1
USPRIV	All Employees: Total Private Industries	5	2
MANEMP	All Employees: Manufacturing	5	2
DMANEMP	All Employees: Durable Goods	5	0
USCONS	All Employees: Construction	5	0
USEHS	All Employees: Education and Health Services	5	0
USFIRE	All Employees: Financial Activities	5	0
USINFO	All Employees: Information Services	5	0
USPBS	All Employees: Professional and Business Services	5	0
USLAH	All Employees: Leisure and Hospitality	5	0
USSERV	All Employees: Other Services	5	0
USMINE	All Employees: Mining and Logging	5	0
USTPU	All Employees: Trade, Transportation and Utilities	5	0
USTRADE	All Employees: Retail Trade	5	0
USWTRADE	All Employees: Wholesale Trade	5	0
CES9091000001	All Employees: Federal Government	5	0
CES9092000001	All Employees: State Government	5	0
CES9093000001	All Employees: Local Government	5	0
UNRATE	Civilian Unemployment Rate (Percent)	2	2
LNS14000012	Unemployment Rate - 16 to 19 years (Percent)	2	0
LNS14000025	Unemployment Rate Men - 20 years and Over (Percent)	2	0
LNS14000026	Unemployment Rate Women - 20 years and Over (Percent)	2	0
UEMPLT5	Number of Civilians Unemployed - Less than 5 Weeks	5	0
UEMP5TO14	Number of Civilians Unemployed - 5 to 14 Weeks	5	0
UEMP15T26	Number of Civilians Unemployed - 15 to 26 Weeks	5	0
UEMP27OV	Number of Civilians Unemployed - More than 27 Weeks	5	0
LNS13023621	Unemployment Level - Job Losers	5	0
LNS13023557	Unemployment Level - Reentrants to Labor Force	5	0
LNS13023705	Unemployment Level - Job Leavers	5	0
LNS13023569	Unemployment Level - New Entrants	5	0
LNS12032194	Employment Level - Part-Time for Economic Reasons	5	0
AWHMAN	Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	1	0
AWHNONAG	Average Weekly Hours of Production and Nonsupervisory Employees: Total Private	2	0
AWOTMAN	Average Weekly Overtime Hours of Production and Nonsupervisory Employees: Manufacturing	2	0

Data Group 4: Housing

Variable	Description	Transformation	Dataset
HOUST	Total Housing Starts: New Privately Owned Housing Units	5	1
HOUST5F	Housing Starts: New Privately Owned 5 or More Unit Structures	5	1
PERMIT	New Private Housing Units Authorized by Building Permits	5	1
HOUSTMW	Housing Starts in Midwest Census Region	5	1
HOUSTNE	Housing Starts in Northeast Census Region	5	1
HOUSTS	Housing Starts in South Census Region	5	1
HOUSTW	Housing Starts in West Census Region	5	1
midwest_hp*	FRED: Average of All-Transactions House Price Indices for the East North Central and West North Central Census Division	5	1
northeast_hp*	FRED: Average of All-Transactions House Price Indices for the New England and Middle Atlantic Census Division	5	1
south_hp*	FRED: Average of All-Transactions House Price Indices for the South Atlantic, East South Central and West South Central Census Division	5	1
west_hp*	FRED: Average of All-Transactions House Price Indices for the Mountain and Pacific Census Division	5	1
SPCS10RSA	S&P/Case-Shiller 10-City Composite Home Price Index	5	1
PERMITNE	New Private Housing Units Authorized by Building Permits in Northeast Census Region	5	1
PERMITMW	New Private Housing Units Authorized by Building Permits in Midwest Census Region	5	1
PERMITS	New Private Housing Units Authorized by Building Permits in South Census Region	5	1
PERMITW	New Private Housing Units Authorized by Building Permits in West Census Region	5	1

Data Group 5: Inventories, Orders, and Sales

Variable	Description	Transformation	Dataset
RSAFSx	Real Retail and Food Services Sales	5	0
AMDMNOx	Real Manufacturers' New Orders: Durable Goods	5	0
AMDMUOx	Real Value of Manufacturers' Unfilled Orders: Durable Goods Industries	5	0
ANDENOx	Real Value of Manufacturers' New Orders for Capital Goods: Nondefense Capital Goods Industries	5	0
INVCQRMTSPL	Real Manufacturing and Trade Inventories	5	0

Data Group 6: Prices

Variable	Description	Transformation	Dataset
PCECTPI	Personal Consumption Expenditures Price Index	6	1
PCEPILFE	Personal Consumption Expenditures Price Index excl. Food and Energy	6	1
GDPCTPI	Gross Domestic Product Price Index	6	2
GPDICTPI	Gross Private Domestic Investment Price Index	6	0
IPDBS	Business Sector: Implicit Price Deflator	6	0
DMOTRG3Q086SBEA	Personal Consumption Expenditures Price Index: Durable Goods: Motor Vehicles and Parts	6	0
DFDHRG3Q086SBEA	Personal Consumption Expenditures Price Index: Durable Goods: Furnishings and Durable Household Equipment	6	0
DREQRG3Q086SBEA	Personal Consumption Expenditures Price Index: Durable Goods: Recreational Goods and Vehicles	6	0
DODGRG3Q086SBEA	Personal Consumption Expenditures Price Index: Durable Goods: Other Durable Goods	6	0
DFXARG3Q086SBEA	Personal Consumption Expenditures Price Index: Non- durable Goods: Food and Beverages	6	0
DCLORG3Q086SBEA	Personal Consumption Expenditures Price Index: Non- durable Goods: Clothing and Footwear	6	0
DGOERG3Q086SBEA	Personal Consumption Expenditures Price Index: Non- durable Goods: Gasoline and Other Energy Goods	6	0
DONGRG3Q086SBEA	Personal Consumption Expenditures Price Index: Non- durable Goods: Other Nondurable Goods	6	0
DHUTRG3Q086SBEA	Personal Consumption Expenditures Price Index: Ser- vices: Housing and Utilities	6	0
DHLCRG3Q086SBEA	Personal Consumption Expenditures Price Index: Ser- vices: Health Care	6	0
DTRSRG3Q086SBEA	Personal Consumption Expenditures Price Index: Ser- vices: Transportation	6	0
DRCARG3Q086SBEA	Personal Consumption Expenditures Price Index: Ser- vices: Recreation Services	6	0
DFSARG3Q086SBEA	Personal Consumption Expenditures Price Index: Ser- vices: Food and Accommodations	6	0
DIFSRG3Q086SBEA	Personal Consumption Expenditures Price Index: Ser- vices: Finance and Insurance	6	0
DOTSRG3Q086SBEA	Personal Consumption Expenditures Price Index: Ser- vices: Other Services	6	0
WPSFD49502	Producer Price Index by Commodity for Finished Goods	6	0
WPSFD4111	Producer Price Index by Commodity for Finished Con- sumer Goods	6	0
PPIIDC	Producer Price Index by Commodity Industrial Com- modities	6	0
WPSID61	Producer Price Index by Commodity Intermediate Ma- terials: Supplies and Components	6	0
WPU0531	Producer Price Index by Commodity for Fuels and Re- lated Products and Power: Natural Gas	5	0
WPU0561	Producer Price Index by Commodity for Fuels and Re- lated Products and Power: Crude Petroleum	5	0

Data Group 7: Earnings and Productivity

Variable	Description	Transformation	Dataset
COMPRMS	Manufacturing Sector: Real Compensation Per Hour	5	0
COMPRNFB	Nonfarm Business Sector: Real Compensation Per Hour	5	0
RCPHBS	Business Sector: Real Compensation Per Hour	5	0
OPHMFG	Manufacturing Sector: Real Output Per Hour of All Persons	5	0
OPHNFB	Nonfarm Business Sector: Real Output Per Hour of All Persons	5	0
ULCMFG	Manufacturing Sector: Unit Labor Cost	5	0
ULCNFB	Nonfarm Business Sector: Unit Labor Cost	5	0
UNLPNBS	Nonfarm Business Sector: Unit Nonlabor Payments	5	0

Data Group 8: Interest Rates

Variable	Description	Transformation	Dataset
FEDFUNDS	Effective Federal Funds Rate	1	1
TB3MS	3-Month Treasury Bill: Secondary Market Rate	1	1
MORTGAGE30US	30-Year Conventional Mortgage Rate	1	1
BAA10YM	Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity	1	0
MORTG10YRx	30-Year Conventional Mortgage Rate Relative to 10-Year Treasury Constant Maturity	1	1
TB6M3Mx	6-Month Treasury Bill Minus 3-Month Treasury Bill	1	0
GS1TB3Mx	1-Year Treasury Constant Maturity Minus 3-Month Treasury Bill	1	0
GS10TB3Mx	10-Year Treasury Constant Maturity Minus 3-Month Treasury Bill	1	0
CPF3MTB3Mx	3-Month Commercial Paper Minus 3-Month Treasury Bill	1	0
ShadowRate*	Quantifies the stance of monetary policy in zero lower bound environment and characterizes the term structure of interest rates (see Wu and Xia, 2016)	1	1

Data Group 9: Credit

Variable	Description	Transformation	Dataset
BUSLOANSx	Real Commercial and Industrial Loans, All Commercial Banks	5	1
NONREVSLx	Total Outstanding Real Nonrevolving Credit Owned and Securitized	5	1
REALLNx	Real Real Estate Loans, All Commercial Banks	5	1
REVOLSLx	Total Real Revolving Credit Owned and Securitized, Outstanding	5	1
TOTALSLx	Total Consumer Credit Outstanding	5	1
DRIWCIL	FRB Senior Loans Officer Opinions. Net Percentage of Domestic Respondents Reporting Increased Willingness to Make Consumer Installment Loans	1	0
LTV*	Loan-to-Value Ratio. FRED Variables: Total Credit to Private Non-Financial Sector, Adjusted for Breaks; and Households and Nonprofit Organizations: Real Estate at Market Value	2	1

Data Group 10: Exchange Rates

Variable	Description	Transformation	Dataset
TWEXAFEGSMTHx	Trade Weighted U.S. Dollar Index: Major Currencies	5	0
EXSZUSx	Switzerland / U.S. Foreign Exchange Rate	5	0
EXJPUSx	Japan / U.S. Foreign Exchange Rate	5	0
EXUSUKx	U.S. / U.K. Foreign Exchange Rate	5	0
EXCAUSx	Canada / U.S. Foreign Exchange Rate	5	0

Data Group 11: Other

Variable	Description	Transformation	Dataset
UMCSENTx	University of Michigan: Consumer Sentiment Index	1	0
USEPUINDXM	Economic Policy Uncertainty Index for United States	2	0

Data Group 12: Stock Markets

Variable	Description	Transformation	Dataset
S&P 500	S&P's Common Stock Price Index: Composite	5	1
VXOCLSx	CBOE S&P 100 Volatility Index: VXO	1	0

Data Group 13: Household Balance Sheet by Wealth

Variable	Description	Transformation	Dataset
real_estate_bottom50*	FRED: Real Estate Held by the Bottom 50%	5	1
mortgages_bottom50*	FRED: Mortgages Held by the Bottom 50%	5	1
consumer_durables_bottom50*	FRED: Consumer Durables Held by the Bottom 50%	5	1
consumer_credit_bottom50*	FRED: Consumer Credit Held by the Bottom 50%	5	1
financial_bottom50*	FRED: Financial Assets Held by the Bottom 50%	5	1
total_net_bottom50*	FRED: Total Net Worth Held by the Bottom 50%	5	1
real_estate_50to90th*	FRED: Real Estate Held by the 50th to 90th Wealth Percentiles	5	1
mortgages_50to90th*	FRED: Mortgages Held by the 50th to 90th Wealth Percentiles	5	1
consumer_durables_50to90th*	FRED: Consumer Durables Held by the 50th to 90th Wealth Percentiles	5	1
consumer_credit_50to90th*	FRED: Consumer Credit Held by the 50th to 90th Wealth Percentiles	5	1
financial_50to90th*	FRED: Financial Assets Held by the 50th to 90th Wealth Percentiles	5	1
total_net_50to90th*	FRED: Total Net Worth Held by the 50th to 90th Wealth Percentiles	5	1
real_estate_90to99th*	FRED: Real Estate Held by the 90th to 99th Wealth Percentiles	5	1
mortgages_90to99th*	FRED: Mortgages Held by the 90th to 99th Wealth Percentiles	5	1
consumer_durables_90to99th*	FRED: Consumer Durables Held by the 90th to 99th Wealth Percentiles	5	1
consumer_credit_90to99th*	FRED: Consumer Credit Held by the 90th to 99th Wealth Percentiles	5	1
financial_90to99th*	FRED: Financial Assets Held by the 90th to 99th Wealth Percentiles	5	1
total_net_90to99th*	FRED: Total Net Worth Held by the 90th to 99th Wealth Percentiles	5	1
real_estate_top1*	FRED: Real Estate Held by the Top 1%	5	1
mortgages_top1*	FRED: Mortgages Held by the Top 1%	5	1
consumer_durables_top1*	FRED: Consumer Durables Held by the Top 1%	5	1
consumer_credit_top1*	FRED: Consumer Credit Held by the Top 1%	5	1
financial_top1*	FRED: Financial Assets Held by the Top 1%	5	1
total_net_top1*	FRED: Total Net Worth Held by the Top 1%	5	1

Notes: To ensure comparability between the household balance sheet series we eliminate population differences by dividing the series of each group by the respective number of population percentiles. All household balance sheet series are deflated using the core PCE deflator.