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Staff Working Paper/Document de travail du personnel 2016-62

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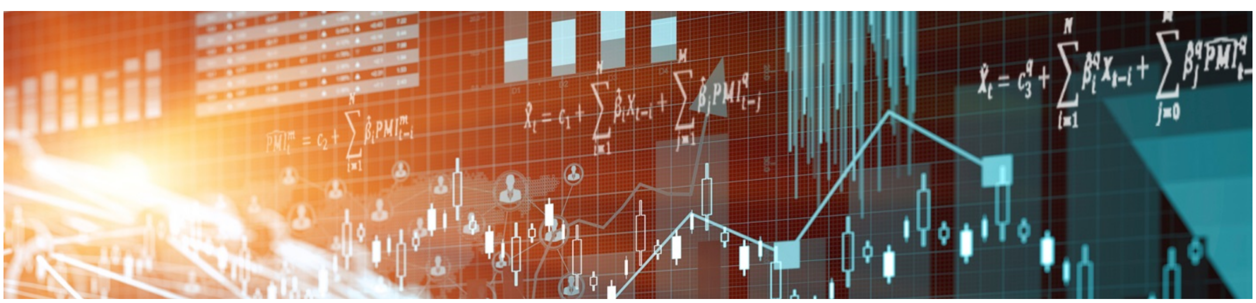

by Narayan Bulusu, Jefferson Duarte and Carles Vergara-Alert

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Bank of Canada Staff Working Paper 2016-62

December 2016

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Narayan Bulusu,[1] Jefferson Duarte[2] and Carles Vergara-Alert[3]

[1]Funds Management and Banking Department
Bank of Canada
Ottawa, Ontario, Canada K1A 0G9
nbulusu@bankofcanada.ca

[2]Jesse H. Jones Graduate School of Business
Rice University
jefferson.duarte@rice.edu

[3]IESE Business School
University of Navarra
CVergara@iese.edu

ISSN 1701-9397

Acknowledgements

We thank David De Angelis, Kerry Back, Charles Calomiris, Alan Crane, Morris Davis, Scott Hendry, Matteo Iacoviello, Leonid Kogan, Vincent Labhard, William Lastrapes, David Williams, Callan Windsor, Shaofeng Xu, as well as participants of seminars at the Bank of Canada Fellowship Exchange and University of Washington for their helpful comments. Carles Vergara-Alert acknowledges the financial support of the Public-Private Sector Research Center at IESE, the Ministry of Economy of Spain (ref. ECO2015-63711-P) and the Government of Catalonia (ref: 2014-SGR-1496). The views expressed in this paper are those of the authors. No responsibility for them should be attributed to the Bank of Canada.

Abstract

The common-factor hypothesis is one possible explanation for the housing wealth effect. Under this hypothesis, house price appreciation is related to changes in consumption as long as the available proxies for the common driver of housing and non-housing demand are noisy and housing supply is not perfectly elastic. We simulate a model in which a common factor drives the relation between house prices and consumption to examine the extent to which the common-factor hypothesis can explain the housing wealth effect. Our results indicate that the common-factor hypothesis can easily explain the strong housing wealth effect estimated with US state-level data.

Bank topics: Economic models; Housing
JEL codes: E21; R31

Résumé

L'hypothèse du facteur commun offre une piste pour comprendre l'effet de richesse immobilière. Selon cette hypothèse, l'appréciation du prix des logements est corrélée à l'évolution de la consommation tant que les variables d'approximation du facteur commun à la demande de logements et à la demande hors logements sont mesurées de manière imprécise et que l'offre de logement n'est pas parfaitement élastique. Nous procédons à une modélisation afin d'évaluer la validité de l'hypothèse du facteur commun. Dans le modèle, la relation entre les prix des logements et la consommation est déterminée par un facteur commun. D'après les résultats, l'hypothèse du facteur commun permet de bien expliquer l'importance de l'effet de richesse immobilière estimé à partir de données des États américains.

Sujets : Modèles économiques; Logement
Codes JEL : E21; R31

Non-Technical Summary

The relation between growth in non-housing consumption and growth in house prices is large and positive, which has led some economists to argue for the existence of a housing wealth effect. Standard economic theory suggests that the elasticity of consumption to housing wealth should be close to zero because increases in housing wealth are offset by an equivalent increase in the costs of housing services.

One explanation that has been proposed for the estimated housing wealth effect is the common-factor hypothesis. Under this hypothesis, shocks to a common unobservable factor, such as expected future income, simultaneously affect both house prices and non-housing consumption. In this paper, we analyze the extent to which the common-factor hypothesis can explain the magnitude of the observed housing wealth effect.

To do so, we follow a three-step procedure. First, we calibrate Kogan's (2001) two-sector general equilibrium model to match the observed moments of consumption and house price growth in each US state and the District of Columbia. In this model, one underlying variable drives both consumption and house prices, which vary since housing supply is inelastic. Second, we simulate the model to generate panels of consumption growth, housing price appreciation and changes in non-housing capital. In our simulations, we assume that these variables are observed with measurement errors. Hence, we mimic the assumption embedded in the common-factor hypothesis; that is, we do not perfectly observe the common driver of consumption and housing prices. Third, we estimate panel models analogous to those used in the housing wealth effect literature with simulated data to gauge the amount of measurement error necessary to achieve the same level of elasticity of consumption to housing wealth that we observe in the US state-level data.

Our results indicate that the common-factor hypothesis can easily explain the large elasticity of consumption to housing wealth estimated with US state-level data. Specifically, we find that small errors (as low as 3%) in the proxy for the common factor could plausibly drive the estimate of the housing wealth effect. We obtain this result despite the fact that our model does not consider many effects recognized in the literature (e.g., the use of housing as collateral) that might affect consumption through changes in house prices. Our contribution is therefore to show that the large observed elasticity of consumption to housing wealth is not puzzling once properly benchmarked against a model that takes the common-factor hypothesis into account.

1 Introduction

For years, economists have been puzzled by the strong housing wealth effect, that is, the positive relation between growth in non-housing consumption and growth in house prices as reflected in available data. Empirical estimates of the elasticity of consumption to housing wealth are usually large and positive (e.g., Case et al. [2005]). However, standard economic theory suggests that the elasticity of consumption to housing wealth should be close to zero because increases in housing wealth offset increases in the costs of housing services (e.g., Sinai and Souleles [2005] and Buiter [2010]).

One explanation for the estimated housing wealth effect is the common-factor hypothesis (Attanasio et al. [2009]). Under this hypothesis, shocks to a common unobservable factor, such as expected future income, simultaneously affect the demand for housing services (which, with an inelastic supply, in turn affects house prices) and non-housing consumption. Therefore, house price appreciation is statistically related to changes in consumption as long as the available proxies for the unobservable underlying driver of consumption are noisy. Interestingly, economists agree on the empirical validity of the building blocks of the common-factor hypothesis. That is, it is well-known that the supply of housing is somewhat inelastic (e.g., Gyourko et al. [2008] and Saiz [2010]) and that data on wealth as well as income growth are plagued with noise and hence do not fully capture the effect of the underlying drivers of consumption growth, such as shocks to expected income (e.g., Muellbauer [2007] and Calomiris et al. [2012]). We do not know, however, the extent to which the common-factor hypothesis can explain the magnitude of the observed housing wealth effect. In this paper, we address this question.

To do so, we benchmark the housing wealth effect with a model in which one underlying variable drives both consumption and house prices. The model is an application of Kogan's (2001, 2004) general equilibrium model to housing. The representative agent in the model has utility for housing services and consumption goods. There are two types of capital in this model, housing capital and non-housing capital. Non-housing capital is used to fund consumption and invest in housing, while housing capital is needed to produce housing services. Housing supply is inelastic in this model, and, as a consequence, shocks to non-housing capital drive shocks to both consumption and house prices.

We use this model to gauge the extent to which the common-factor hypothesis can explain the large elasticity of consumer spending to housing wealth as estimated in the literature. Specifically, we follow a three-step procedure. First, we calibrate the model to match the observed moments of consumption and house price growth in each US state and the District of Columbia. Second, we simulate the model to generate panels of consumption growth, house price appreciation, and changes in non-housing capital. In our simulations, we assume that these variables are observed with measurement errors. By doing so, we mimic the assumption embedded in the common-factor hypothesis; that is, we do not perfectly observe the common driver of consumption and house prices. Third, we estimate panel models analogous to those used in the housing wealth effect literature with simulated data to gauge the amount of measurement error necessary to achieve the same level of elasticity of consumption to housing wealth that we observe in the US state-level data.

We find fairly large housing wealth effects in our simulated panels for a wide range of measurement errors, thus indicating that the large empirical housing wealth effect is consistent with the calibrated model.[1] With measurement errors making a negligible contribution to the variance of the underlying variables, the magnitude of the wealth effect that we obtain from our model-simulated panels is similar to the effect we find in the actual data. For instance, when 5% of the variance in the observed non-housing capital and house price growth is due to noise (i.e., a noise-to-signal ratio of 5%), the elasticity of consumption to housing wealth is about 15%. This is close to the 13% level of elasticity of consumption to housing wealth that we estimate using state-level actual data and is within the range of 2% to 19% in the literature.[2] With noise-to-signal ratios large enough to match the T-statistics and R^2s that we observe in the actual data panels, the elasticity to housing wealth is about 30%, which is larger than findings in the empirical literature. For all (non-zero) noise-to-signal

[1] Many papers estimated the size of measurement errors in the variables used in the housing wealth effect literature. We briefly review this literature in Section 5. We obtain large housing wealth effects for measurement errors that are within the range of measurement errors described in this literature.

[2] Using US and non-US data, many studies find a positive elasticity of consumption to housing wealth that is larger than the elasticity to financial wealth. See, for instance, Benjamin et al. [2004], Bostic et al. [2009], Calomiris et al. [2012], Case et al. [2005, 2013], Carroll et al. [2011], Dvornak and Kohler [2007], Labhard et al. [2005], and Ludwig and Sløk [2002]. See Mishkin [2007] and Paiella [2009] for reviews of this literature.

ratios that we analyze, the minimum elasticity to housing wealth that we find is about 8%. This minimum occurs when the noise-to-signal ratios of non-housing capital growth and house price growth are 5% and 30%, respectively. That is, even when house price growth is six times noisier (30% versus 5%) than non-housing capital growth, the simulated elasticity of consumption to housing wealth is well within the range of elasticities estimated in the literature. Hence, when benchmarked with Kogan's (2001) model, the large observed elasticity of consumption to housing wealth at the state level is not puzzling.

Our results are not due to an exogenously specified elasticity of housing supply. In fact, elasticity of housing supply is endogenous in Kogan's (2001) model. In addition, housing supply can be inelastic even in large geographical units, such as states and countries, where the supply of land is effectively unconstrained. Housing supply is inelastic in the simulated model because investment in housing is irreversible; that is, housing stock cannot be converted into non-housing capital. Therefore, situations in which there is "too much" housing can exist in this model. In these states of the world, house prices are lower than housing replacement costs, and new housing is not built.[3] Housing supply in the model is inelastic up to the point that house prices equal housing replacement costs and is perfectly elastic when house prices are equal to housing replacement costs. As a result, the model creates a housing supply curve that resembles the "kinked" real estate supply common in real estate textbooks (e.g., Geltner et al. [2013]).

Our simulated model is fairly simple and does not consider many effects that might affect house prices and consumption. Because of its simplicity, the simulated model is ideal for gauging the extent to which the common-factor hypothesis explains the housing wealth effect. The simulated model does not include many potentially important features of the housing sector. For instance, it does not consider that non-separable preferences between non-housing and housing consumption can lead to composition risk (Piazzesi et al. [2007]). Moreover, the simulated model does not include labour income, which has long been recognized as an important determinant of consumption (Iacoviello [2012]). In fact, the only mechanism by which the simulated model can generate housing wealth effects is through

[3]Since irreversibility of housing investment is the cornerstone of this model, it is perhaps natural to question the empirical validity of this assumption. Note, however, that it is always the case that, in aggregate, housing is not reversible since we cannot convert housing into non-housing consumption.

a common factor: shocks to non-housing wealth explain shocks to both consumption and housing wealth. This happens because our simulated model relies on two generally accepted premises: first, that housing cannot be converted into non-housing consumption in aggregate; and second, that econometricians can only observe noisy proxies of the variables affecting consumption. Therefore, any housing wealth effect that we find in our simulations cannot be confounded by effects unrelated to the common-factor hypothesis.[4]

Our analysis is not designed to test the common-factor hypothesis against alternative explanations for the housing wealth effect. We aim instead to determine the extent to which a common factor can explain the large magnitude of the estimated elasticity of consumption to housing wealth in the literature. In addition to the common-factor hypothesis, two other explanations for the large housing wealth effect are prominent in the literature. One hypothesis is the direct housing wealth effect, which posits that an increase in housing wealth has a direct causal effect on increases in consumption (Gan [2010]). Another explanation is related to the role of housing as collateral for loans (Hurst and Stafford [2004], Aoki et al. [2004], Iacoviello [2004, 2005], Lustig and Van Nieuwerburgh [2005], Leth-Petersen [2010], Abdallah and Lastrapes [2012], Agarwal and Qian [2016], and Berger et al. [2016]). Under this explanation, as house prices increase, credit-constrained homeowners use their homes as collateral to borrow more to increase non-housing consumption.

We contribute to the literature because we show that our simulated model can easily generate housing wealth effects that are consistent with, or even larger than, those observed in the data despite omitting mechanisms suggested in the literature, such as the relaxation of collateral constraints or direct housing wealth effects. In fact, our simulated model relies only on generally accepted premises, that is, the irreversibility of housing investment and measurement errors, to generate housing wealth effects through a common factor. Naturally, our paper is not the first to suggest that the common-factor hypothesis is a possible expla-

[4]In the model we calibrate, the common factor is the growth in the log of non-housing capital. However, we do not make any statements about the economic nature of the common factor that drives the housing wealth effects in the actual data. For instance, in reality, this common factor could be shocks to expected income (e.g., Attanasio et al. [2009] and Calomiris et al. [2009]), general confidence in the economy (e.g., Case et al. [2005, 2013]), or changes in the non-housing wealth. Our econometric results do not rely on the economic nature of the common factor; instead, they rely on two assumptions. First, the common factor affects consumption as well as house prices. Second, a proxy for the common factor is observed with measurement errors.

nation for the observed housing wealth effect (e.g., Attanasio et al. [2009] and Calomiris et al. [2009]). To the best of our knowledge, however, our paper is the first to actually gauge the extent to which the common-factor hypothesis can explain the strong observed housing wealth effect. Therefore, our contribution is to show that the large observed elasticity of consumption to housing wealth is not puzzling once properly benchmarked against a model that takes the common-factor hypothesis into account.

Many papers empirically analyze the possible mechanisms behind the housing wealth effect. The majority of these papers, with the exception of Mian et al. [2013], do not account for the elasticity of housing supply. Mian et al. [2013] use variation of elasticity of supply across metropolitan statistical areas (MSAs) as a means to identify exogenous shocks to house prices and address the omitted variable problem underlying the common-factor hypothesis. Their results are direct evidence of a strong collateral effect during the 2002 to 2006 period. Since our results do not rule out the existence of collateral effects, we do not contradict Mian et al. [2013]. In fact, our work extends this study in two ways: First, we show that elasticity of housing supply matters for the study of housing wealth effects even when the empirical analysis uses data aggregated over large geographical units (i.e., states and countries) in which land and regulatory constraints play a smaller role. Second, our results show the importance of controlling for common factors driving consumption and housing wealth, as Mian et al. [2013] do. A number of papers analyze how the housing wealth effect varies with household age or wealth (e.g., Lehnert [2004], Campbell and Cocco [2007], Attanasio et al. [2009] and Calomiris et al. [2012]). Our results concern aggregate housing wealth effects and do not have any implications for the housing wealth effects within household groups. In fact, using a life-cycle model, Li and Yao [2007] find significant wealth effects within household groups that cancel out in aggregated data. Our results, however, indicate that controlling for housing supply effects can be important. Hence, to the extent that elasticity of housing supply is correlated with household age or wealth, the results in this literature can be driven by heterogeneity of the elasticity of supply, and not by the heterogeneity of the households.

Iacoviello and Neri [2010] is perhaps the closest study to ours in the literature. The authors develop a dynamic stochastic general equilibrium model with housing and non-housing sectors, nominal rigidities, and financial frictions in the household sector. They calibrate their model using data from 1965 to 2006. Using simulated data from their model, they regress consumption growth on lagged house price appreciation without controlling for other macroeconomic variables such as income growth, and assuming that both consumption and house price growth are observed without measurement error. They conclude from this regression that about 2.5% out of a 13.5% elasticity of consumption to housing wealth is due to the housing collateral effect. Our study differs from theirs in important ways. Unlike Iacoviello and Neri [2010], we aim to gauge the extent to which the common-factor hypothesis can explain the elasticity of consumption to housing wealth estimated in the empirical literature. To address this question, we include in our regressions a noisy proxy for the common factor driving both consumption growth and housing wealth in our model. By doing so, we mimic the panel regressions used in the empirical literature (e.g., Case et al. [2005]), which always include variables such as income growth that are possibly correlated with the macroeconomic factors driving consumption growth and house prices. Iacoviello and Neri [2010], on the other hand, focus only on the extent to which spillover effects related to the housing collateral hypothesis drive the elasticity of consumption to housing wealth, and hence they do not address the common-factor hypothesis.[5] Taking our results together with those in Iacoviello and Neri [2010], we conclude that the majority of the estimated housing wealth effect during the 1976–2012 period can be attributed to the common-factor hypothesis and that about 2.5% of the estimated elasticity of consumption to housing wealth is due to a causal relation between housing wealth and consumption.

Empirical studies that use microdata to analyze wealth effects have addressed the attenuation bias.[6] Our paper contributes to this literature because we show that measurement errors have consequences for the wealth effects literature that go beyond the attenuation bias. The attenuation bias is a result related to measurement error in one independent variable (see Wooldridge [2010]), while, in a multivariable context, the measurement errors of two different types of wealth may result in a stronger estimated wealth effect for one type of wealth. For instance, our results show that if there is a non-housing wealth effect and

[5]To see this, note that Iacoviello and Neri [2010] do not include income growth or assume measurement errors in their regression.

[6]The bias of the regression coefficient towards zero is caused by errors in the independent variable. See for instance Brunnermeier and Nagel [2008], Juster et al. [2006] and Filmer and Pritchett [2001].

housing wealth is correlated to non-housing wealth, an increase in the measurement error of non-housing wealth will increase the estimated housing wealth effect.

The rest of this paper is organized as follows. Section 2 describes our data and shows estimates of the housing wealth effect at the state level. Section 3 explains the simulated model. Section 4 describes the results of the model calibration at the state level. Section 5 shows the estimation of the housing wealth effect in the simulated data. Section 6 concludes.

2 Data and estimation of housing wealth effects

We describe the data used in this paper in Section 2.1. Section 2.2 shows the presence of housing wealth effects in our data by estimating panel regressions similar to those used in Case et al. [2005].

2.1 Data description

Table 1 describes the variables used in our empirical work. Our empirical analysis relies on four data series: annual growth in real housing wealth (Δw^H), annual growth in real aggregate income (Δy), annual growth in real non-housing tradable wealth (Δw^{TR}), and annual growth in real log-consumption (Δc). We build the Δw^H series based on the Federal Housing Finance Agency (FHFA) house price index at the state level. Since FHFA-index data start in 1975, our state-level growth data set starts in 1976 and ends in 2012. We build the Δy series from Bureau of Economic Analysis (BEA) total nominal income data. We build the Δw^{TR} data series from total nominal tradable assets in the United States ($Total^{TR}$) and the growth of cumulative disposable income (CDI) in each state between 1960 and year t. Specifically, the total real tradable wealth ($w_{i,t}^{TR}$) for state i at year t is $Total^{TR} \times CDI_{i,t}/\sum_{i=1}^{50} CDI_{i,t}$ deflated by CPI. CDI is calculated from 1960 because this is the first year for which we have disposable income data for all states.

We use a different procedure from that in Case et al. [2005] to calculate $w_{i,t}^{TR}$. Case et al. [2005] use mutual fund holdings by state from the Investment Company Institute to allocate national tradable wealth data to states. Their working assumption is that the total financial assets in a state as a proportion of nationwide financial assets is equal to the mutual fund assets in the state divided by total mutual fund assets in the United States. They recognize that this is clearly a strong assumption. Our procedure, on the other hand, is based on the working assumption that cumulative disposable income from 1960 to year t is a proxy for accumulated savings in state i. This is also a strong assumption, but if our procedure is materially different from that of Case et al. [2005], then we would expect to find different wealth effects than they did. As we show in Section 2.2, our estimated wealth effects are similar to those in the literature.

We use state-level consumption growth estimates from Zhou [2010] and Zhou and Carroll [2012]. The consumption growth data start in 1971 for all but six states (Alaska, Delaware, Montana, Nevada, New Hampshire and Oregon), whose consumption growth data are available only from 1998 onward.

Table 2 displays summary statistics, and Table 3 shows the correlations among the consumption growth of different states. We use these summary statistics and correlations to calibrate the model at the state level in Section 4. Consumption growth in different states tends to be positively correlated, with the exception of Hawaii, where it is negatively correlated with that of most of the other states. These correlations are somewhat noisy because they are based on a sample of consumption growth that starts in 1998 due to the six states that had available data starting only that year. In fact, if we estimate the correlation of consumption growth in Hawaii with that in other states using the entire sample, we find that the consumption growth in Hawaii is not as negatively correlated with that of the rest of the United States as Table 3 suggests.

2.2 Housing wealth effect

Following the prior literature on housing wealth effects (e.g., Case et al. [2005]), we test for the presence and magnitude of the housing wealth effect in panel regressions of the type

$$\Delta c_{it} = \alpha_i + \beta_{w^H} \Delta w_{it}^H + \beta_{w^{TR}} \Delta w_{it}^{TR} + \beta_y \Delta y_{it} + \epsilon_{it}, \tag{1}$$

where i is the state index and t is the time at which the variables are being measured. Δc_{it}, Δw_{it}^H, Δw_{it}^{TR} and Δy_{it} are, respectively, the log growth in aggregate consumption, housing wealth, tradable wealth, and income in geographic area i from $t-1$ to t. All regressions include state fixed effects.

Table 4 reports the results of the regression in equation 1. The results in specification (5) show an economically and statistically significant wealth effect.[7] The estimated elasticity of consumption with respect to housing wealth is 13%. Moreover, there is no significant relation between growth in tradable wealth and consumption growth. It is possible that the weak relation between changes in tradable wealth and consumption growth stem from the fact that measures of changes in tradable wealth are noisy. Indeed, Case et al. [2013] point out that staff from the Federal Reserve maintain that data from the Survey of Consumer Finances are not appropriate to estimate the stock-market wealth effect at the state level. Of the three estimated elasticities of consumption, the elasticity of consumption with respect to income is the largest at 64%. Income growth also explains a relatively large portion of the variation in consumption growth. Indeed, the R^2 in specification (2) is approximately 15%; when we add housing wealth, this R^2 increases to 17%, indicating that housing wealth explains only a small part of the variation in consumption growth after accounting for income growth.

Overall, our results are consistent with those in the literature that uses state-level data. The housing wealth and the income elasticities in specification (5) are in line with those in Case et al. [2013]. Moreover, even though our estimated tradable wealth elasticity is low compared with that of other studies, the results are in accordance with the finding that housing elasticity is larger than stock elasticity (e.g., Bostic et al. [2009]).

The common-factor hypothesis is one possible explanation for the strong elasticity of consumption with respect to housing wealth that we observe in the data. This hypothesis states that an omitted variable drives both house prices and consumption in regression 1. Instrument variables (IVs) can be used to deal with omitted variables in equation 1. For example, Calomiris et al. [2009], Calomiris et al. [2012] and Case et al. [2013] use lagged variables as instruments. Their objective is to address the common-factor hypothesis under the premise that the permanent-income hypothesis (PIH) holds.[8] This IV approach does not rule out that a common factor drives the strong observed wealth effect for at least two

[7] Results with T-statistics based on standard errors clustered by geographical region are qualitatively similar to those in Table 4 and are available upon request.

[8] The PIH states that consumption at a point in time is function not only of current income but also of expected future income (permanent income). As a result, under the PIH, changes in consumption behave as a random walk because only unexpected changes in permanent income drive changes in consumption (Hall [1988]). Moreover, under the PIH, changes in consumption are uncorrelated with lagged changes in housing wealth.

reasons. First, the choice of lagged variables as instruments rules out the common-factor hypothesis only if the PIH holds, and there is plenty of empirical evidence that the PIH does not hold (e.g., Campbell and Deaton [1989] and Campbell and Mankiw [1990]). Second, the common factor that drives demand for housing and non-housing consumption does not need to be permanent income. For instance, Case et al. [2005, 2013] point out that general confidence in the economy can be the common factor driving non-housing consumption and housing wealth. Another example of the IV approach is Mian et al. [2013]. They use variation of elasticity of supply across MSAs as a means to identify exogenous shocks to house prices during the 2002 to 2006 period. Naturally, the challenge of using IV to estimate equation 1 is to find instruments that are related to house prices and are unrelated to omitted variables driving consumption growth. We show that our results are robust to using lagged variables as instruments in Appendix D. However, our main focus is to analyze the estimation of regression 1 without IVs since the analysis of an IV estimation boils down to the quality of the instruments.

3 A model with inelastic housing supply

To gauge the extent to which the common-factor hypothesis can explain the housing wealth effect at the state level, we use the general equilibrium model of a two-sector production economy developed in Kogan [2001, 2004], where we interpret the durable goods sector with irreversible capital stock as housing. We do not claim that this model explains consumption growth well, as it does not include labour income, which is an important driver of consumption decisions. However, this model is well suited to examining the common-factor hypothesis because it allows consumption and house prices to be driven by a common factor (non-housing capital). Next, we briefly describe this model.[9]

In Kogan's (2001) model, there are two productive sectors, each with the specialized capital input required to produce the two types of consumption goods or services in the economy. Capital in sector H (the housing sector) can only produce housing services. Capital in sector K (the non-housing sector) can be either used to produce the consumption good, C, or converted into housing stock, H. Investment in the housing sector is irreversible; that

[9] See Kogan [2001, 2004] for a detailed description of the model.

is, houses cannot be liquidated into consumption goods or transformed into non-housing capital.

The stock of non-housing capital (K_t) follows the equation of motion:

$$dK_t = (\alpha K_t - C_t)dt + \sigma K_t dW_t - dI_t, \tag{2}$$

where α and σ are, respectively, the mean and the volatility of shocks to growth in non-housing capital, and dW is an increment of a standard Brownian motion. Changes in the housing stock are given by

$$dH_t = -\delta H_t dt + dI_t, \tag{3}$$

where δ is the rate of depreciation. The choice variables are consumption (C_t) and investment in the housing sector in each period (dI_t), both of which are non-negative. We follow Kogan [2001] and set the housing replacement cost to unity.[10]

Households maximize their expected lifetime utility:

$$\max_{\{C_t, I_t\}_{0 \leq t < \infty}} E_0 \left[\int_0^\infty e^{-\rho t} U(C_t, XH_t) dt \right], \tag{4}$$

where ρ is the parameter that specifies household impatience. Households have separable utility over consumption good, C_t, and housing services, XH_t, given by

$$U(C_t, XH_t) = \frac{1}{1-\gamma} (C_t)^{1-\gamma} + \frac{b}{1-\gamma} (XH_t)^{1-\gamma}, \gamma > 0, \gamma \neq 1, \tag{5}$$

where γ is the curvature of the utility function, b can be interpreted as the parameter that captures the size of the housing sector as a fraction of the whole economy, and X represents the productivity of the housing sector.

Kogan [2001] shows that an equilibrium exists in which the process for K_t, H_t, C_t and I_t are equivalent to the solution of a central planner problem that chooses C_t and I_t to solve equation 4 subject to equations 2 and 3. Appendix A provides details about this equilibrium.

Because housing investment is irreversible, the central planner wants to avoid an excess of housing. Therefore, in this model, no increase in housing supply inheres unless the level of housing capital relative to non-housing capital is below a certain threshold. In fact, the central planner's choice of the control variables depends only on the state variable $\omega_t =$

[10] One unit of non-housing capital builds one unit of housing.

$\ln(\Omega_t) = \ln(H_t/K_t)$, and the optimum housing investment policy is such that investment in housing only happens if ω is smaller than or equal to an endogenously determined threshold, ω^*. Formally, the agent chooses $I_t = 0$ at t when $\omega_t > \omega^*$ and $I_t > 0$ otherwise. When $\omega_t = \omega^*$, the agent invests "just enough" to revert to ω^*. That is, ω_t can never be below its corresponding ω^*; thus, investment occurs when $\omega_t = \omega^*$, and the inelasticity of the housing supply is driven only by the irreversibility of housing investments.[11]

The Tobin's q of housing (i.e., the ratio of the market value of housing to its replacement value) is equal to the market value of housing because the replacement value of housing is assumed to be one. Tobin's q of housing is smaller than or equal to one. The market value of housing cannot exceed its replacement value because as soon as the two are equal, housing supply increases and applies downward pressure on the market value of housing.

In the absence of a known analytical characterization, we solve the model numerically to better explain its inner workings. Table 5 reports the parameters used in the numerical solution of the model: b, δ, ρ, γ and X. Recall that b parameterizes the size of the housing sector as a fraction of the total economy. To choose this parameter, we begin by partitioning total wealth into housing wealth, tradable asset wealth and human capital. In the United States, the ratio of human capital to total wealth is estimated to be between 0.75 and 0.92 (see Lustig et al. [2013]; Palacios [2015]; Di Giovanni and Matsumoto [2011]; Jorgenson and Fraumeni [1989]). Assuming that the ratio of housing to tradable asset wealth is between 0.67 and 1.50, we calculate that b should be between 0.03 and 0.15. We set $b = 0.1$, close to the midpoint of this range. The value of the time-discounting parameter that considers both housing and consumption, ρ, lies between 0.01 and 0.05 (see Flavin and Nakagawa [2008]; Piazzesi et al. [2007]; Cocco [2005]; Lustig and Van Nieuwerburgh [2005]). We set $\rho = 0.02$. The parameter δ is the rate of depreciation of housing stock. We assume a value of $\delta = 1.3\%$, which falls within the range of estimates produced in the literature. Harding et al. [2007], Knight and Sirmans [1996], Shilling et al. [1991], Leigh [1980] and Malpezzi et al. [1987], using data at various levels of aggregation and for different time periods, estimate that the

[11]Kogan [2004] also extends this model in which investment is bounded below an exogenously specified bound. In this extension, housing supply is not perfectly elastic when house prices are equal to housing replacement costs. This upper bound on housing supply can potentially be important to match house price dynamics in areas with restricted land availability, such as geographically constrained cities. We do not use the extended model in our simulations because we focus on state-level data.

rate of housing stock depreciation is between 0.43% and 2.18%. For the curvature of the utility function parameter γ, we use a value of 1.2 and set the productivity of the housing sector parameter X equal to 1/30.

It is natural to assume that the parameters in Table 5 are constant across different US states. These parameters are related to the utility function of the households in the model; hence, we should not expect major variation in these parameters across different states. On the other hand, the rate of growth (α) and volatility (σ) of non-housing capital as well as the initial value of the state variable (ω_0) may have some variation across different states, for example because the economies in different states are based on different industries. For the example solution of the model in Figure 1, we set α, σ and ω_0 equal to 4.05%, 6.18% and 1.58%, respectively.[12]

Panel A of Figure 1 plots price per unit of housing and the ratio of consumption to non-housing capital (C/K) as a function of ω (the logarithm of the ratio of housing to non-housing capital). The fact that the agent is always able to transfer an unlimited amount from non-housing capital to housing stock ensures that ω never falls below ω^*, which means that the investment region is the point $\omega = \omega^*$ and the non-investment region is the entire region to the right of ω^* in Panel A. Note that the ratio of consumption to non-housing capital decreases slightly as ω gets closer to ω^*; essentially, households consume less non-housing capital, anticipating the possibility of investment in housing. Moreover, since the housing sector is perfectly competitive, the ability to invest without limits ensures that the market value of housing stock never rises above its replacement value, and Tobin's q reaches its maximum value of one when the agent invests in housing. Within the no-investment region, as ω increases, house prices drop. There is "too much" housing in the non-investment regions and house prices adjust, since housing capital cannot be transformed into non-housing consumption.

Indeed, the non-linearity in C/K and Tobin's q with respect to ω is due to the irreversibility of housing investment. If housing capital were fully reversible to non-housing capital, then

[12] As we show in Section 4, these parameter values allow us to match the model mean consumption growth, volatility and mean housing wealth growth to those observed in Minnesota from 1987 to 2010. We use Minnesota as an example because its mean consumption and housing wealth growth are close to the mean across all 50 states and the District of Columbia in our sample.

the house price would be equal to the replacement cost (which is a constant in this model). Further, consumption would be a constant fraction of non-housing wealth. Thus, if housing investment were perfectly reversible, consumption would be a linear function of non-housing capital, and would be unrelated to house price, which would be constant.

Panel B of Figure 1 plots the log of house price (p) and the log of consumption (c) as functions of the log of non-housing capital (k) under the assumption of a fixed housing capital (H).[13] Panel B shows that c is very close to a linear function of k in this model, given that the variation in C/K is small. Moreover, except for when investment in housing is proximate, p is also close to a linear function of k. Housing wealth increases with non-housing capital due to the irreversibility of housing capital. Indeed, if investment in housing were completely reversible, its price would be a constant in this model and would not covary with consumption.

To understand the extent to which the common-factor hypothesis can explain the housing wealth effect observed in the state-level data, we calibrate this model and estimate a regression analogous to regression 1 with simulated data.

4 Model calibration

Table 5 reports the values we use in the simulation exercise for the parameters common across all states. We assume that non-housing capital shocks (dW) are correlated across states to match the correlation of consumption growth across states shown in Table 3. The parameters α_i, σ_i and $\omega_{0,i}$ vary across states. Specifically, we choose α_i and σ_i to match the mean and volatility of consumption growth in state i in our sample (see Table 2). We have two different procedures to calibrate $\omega_{0,i}$.[14]

In our first calibration procedure, we choose $\omega_{0,i}$ for each state i to match the mean growth in housing stock in Table 2. Panel A of Table 6 displays the average of the mean and volatility of log consumption growth as well as of the mean and volatility of log house price growth across 500 simulations of the model. Panel A of Table 6 also displays the parameters α_i, σ_i and $\omega_{0,i}$ calibrated at the state level. This calibration shows that the model matches

[13]Appendix A gives details about the procedure to plot this figure.
[14]See Appendix B for details about this simulation. Appendix C gives details about the calibration.

the moments of log-consumption growth and the growth in house prices quite well.[15] The calibration, however, generates house price volatility that is smaller than that observed in the actual data. This result is not unexpected since none of the parameters in the calibration are chosen to match the volatility of house prices.

Because our first calibration procedure results in house price volatilities smaller than those observed in the data, we need to assess the robustness of our conclusion to this calibration shortcoming. To do so, we implement a second calibration procedure in which we choose the parameter $\omega_{0,i}$ for each state i to match the volatility—as opposed to the mean—in housing wealth. Panel B of Table 2 displays the results of this calibration. This calibration still matches the moments of consumption growth quite well; however, the mean housing wealth growth in the simulated data is about 1.43% larger than that in the historical data (2.60% versus 1.17%). This worse fit for mean housing wealth growth is the cost of having a better fit for the volatility of housing wealth. The mean volatility in housing wealth growth across all states in the second calibration procedure is 4.05%, which is almost twice as large as that in the first calibration procedure (2.20%) and closer to the mean volatility in the actual data (6.54%).

5 Housing wealth effects in the calibrated model

We use the model calibrated in Section 4 to simulate 500 panels composed by a time series of $\{c_t, k_t, w_t^H\}_{t\in\{1,2,\cdots,T\}}$ for each state i. We set T equal to 30 years and assume that we observe annual consumption growth measured with error ($\Delta\widetilde{c}_{i,t} = \Delta c_{i,t} + \varepsilon_{i,t}^{\widetilde{c}}$), growth in non-housing capital measured with error ($\Delta\widetilde{k}_{i,t} = \Delta k_{i,t} + \varepsilon_{i,t}^{\widetilde{k}}$), and growth in housing wealth measured with error ($\Delta\widetilde{w^H}_{i,t} = \Delta w_{i,t}^H + \varepsilon_{i,t}^{\widetilde{w^H}}$). The noise terms ($\varepsilon_{i,t}^{\widetilde{c}}$, $\varepsilon_{i,t}^{\widetilde{k}}$ and $\varepsilon_{i,t}^{\widetilde{w^H}}$) are zero-mean, normally distributed with variances $\sigma^2_{i,\widetilde{c}}$, $\sigma^2_{i,\widetilde{k}}$ and $\sigma^2_{i,\widetilde{w^H}}$, respectively. The noise terms are independent of each other and of the shocks to non-housing capital.

Using each simulated panel, we estimate panel regressions to assess the housing wealth

[15] To see this, note that the means across all states of the mean and volatility of consumption growth in the simulated data are very close to the means in the real data in Table 2. Also note that the mean across all states of mean growth in housing wealth is 1.13% in simulated data and is 1.17% in Table 2.

effect in the simulated model. Specifically, we estimate the following panel models:

$$\Delta\widetilde{c}_{i,t} = \alpha_i + \beta_{w^H}\Delta\widetilde{w^H}_{i,t} + \beta_k\Delta\widetilde{k}_{i,t} + \epsilon_{i,t}. \tag{6}$$

These panel regressions are analogous to the ones in Section 2.2. Recall that in the simulated model, variations in the log of non-housing capital (k) drive variations in both the log of non-housing consumption (c) and the log of housing wealth (w^H). Besides, if observed without any measurement errors, the common factor (k) would explain the variation in non-housing consumption perfectly. However, our goal is to use the simulations to gauge the extent to which the common-factor hypothesis can explain the observed elasticity of consumption to housing wealth. Thus, we assume that we observe only a noisy proxy for Δk because the hypothesis posits that an unobservable common factor is driving both non-housing consumption and real estate wealth.

Naturally, it is important to know the amount of noise in the variables to analyze the results of our simulations. Even though there is long literature trying to gauge the level of measurement errors in the variables used in the housing wealth effect literature, the noise-to-signal ratios $\sigma^2_{\widetilde{k}}/\sigma^2_k$, $\sigma^2_{\widetilde{w^H}}/\sigma^2_{w^H}$ and $\sigma^2_{\widetilde{c}}/\sigma^2_c$ are ultimately unknown. Because of this, we give results for a wide range of noise-to-signal ratios, and we show that we obtain estimates for β_{w^H} that are consistent with those observed in the actual data even when the noise-to-signal ratios are small compared with those described in the literature.

There is a consensus in the literature about the existence of measurement errors in house prices. Indeed, the literature documents that the overestimation of reported house values is between -2% and 16%.[16] There is no simple direct mapping between these estimates in the literature and the noise-to-signal ratios in our simulations. However, under the following assumptions we obtain that the standard deviation of measurement errors in housing wealth return ($\sigma_{\widetilde{w^H}}$) is equal to 3.67%: First, the observed housing wealth is $\widetilde{W^H}_t = W^H_t e^{x_t}$, where W^H_t is the true housing wealth and x_t is a triangular distributed measurement error within -2% and $+16\%$ and mean 7%. Second, the measurement errors x_t are not autocorrelated. A standard deviation of 3.67% for the noise component of house price changes ($\sigma_{\widetilde{w^H}}$) is about

[16] See Kish and Lansing [1954], Kain and Quigley [1972], Robins and West [1977], Follain and Malpezzi [1981], Ihlanfeldt and Martinez-Vazquez [1986], Goodman and Ittner [1992], Kiel and Zabel [1999], Agarwal [2007], and Benítez-Silva et al. [2015].

50% those in Table 2. This suggests that the estimates of house price biases in the literature imply large noise-to-signal ratios in housing wealth return.

The magnitude of the measurement errors in income is possibly also sizeable. In our setting, income growth is a potential proxy for the common variable (e.g., changes in expected income) driving both consumption and housing wealth growth. Since changes in expected income are not observed, we cannot possibly infer how well changes in actual income proxy changes in expected income. We can, however, have an idea of the magnitude of measurement errors by analyzing how the available data on income growth measure the actual change in income growth. The income data normally used in housing wealth effect studies are from the BEA. The BEA methodology for compiling income data involves surveys, state-level records (tax filings, etc.) and further needs imputations of residential status. Moore et al. [2000] provide a literature review of the quality of survey measures of income and report measurement errors that range from 2% to above 50%. Therefore, the literature indicates that the survey component in the BEA methodology may have sizeable errors.

Measurement error in wealth is a long-standing concern (see Ferber [1959] and Curtin et al. [1989]). Juster and Smith [1997] quantify some of the magnitudes of measurement errors in wealth due to survey techniques. They find that household surveys may understate wealth in the pre-retirement years by 10% relative to the post-retirement years. Juster et al. [1999] compare the wealth reported in two large American household surveys: the Panel Study of Income Dynamics (PSID) and the Survey of Consumer Finances (SCF). They find that PSID understates wealth in home equity, other real estate, stocks and mutual funds, liquid assets, and other debts by 13.2%, 3.6%, 16.6%, 5.5% and 26.9%, respectively, compared with SCF. However, PSID overstates wealth in vehicles by 38.5% compared with SCF. Finally, they show that the differences in the estimation of wealth across surveys vary over time. Their results suggest that the magnitude of the measurement error in wealth is large and time-varying.

Table 7 displays the mean parameters of the estimated wealth effect regression across the 500 simulated panels. Table 7 shows results for different noise-to-signal ratios $\sigma^2_{\tilde{k}}/\sigma^2_k$, $\sigma^2_{\widetilde{w^H}}/\sigma^2_{w^H}$ and $\sigma^2_{\tilde{c}}/\sigma^2_c$, where σ^2_k, $\sigma^2_{w^H}$ and σ^2_c are the variances of Δk, Δw^H and Δc, respectively, without errors. To be parsimonious, we set the noise-to-signal ratios ($\sigma^2_{\tilde{k}}/\sigma^2_k$, $\sigma^2_{\widetilde{w^H}}/\sigma^2_{w^H}$

and $\sigma_{\tilde{c}}^2/\sigma_c^2$) equal to each other. The results in this table allow us to infer the amount of noise needed in all three variables to match the T-statistics and R^2s in the simulated panels with those in the actual data.

Panel A of Table 7 displays the results of the analysis when the noise-to-signal ratio is zero, that is, when we observe the underlying variables without any measurement errors. This panel shows the baseline of the housing wealth effects in the model.[17] The first column shows the results of the panel data regression of Δw^H on Δk. This specification confirms that changes in housing wealth are positively correlated with changes in non-housing capital in this model. The R^2 in this specification is about 61%, which indicates that even when there are no measurement errors, variation in non-housing capital cannot perfectly explain changes in housing wealth. This result is consistent with the fact that house prices are a non-linear function of k in the model (Figure 1, Panel B). In specifications (1) to (3), Δc is the dependent variable. Specification (1) shows that Δw^H explains some of the variation in Δc even when Δk is not an independent variable. Specification (2) shows that Δk explains nearly all of the variation in Δc. In fact, the R^2 in specification (2) is almost one (99.74%). Specification (3) shows that even though Δk almost completely explains variations in Δc, Δw^H plays a very small role in explaining such variations due to the fact that c is not a perfectly linear function of k (see Figure 1, Panel A). However the incremental explanatory power of Δw^H is very small. Indeed, the R^2 in specification (3) is only 0.01% larger than that in specification (2).

Panels B, C and D of Table 7 show the results of the simulated panel regressions with noise-to-signal ratios of 50%, 100% and 150%, respectively. These results indicate that noise-to-signal ratios of around 150% are required to match the R^2s and T-statistics obtained using historical data. While a noise-to-signal ratio of 150% could be considered implausibly high, it is interesting to note that the housing wealth effects estimated when using such a large level of noise are around 37%, which is much higher than the 13% observed in the data. The results also indicate that for any of the considered non-zero noise-to-signal ratios, the estimated elasticity of consumption to housing wealth effect (β_{w^H}) is around 40%, which is

[17] In the following discussion, for convenience, we omit the tilde over the variables even when the variables are measured with errors.

much larger than that in the actual data.

It is interesting to note that the results in Table 7 are consistent with the attenuation bias commonly described in the literature. To see this, note that the coefficients in the univariate specifications decrease as the noise-to-signal ratio increases across the panels in Table 7. At first glance, the only result that is not consistent with the classic attenuation bias is the increase in the point estimate of β_{w^H} from Panel A to Panel B. To understand this apparent inconsistency, note that the attenuation bias is a result related to measurement error in *one* independent variable (see Wooldridge [2010]) while the measurement errors of *two* independent variables change between Panels A and B of Table 7. The intuition for the increase in β_{w^H} from Panel A to Panel B is in fact simple. In Panel A, growth in housing wealth plays a very small role in explaining consumption growth because growth in non-housing capital completely drives consumption growth in the model. On the other hand, in Panel B, both $\Delta\widetilde{w^H}$ and $\Delta\widetilde{k}$ are noisy proxies for the true variation in non-housing capital, and hence they both contribute to explaining consumption growth.

Figure 2 shows that a large, and statistically significant, housing wealth effect is estimated in panel regressions even when measurement errors are fairly small. Figure 2 plots the estimated elasticity of consumption to housing wealth (β_{w^H}) as a function of the noise-to-signal ratio of Δc, Δw^H and Δk. Interestingly, β_{w^H} increases very sharply when the errors in variables are small (see the inset figure on the bottom-left part of the graph). An increase from 0% to 1% in the noise-to-signal ratio of Δc, Δw^H and Δk increases β_{w^H} by 4%. The mean estimate of β_{w^H} for a noise-to-signal ratio of 3% is 11.9%, close to the estimate in the historical data (see Table 1).

Recall that our calibrations do not generate the same level of housing wealth volatility as that in the actual data. The results in Table 8—which displays the results of simulations based on the calibration of the model designed to match the volatility rather than the mean of housing wealth (see Panel B of Table 6)—indicate that this calibration shortcoming does not make a qualitative difference to the results. Even though the volatility of housing wealth doubles from Table 7 to Table 8, the elasticity of consumption to housing wealth remains high. In fact, the estimated elasticity is about 30% in Panel D of Table 8, which is much larger than that observed in the empirical literature.

It is plausible that some of the variables are better measured than others. To understand the contribution of measurement errors in the different variables to the housing wealth effect, we run regressions on panels generated with combinations of different noise-to-signal ratios in the independent variables, $\Delta\widetilde{w^H}$ and $\Delta\widetilde{k}$.[18] Specifically, we set the noise-to-signal ratios of the dependent variables to values between 5% and 30%. The mean estimated coefficients, T-statistics and R^2s over 500 simulations are presented in Tables 9 and 10. The results in Table 9 (Table 10) are based on simulations with $\omega_{0,i}$ set to match the mean (volatility) of house price growth in state i.

The results in Tables 9 and 10 are consistent with the attenuation bias in the presence of measurement errors in the independent variables. For instance, the results indicate that for a given value of $\sigma^2_{\widetilde{k}}/\sigma^2_k$, the coefficient on housing wealth decreases with $\sigma^2_{\widetilde{w^H}}/\sigma^2_{w^H}$. The fact that these results are consistent with the attenuation bias is unsurprising since both log-consumption growth and log-housing wealth growth are close to linear functions of the log of non-housing wealth in the model (see Figure 1). The attenuation bias has received attention in the wealth effects literature (e.g., Brunnermeier and Nagel [2008], Juster et al. [2006], and Filmer and Pritchett [2001]). The results in Tables 9 and 10 point out another effect related to measurement errors that has not received attention and is important. Specifically, notice that for a given value of $\sigma^2_{\widetilde{w^H}}/\sigma^2_{w^H}$, the coefficient on housing wealth increases with $\sigma^2_{\widetilde{k}}/\sigma^2_k$. That is, even if there is no causal relation between housing wealth and consumption growth, we can estimate very large elasticities of consumption to housing wealth if our proxies of non-housing wealth are noisy and there is a non-housing wealth effect.

The relation between Δw^H and Δk in the calibrated model combined with even small errors in Δk are sufficient to generate housing wealth effects larger than those observed in the data. Note in Table 9 that even with a noise-to-signal ratio of 5% in Δk, the average point estimate of β_{w^H} is around 15%. In other words, our simulation results indicate that it is easy to generate economically large housing wealth effects when the common factor that is the sole driver of house price and consumption growth is measured with error. Table 10, which presents results when $\omega_{0,i}$ is chosen to match the volatility of house price growth,

[18] For these simulations, we do not add noise to consumption growth, since noise in the dependent variable affects the T-statistics and the regression R^2s but does not change the point estimates of the coefficients.

shows that the above conclusions are not due to the model's inability to generate sufficiently volatile house price growth.

Overall, our results suggest that a large amount of the housing wealth effect estimated at the state level can be explained by the common-factor hypothesis. It is perhaps surprising that our structural model can generate wealth effects that are consistent with or even larger than those in the data despite omitting other mechanisms suggested in the literature, such as the relaxation of collateral constraints. Our structural model is a fairly simplified version of reality, and a large literature examining the equity premium puzzle shows that consumption models based on simple power utility normally do not match some of the asset returns moments well. However, our results suggest that matching model-generated β_{w^H} with the values that we observe in the actual data is not a problem for models based on simple power utility as long as housing is inelastic and the common factor driving both non-housing consumption and demand for housing is measured with errors.

6 Conclusion

The common-factor hypothesis is one possible explanation for the large housing wealth effect that is commonly estimated in the literature. According to this hypothesis, shocks to a common unobservable factor, such as expected future income, simultaneously affect the demand for housing services and non-housing consumption. Even though the building blocks of the common-factor hypothesis are well established in the literature (the supply of housing is somewhat inelastic and consumption as well as wealth data are plagued with noise), it is an open question how much of the large elasticity of consumption to housing wealth can be explained by this hypothesis.

Our results indicate that the common-factor hypothesis possibly accounts for a large portion of the estimated elasticity of consumption with respect to housing wealth. Naturally, either our analysis or results can discard the other hypotheses that have been put forward to explain the housing wealth effect. Our simulations, however, show that even when the common variable driving consumption and housing wealth is observed with relatively small measurement errors, we find quite large elasticities of consumption to housing wealth.

Our simulated model can easily generate housing wealth effects that are consistent with or even larger than those observed in the data despite omitting other mechanisms suggested in the literature, such as the relaxation of collateral constraints or direct housing wealth effects. In fact, the mechanism by which the model generates large housing wealth effects relies only on two generally accepted premises: first, that housing cannot be converted into non-housing consumption in aggregate; and second, that econometricians can only observe noisy proxies of the variables affecting consumption. We therefore conclude that, once properly benchmarked with a model that takes into account the common-factor hypothesis, the large elasticity of consumption to housing wealth estimated with US state-level data is not puzzling.

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Appendix

A - Details about the model

Kogan's (2001, 2004) model features two productive sectors, each with a specialized capital input required to produce the two types of consumption goods or services in the economy. Capital in sector H (the housing sector) can only produce housing services. Capital in sector K (the non-housing sector) can either be used to produce the consumption good, C, or converted into housing stock, H. Investment in the housing sector is irreversible; that is, houses cannot be liquidated and turned into the consumption good.

The stock of non-housing capital (K_t) follows the equation of motion:

$$dK_t = (\alpha K_t - C_t)dt + \sigma K_t dW_t - dI_t, \tag{7}$$

where α and σ are, respectively, the mean and volatility of shocks to growth in non-housing capital, and dW_t is an increment of a standard Brownian motion. dI_t is the investment in the housing sector at time t.

Identical, perfectly competitive firms own all of the capital in sector H used to produce the housing service XH_t for consumption, with X representing the productivity of the housing sector; firms rent out the houses that they own. Firms determine the level of investment at each t to solve the maximization problem

$$\max_{\{I\}_{0\leq t<\infty}} E_0 \left[\int_0^\infty \eta_{0t} S_t X H_t dt - \eta_{0t} dI_t \right], \tag{8}$$

where S_t is the rent for one unit of housing in units of the consumption good C at time t, and η_{0t} is the stochastic discount factor. The first term in the integral above is the present value of all the rents that firms receive from housing. The second term is the present value of all the investment in housing. Changes in the housing stock are given by

$$dH_t = -\delta H_t dt + dI_t, \tag{9}$$

where δ is the rate of depreciation.

Households maximize their expected lifetime utility:

$$\max_{\{C_t, I_t\}_{0\leq t<\infty}} E_0 \left[\int_0^\infty e^{-\rho t} U(C_t, XH_t) dt \right], \tag{10}$$

where ρ is the parameter that specifies household impatience. Households whose coefficient of risk aversion is γ have utility separable over the consumption good, C_t, and housing services, XH_t, given by[19]

$$U(C_t, XH_t) = \frac{1}{1-\gamma}(C_t)^{1-\gamma} + \frac{b}{1-\gamma}(XH_t)^{1-\gamma}, \gamma > 0, \gamma \neq 1, \tag{11}$$

where b can be interpreted as the parameter that captures the size of sector H as a fraction of the whole economy.

Households also have access to two long-term financial assets. The value of the first asset at time t is v_t, and it follows the dynamic $dv_t = \alpha v_t dt + \sigma v_t dW_t$. The second asset is a claim on all housing sector cash flows; in other words, the second claim is equivalent to the stock in the housing sector firms. In addition, households have access to a short-term bond.

Kogan [2001] shows that an equilibrium exists in which the processes for K_t, H_t, C_t and I_t are equivalent to the solution of a central planner problem that chooses C_t and I_t to solve the maximization in equation 10, subject to equations 7 and 9. In fact, the central planner's choice of the control variables depends only on the state variable $\omega_t = \ln(\Omega_t) = \ln(H_t/K_t)$. In equilibrium, the optimal consumption policy is given by the following equation:

$$\tilde{c}(\omega_t) = \frac{C_t}{K_t} = \left(f(\omega_t) - \frac{1}{1-\gamma}f'(\omega_t)\right)^{-\frac{1}{\gamma}}, \tag{12}$$

where f is the function that satisfies the ordinary differential equation (ODE):

$$p_2 f''(\omega) + p_1 f'(\omega) + p_0 f(\omega) + \gamma\left(f(\omega) - \frac{1}{1-\gamma}f'(\omega)\right)^{1-\frac{1}{\gamma}} = -be^{(1-\gamma)\omega}, \tag{13}$$

subject to the boundary conditions

$$f'(\omega^*)(1+\Omega^*) = f(\omega^*)\Omega^*(1-\gamma) \tag{14}$$

$$f''(\omega^*)(1+\Omega^*) = f'(\omega^*)(1+(1-\gamma)\Omega^*) \tag{15}$$

$$\lim_{\omega\to\infty} f(\omega) = \left(\alpha\frac{\gamma-1}{\gamma} - \frac{\sigma^2}{2}(\gamma-1) + \frac{\rho}{\gamma}\right)^{-\gamma}, \tag{16}$$

[19]Kogan [2001] also considers the case $\gamma = 1$; the qualitative relationships between the variables that we investigate in our study—consumption, investment, and prices—do not change if we use $\gamma = 1$.

and p_0, p_1, p_2 are constants with the following values:

$$p_0 = (1-\gamma)\alpha - \gamma(1-\gamma)\frac{\sigma^2}{2} - \rho \quad (17)$$

$$p_1 = -\alpha - \delta + (2\gamma - 1)\frac{\sigma^2}{2} \quad (18)$$

$$p_2 = \frac{\sigma^2}{2}. \quad (19)$$

The optimal housing investment policy is such that investment in housing only happens if ω is equal to an endogenously determined threshold, ω^*. Formally, the agent chooses $I_t = 0$ at t when $\omega_t > \omega^*$ and $I_t > 0$ when $\omega_t = \omega^*$. The variable ω follows the process:

$$d\omega = \mu_\omega(\omega_t)dt - \sigma dW_t + dL_t$$
$$\mu_\omega(\omega_t) = -\alpha - \delta + \tilde{c}_t(\omega_t) + \frac{\sigma^2}{2}$$

where dL_t is zero when $\omega_t > \omega^*$ and is larger than zero when $\omega_t = \omega^*$. Consequently, dL_t is different from zero only when investment in the housing sector occurs. Specifically, $dL_t = (1 + \Omega^*)H_t^{-1}dI_t$, and ω is a process with a reflexive boundary at ω^*.

The market value of one unit of housing is given by

$$P(\omega_t) = \frac{f'(\omega)\Omega^{-1}}{(1-\gamma)\, f(\omega) - f'(\omega)}, \quad (20)$$

which is bounded by the replacement cost. This market value is equal to the Tobin's q of housing since the replacement cost is assumed to be equal to one.

We use equations 12 and 20 to plot the consumption-to-capital ratio (C/K) and house price (P) as a function of ω in Panel A of Figure 1. For a fixed value of the housing stock, ω is a linear transformation of $\ln K$ (k), and we can rewrite equations 12 and 20 to make C/K and P functions of k. In Panel B of Figure 1, we set H arbitrarily equal to 10, and plot $\ln P$ (p) and $\ln C$ (c) as functions of k using the parameters α and σ used to calibrate the model to Minnesota. (See Appendix C for details about this calibration.)

B - Simulating the model

We simulate panels of house price appreciation, consumption growth and non-housing capital following Kogan's model. Each panel is composed of 30 annual observations of each variable of interest for each simulated state i. The model parameters are those in Table 5 along with α_i, σ_i, $\omega_{0,i}$ and Σ (the correlation matrix of shocks in non-housing capital across states). We choose the parameters based on the calibration procedure described in Appendix C. For given values of the model parameters, we first solve the ODE in Appendix A to obtain the functions $f(\omega)$, $\tilde{c}(\omega_t)$, $q(\omega_t)$ and ω^* for each state. Once we have these functions, we simulate the time series of ω using the following algorithm.

1. For a given $\omega_{0,i}$, obtain the values of $\tilde{c}(\omega_{0,i})$ and $q(\omega_{0,i})$.

2. Generate a random shock to the growth rate of non-housing capital $\Delta W_{\Delta t,i} \sim \mathcal{N}\left(\mathbf{0}, \sigma^2 \Delta t\right)$. The correlation of these random shocks across states is Σ. We set $\Delta t = 1/1000$ in all our simulations.

3. Find $\omega_{\Delta t,i}$ with the discrete approximation $\omega_{\Delta t,i} = \omega_{0,i} + \mu_\omega(\omega_{0,i})\Delta t - \sigma_i \Delta W_{\Delta t,i}$.

4. If $\omega_{\Delta t,i} > \omega_i^*$ proceed to next point; otherwise, make $\Delta L_{0,i} = \omega_i^* - \omega_{\Delta t,i}$, and $\omega_{\Delta t,i} = \omega_{\Delta t,i} + \Delta L_{0,i}$.

5. Calculate $\Delta I_{0,i}$ as $(1 + \Omega_i^*)^{-1} H_{t,i} \Delta L_{0,i}$, $\Delta H_{\Delta t,i}$ and $\Delta K_{\Delta t,i}$ with the Euler discrete approximation of equations 9 and 7. Without loss of generality, we set $K_{0,i}$ equal to one.

6. Repeat Step 1 with $\omega_{\Delta t,i}$ instead of $\omega_{0,i}$ until a time series with length T for the variables of interest is obtained.

C - Model calibration

In the calibration, we choose the model parameters α_i, σ_i, $\omega_{0,i}$ for each state that match the mean and volatility of consumption growth as well as the mean house price appreciation displayed in Table 2.

We choose the parameters α_i and σ_i to enable the mean and volatility of consumption growth in the simulations to match the data from state i. We choose the parameter $\omega_{0,i}$ to match either the mean or the volatility of house price appreciation shown in Table 2. We choose the correlation matrix Σ to match the correlations of consumption growth in Table 3.

The starting point of our calibration is the observation that although $\tilde{c}(\omega_{t,i})$ is a non-linear function (see Figure 1), the variation in $\tilde{c}(\omega_{t,i})$ is small, and $\tilde{c}(\omega_{t,i})$ is close to a constant. In fact, $\tilde{c}(\omega_{t,i})$ is close to:

$$\tilde{c}_i = \lim_{\omega_{t,i}\to\infty} \tilde{c}(\omega_{t,i}) = \frac{\gamma-1}{\gamma}\alpha_i - \sigma_i^2 \frac{\gamma-1}{2} + \frac{\rho}{\gamma}. \tag{21}$$

As a result, in our calibration we choose the parameters α_i, σ_i and Σ in which the amount of housing capital is much larger than the amount of non-housing capital ($\omega_{t,i} \to \infty$). In this economy, the investment in housing is zero, and the log of non-housing capital follows an arithmetic Brownian motion

$$dk_{t,i} = \left(\alpha_i - \tilde{c}_i - \frac{1}{2}\sigma_i^2\right) dt + \sigma_i dW_{t,i}.$$

Because the level of consumption is $C_{t,i} = \tilde{c}_i K_{t,i}$, the log-consumption process has the same drift and volatility as $k_{t,i}$. We therefore set σ_i equal to the estimated volatility of consumption growth in Table 2 for the state i. We set the correlation matrix Σ equal to the matrix in Table 3. We use the parameter α_i to solve the following equation:

$$\left(\alpha_i - \tilde{c}_i - \frac{1}{2}\sigma_i^2\right) = \bar{c}_i,$$

where $\bar{c}_i$ is the mean consumption growth in Table 2 for the state i.

Once the parameters α_i and σ_i are set, we solve the ODE in Appendix A and then simulate the model for each state as described in Appendix B using different starting values $\omega_{0,i}$. We then search for the $\omega_{0,i}$ that creates the mean or volatility of house price appreciation closest to that displayed in Table 2 for state i.

D - Robustness of results using lagged variables as instruments

Under the PIH, current period consumption growth is driven by contemporaneous innovations in the permanent income and is independent of lagged changes in permanent income. Hence, one way to address the common-factor hypothesis under the assumption that the PIH holds is to use lagged values of growth in consumption, income, housing, and non-housing wealth as instruments in an IV estimation of equation 1.

In this appendix we show that our results are robust to using lagged variables as instruments. First, we verify that the results in Table 4 are robust to using the first four lags of the growth of consumption, income, tradable wealth and housing wealth as instruments. The estimate of the wealth effect, β_{w^H}, reported in Appendix Table 1 is 11.17% for the full model, which is very similar to 12.66% obtained in fixed-effects regressions reported in Table 4. Second, we verify that our simulation results are not changed with this IV approach. The results of the fixed-effects regressions using the first four lags of the growth of consumption, housing wealth and non-housing wealth as instruments are shown in Appendix Table 2. Comparing Appendix Table 2 with Table 9, we see no significant differences in the magnitude of β_{W^H} estimated with or without IVs.

Table 1: **Variable Definitions.** This table contains the description and sources of all data variables used in this paper.

Variable name	Variable definition
$Total^{TR}$	Total nominal tradable assets in the United States. Obtained by adding the following item lines from the Federal Reserve Flow of Accounts: corporate equities, mutual fund shares and private pension fund reserves. Source: http://www.federalreserve.gov/releases/z1/Current/data.htm
CPI	US-level consumer price index. Source: http://www.bls.gov/cpi/#tables
CDI	Cummulative disposible income for each state between 1960 and year t. $CDI_{i,t}$ for state i at year t is the sum of the total disposable income for state i for every year between 1960 and t. The $CDI_{i,t}$ calculation starts in 1960 because this is the first year that income data are available for every state. Sources: Historical series of disposable income for states are in Table SA51 of the US Bureau of Economic Analysis. http://www.bea.gov/itable/iTable.cfm?ReqID=70&step=1#reqid=70&step=1&isuri=1
Δc	Difference in the log of aggregate real non-housing consumption between years $t-1$ and t. At the state level, this is calculated by adding the log growth in population to the estimates of real non-housing consumption growth in Zhou (2010), which are available since 1971 for most states with the exception of Alaska, Delaware, Montana, Nevada, New Hampshire and Oregon, which have consumption growth data available from 1998 onwards.
$FHFA\_index$	All-transactions FHFA house price index for US states. All-transactions indices augment purchase-only data with appraisal data; see original data source for details. Source: http://www.fhfa.gov/DataTools/Downloads/pages/house-price-index.aspx
Δw^H	Difference in the logarithm of the aggregate house price index between years $t-1$ and t. The aggregate house price index is obtained by multiplying the $FHFA\_index$ by the aggregate number of households. The number of households in year t is obtained by dividing the total population in a region in year t by the average household size in the region in year t. Data on the population and average household size are both provided by the US Census Bureau. The aggregate nominal housing index is then deflated by CPI. Source: Population and persons per household available from http://www.census.gov/geography.html.
Δw^{TR}	Difference in the logarithm of real non-housing tradable wealth between years $t-1$ and t. Real per-capita non-housing wealth in state i in year t is obtained by $Total^{TR} \times CDI_{i,t} / \sum_{i=1}^{50} CDI_{i,t}$ deflated by CPI.
Δy	Difference between the logarithm of real aggregate income at year $t+1$ and at year t. Total real income is obtained by deflating the estimate of the total nominal income (obtained from the Bureau of Economic Analysis) by CPI. Source: http://www.bea.gov/regional/downloadzip.cfm

Table 2: **Summary Statistics.** This table contains the mean and standard deviation (Std. Dev.) of the annual real log growth of aggregated non-housing consumption (Δc), housing wealth (Δw^H), non-housing tradable wealth (Δw^{TR}) and income (Δy) for all US states and the District of Columbia. Details of variable construction are specified in Table 1. The sample consists of annual observations from 1976–2012, with the exception that non-housing consumption growth data begin in 1998 for Alaska, Delaware, Montana, Nevada, New Hampshire and Oregon.

	Δc		Δw^H		Δw^{TR}		Δy	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
AL	1.25	2.69	0.57	3.80	5.01	12.98	1.49	1.90
AK	2.04	1.92	1.07	9.49	4.26	12.74	0.16	2.92
AZ	0.39	4.97	1.04	8.74	4.43	12.83	1.0	2.50
AR	1.06	3.62	0.50	4.63	5.01	12.97	1.53	2.26
CA	1.46	3.84	2.32	9.95	4.33	12.93	1.11	2.28
CO	1.61	4.40	1.50	5.10	4.66	12.95	1.35	2.14
CT	2.51	8.68	1.85	8.18	5.03	13.04	1.78	2.63
DE	1.49	1.39	1.43	6.02	4.43	12.90	1.13	1.99
DC	3.08	5.71	3.49	8.72	4.72	12.93	1.94	2.54
FL	1.13	3.52	0.59	7.98	4.84	13.00	1.24	2.33
GA	1.24	3.79	0.01	3.96	4.63	12.94	1.38	2.39
HI	2.24	5.27	3.70	16.79	4.36	13.04	0.78	2.09
ID	0.72	4.16	0.55	6.19	4.34	12.97	0.96	2.42
IL	0.47	3.78	0.68	5.67	4.63	12.93	1.16	2.17
IN	0.65	5.36	0.29	3.38	4.57	12.93	1.17	2.48
IA	0.93	4.39	0.27	4.44	4.71	12.93	1.37	3.04
KS	1.31	4.38	0.06	3.55	4.63	12.94	1.27	2.04
KY	2.43	4.36	0.63	3.49	4.88	12.95	1.40	1.98
LA	1.68	5.41	0.80	4.39	5.17	13.16	1.71	2.28
ME	2.17	4.51	2.02	7.27	5.00	13.13	1.63	2.14
MD	1.50	5.07	1.68	6.56	4.85	12.99	1.51	1.84
MA	3.23	6.39	2.70	8.14	5.02	13.04	1.91	2.43
MI	1.31	6.34	0.55	6.13	4.68	12.92	1.00	2.75
MN	1.55	6.18	1.07	5.19	4.78	12.96	1.55	2.44
MS	0.79	3.24	0.10	4.62	5.10	12.96	1.64	1.88
MO	0.37	4.02	0.48	4.22	4.63	12.95	1.23	1.88
MT	2.36	1.53	1.77	6.01	4.38	12.97	1.14	2.38
NE	1.10	6.51	0.13	3.68	4.72	12.95	1.41	2.68
NV	1.02	2.90	0.10	9.66	3.92	12.94	0.62	2.82
NH	1.89	1.47	2.10	9.39	5.24	13.14	1.90	2.56
NJ	1.59	3.79	2.09	7.74	4.92	12.98	1.61	2.22
NM	1.66	5.06	1.09	4.83	4.55	12.88	1.24	1.64
NY	1.29	3.02	1.96	6.97	4.68	12.98	1.58	2.31
NC	2.21	5.11	0.70	3.46	4.74	13.00	1.48	2.21
ND	1.74	5.18	1.17	7.32	4.64	12.94	2.06	6.97
OH	2.64	3.46	0.25	3.86	4.65	12.97	1.18	2.05
OK	1.52	4.52	0.14	4.57	4.73	12.90	1.45	2.61
OR	1.41	2.32	1.78	7.85	4.48	12.99	1.02	2.29
PA	2.00	3.99	1.13	4.99	4.84	12.99	1.45	1.62
RI	1.48	4.93	2.06	8.92	4.85	13.06	1.60	2.06
SC	1.75	6.14	0.90	3.21	4.83	12.99	1.40	1.91
SD	2.35	4.12	0.95	7.36	4.73	12.88	1.70	4.09
TN	1.24	4.04	0.46	3.54	4.95	12.98	1.58	2.24
TX	1.27	3.61	0.13	3.80	4.59	12.89	1.46	2.42
UT	3.02	9.56	0.92	6.19	4.24	12.98	1.25	2.27
VT	2.64	5.41	2.72	15.26	5.17	13.08	1.86	2.22
VA	1.31	3.46	1.48	5.49	4.86	13.02	1.57	1.79
WA	1.72	5.46	2.13	6.97	4.51	12.98	1.29	2.22
WV	1.32	8.02	0.13	7.56	4.94	13.01	1.38	1.70
WI	1.83	5.69	0.76	5.16	4.77	12.98	1.34	1.92
WY	1.09	7.03	1.06	6.21	4.82	13.05	1.58	3.76

Table 3: **Correlation of Consumption Growth.** This table presents the correlation of annual real log growth of aggregated non-housing consumption (Δc) between states in the United States. The sources and details of variable construction are specified in Table 1. Data for the period 1998–2012 are used for estimating the sample correlations.

	AL	AK	AZ	AR	CA	CO	CT	DE	DC	FL	GA	HI	ID	IL	IN	IA	KS
AK	0.54																
AZ	0.80	0.40															
AR	0.69	0.41	0.83														
CA	0.77	0.51	0.95	0.84													
CO	0.58	0.54	0.77	0.82	0.85												
CT	0.82	0.42	0.90	0.69	0.90	0.77											
DE	0.84	0.78	0.78	0.65	0.78	0.73	0.81										
DC	0.51	0.45	0.45	0.14	0.52	0.27	0.52	0.44									
FL	0.75	0.43	0.89	0.70	0.80	0.69	0.77	0.76	0.44								
GA	0.77	0.49	0.89	0.91	0.93	0.91	0.85	0.76	0.27	0.75							
HI	-0.32	0.01	-0.31	-0.56	-0.44	-0.39	-0.37	-0.09	-0.22	-0.10	-0.46						
ID	0.78	0.55	0.91	0.88	0.92	0.82	0.82	0.80	0.38	0.84	0.90	-0.41					
IL	0.70	0.36	0.84	0.82	0.89	0.81	0.79	0.59	0.50	0.81	0.87	-0.60	0.86				
IN	0.81	0.54	0.85	0.86	0.89	0.86	0.87	0.82	0.39	0.81	0.91	-0.50	0.87	0.88			
IA	0.55	0.23	0.70	0.83	0.73	0.74	0.68	0.49	0.22	0.53	0.75	-0.78	0.71	0.80	0.79		
KS	0.58	0.45	0.84	0.82	0.88	0.94	0.81	0.71	0.24	0.75	0.90	-0.40	0.83	0.84	0.86	0.80	
KY	0.80	0.61	0.72	0.67	0.70	0.73	0.83	0.88	0.32	0.70	0.76	-0.30	0.77	0.65	0.82	0.62	0.73
LA	0.13	0.02	0.48	0.26	0.45	0.27	0.37	0.19	0.35	0.54	0.27	-0.18	0.54	0.50	0.29	0.32	0.42
ME	0.61	0.52	0.73	0.63	0.68	0.71	0.78	0.74	0.25	0.70	0.69	-0.11	0.64	0.59	0.74	0.55	0.75
MD	0.67	0.61	0.86	0.79	0.83	0.88	0.75	0.80	0.37	0.87	0.84	-0.11	0.82	0.77	0.80	0.60	0.85
MA	0.61	0.49	0.82	0.80	0.85	0.88	0.74	0.68	0.37	0.77	0.85	-0.28	0.82	0.82	0.83	0.65	0.82
MI	0.63	0.47	0.72	0.90	0.81	0.88	0.74	0.66	0.17	0.56	0.90	-0.67	0.84	0.80	0.88	0.87	0.85
MN	0.63	0.75	0.70	0.74	0.78	0.89	0.75	0.84	0.26	0.66	0.85	-0.26	0.80	0.69	0.84	0.59	0.86
MS	0.77	0.47	0.83	0.74	0.79	0.73	0.86	0.81	0.35	0.80	0.79	-0.37	0.91	0.76	0.82	0.68	0.78
MO	0.62	0.62	0.61	0.65	0.77	0.81	0.76	0.70	0.44	0.45	0.80	-0.56	0.68	0.71	0.79	0.67	0.78
MT	0.76	0.64	0.72	0.49	0.80	0.64	0.86	0.83	0.59	0.63	0.71	-0.25	0.72	0.64	0.73	0.48	0.71
NE	0.65	0.68	0.78	0.81	0.83	0.85	0.78	0.87	0.26	0.66	0.83	-0.33	0.87	0.67	0.86	0.70	0.85
NV	0.81	0.47	0.94	0.72	0.86	0.69	0.86	0.87	0.42	0.86	0.78	-0.08	0.84	0.65	0.77	0.53	0.73
NH	0.70	0.76	0.75	0.82	0.78	0.89	0.73	0.88	0.28	0.72	0.84	-0.25	0.83	0.70	0.86	0.67	0.83
NJ	0.70	0.65	0.85	0.64	0.90	0.79	0.82	0.77	0.65	0.81	0.81	-0.17	0.83	0.81	0.77	0.47	0.78
NM	0.58	0.50	0.78	0.58	0.79	0.65	0.72	0.70	0.47	0.72	0.66	-0.22	0.76	0.70	0.67	0.57	0.77
NY	0.79	0.48	0.88	0.85	0.87	0.87	0.89	0.80	0.35	0.86	0.91	-0.40	0.91	0.88	0.94	0.72	0.86
NC	0.69	0.33	0.86	0.90	0.89	0.89	0.84	0.66	0.27	0.74	0.93	-0.55	0.89	0.88	0.90	0.79	0.86
ND	0.28	0.09	0.06	0.32	0.21	0.13	0.12	0.15	-0.04	0.06	0.27	-0.59	0.25	0.31	0.41	0.34	0.18
OH	0.68	0.66	0.74	0.82	0.82	0.89	0.75	0.77	0.27	0.72	0.90	-0.35	0.82	0.80	0.90	0.63	0.86
OK	0.54	0.13	0.68	0.68	0.72	0.62	0.61	0.45	0.26	0.58	0.68	-0.56	0.72	0.76	0.69	0.75	0.69
OR	0.62	0.19	0.88	0.86	0.88	0.67	0.74	0.50	0.37	0.71	0.80	-0.59	0.83	0.86	0.78	0.82	0.76
PA	0.71	0.75	0.81	0.79	0.83	0.90	0.80	0.91	0.35	0.76	0.85	-0.20	0.86	0.72	0.86	0.62	0.86
RI	0.79	0.65	0.79	0.79	0.78	0.67	0.67	0.78	0.46	0.71	0.77	-0.30	0.84	0.70	0.73	0.52	0.62
SC	0.84	0.45	0.88	0.80	0.87	0.77	0.93	0.79	0.42	0.78	0.86	-0.46	0.90	0.83	0.89	0.74	0.78
SD	0.65	0.36	0.67	0.76	0.70	0.51	0.65	0.59	0.19	0.42	0.67	-0.63	0.70	0.58	0.68	0.76	0.61
TN	0.87	0.47	0.87	0.89	0.86	0.78	0.87	0.78	0.33	0.78	0.91	-0.54	0.90	0.86	0.92	0.80	0.80
TX	0.64	0.41	0.66	0.82	0.74	0.89	0.68	0.64	0.08	0.60	0.89	-0.50	0.75	0.79	0.86	0.76	0.84
UT	0.64	0.21	0.93	0.75	0.89	0.77	0.84	0.62	0.48	0.85	0.80	-0.40	0.81	0.88	0.79	0.73	0.86
VT	0.65	0.09	0.66	0.48	0.62	0.35	0.63	0.39	0.52	0.56	0.50	-0.37	0.54	0.62	0.53	0.57	0.39
VA	0.80	0.69	0.83	0.75	0.87	0.90	0.87	0.89	0.49	0.76	0.89	-0.29	0.85	0.78	0.86	0.62	0.83
WA	0.55	0.37	0.73	0.73	0.77	0.89	0.79	0.62	0.31	0.69	0.80	-0.49	0.71	0.84	0.86	0.82	0.92
WV	0.53	0.57	0.36	0.50	0.40	0.53	0.49	0.50	0.20	0.31	0.54	-0.44	0.50	0.49	0.53	0.55	0.49
WI	0.76	0.48	0.97	0.83	0.94	0.81	0.91	0.80	0.47	0.85	0.87	-0.36	0.92	0.84	0.85	0.75	0.87
WY	0.64	0.36	0.81	0.63	0.82	0.66	0.79	0.67	0.44	0.66	0.70	-0.36	0.80	0.71	0.69	0.70	0.75

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	KY	LA	ME	MD	MA	MI	MN	MS	MO	MT	NE	NV	NH	NJ	NM	NY	NC
LA	0.23																
ME	0.84	0.20															
MD	0.73	0.30	0.80														
MA	0.57	0.28	0.64	0.88													
MI	0.74	0.24	0.61	0.69	0.76												
MN	0.86	0.23	0.80	0.82	0.71	0.81											
MS	0.91	0.57	0.73	0.72	0.64	0.77	0.78										
MO	0.76	0.15	0.64	0.62	0.57	0.82	0.87	0.67									
MT	0.79	0.34	0.68	0.62	0.53	0.58	0.78	0.75	0.83								
NE	0.80	0.29	0.75	0.78	0.80	0.86	0.88	0.81	0.75	0.72							
NV	0.74	0.38	0.72	0.82	0.74	0.61	0.67	0.81	0.51	0.71	0.78						
NH	0.85	0.18	0.79	0.90	0.80	0.84	0.92	0.78	0.75	0.65	0.91	0.76					
NJ	0.66	0.47	0.68	0.85	0.80	0.62	0.80	0.72	0.73	0.83	0.73	0.78	0.74				
NM	0.59	0.56	0.61	0.70	0.66	0.53	0.66	0.71	0.59	0.80	0.74	0.70	0.60	0.80			
NY	0.88	0.40	0.82	0.85	0.83	0.84	0.85	0.91	0.74	0.72	0.83	0.80	0.85	0.81	0.69		
NC	0.71	0.36	0.67	0.78	0.88	0.91	0.75	0.80	0.70	0.58	0.82	0.74	0.78	0.73	0.60	0.93	
ND	0.18	0.03	-0.10	-0.12	0.05	0.39	0.22	0.21	0.36	0.24	0.23	-0.03	0.11	0.02	0.15	0.22	0.25
OH	0.80	0.21	0.79	0.84	0.80	0.83	0.95	0.74	0.84	0.73	0.84	0.65	0.88	0.81	0.66	0.90	0.83
OK	0.37	0.45	0.22	0.49	0.71	0.67	0.39	0.58	0.43	0.46	0.61	0.55	0.45	0.52	0.68	0.62	0.73
OR	0.47	0.53	0.51	0.67	0.77	0.75	0.50	0.67	0.52	0.50	0.67	0.72	0.59	0.67	0.66	0.75	0.85
PA	0.86	0.26	0.83	0.91	0.84	0.79	0.94	0.81	0.77	0.77	0.94	0.80	0.95	0.84	0.76	0.89	0.80
RI	0.70	0.22	0.63	0.79	0.74	0.65	0.70	0.71	0.61	0.66	0.76	0.75	0.75	0.78	0.72	0.78	0.72
SC	0.83	0.39	0.75	0.75	0.81	0.82	0.73	0.90	0.68	0.74	0.84	0.82	0.78	0.76	0.70	0.93	0.90
SD	0.61	0.23	0.53	0.44	0.48	0.73	0.55	0.67	0.62	0.62	0.75	0.58	0.56	0.45	0.67	0.62	0.65
TN	0.88	0.32	0.76	0.77	0.74	0.87	0.79	0.90	0.74	0.72	0.81	0.78	0.82	0.73	0.66	0.95	0.90
TX	0.67	0.08	0.53	0.70	0.79	0.89	0.77	0.64	0.73	0.54	0.75	0.55	0.78	0.59	0.52	0.81	0.85
UT	0.61	0.59	0.64	0.79	0.76	0.66	0.61	0.76	0.60	0.65	0.65	0.81	0.62	0.80	0.77	0.82	0.83
VT	0.32	0.30	0.25	0.44	0.57	0.43	0.14	0.46	0.22	0.35	0.36	0.60	0.35	0.45	0.37	0.48	0.55
VA	0.86	0.22	0.78	0.89	0.83	0.79	0.90	0.81	0.83	0.81	0.85	0.80	0.90	0.88	0.71	0.90	0.83
WA	0.75	0.32	0.80	0.78	0.76	0.79	0.80	0.73	0.78	0.66	0.75	0.59	0.76	0.69	0.70	0.86	0.82
WV	0.77	0.04	0.61	0.48	0.31	0.64	0.68	0.61	0.71	0.53	0.51	0.27	0.65	0.42	0.32	0.59	0.45
WI	0.78	0.52	0.80	0.87	0.82	0.78	0.76	0.87	0.68	0.76	0.85	0.91	0.81	0.85	0.80	0.89	0.86
WY	0.56	0.53	0.47	0.62	0.72	0.65	0.53	0.73	0.53	0.70	0.76	0.76	0.59	0.69	0.85	0.67	0.71

	ND	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI
OH	0.31															
OK	0.45	0.48														
OR	0.24	0.61	0.80													
PA	0.08	0.91	0.50	0.60												
RI	0.13	0.77	0.50	0.65	0.84											
SC	0.21	0.78	0.70	0.79	0.82	0.77										
SD	0.47	0.58	0.63	0.73	0.61	0.69	0.74									
TN	0.32	0.85	0.65	0.79	0.82	0.81	0.95	0.78								
TX	0.43	0.83	0.73	0.64	0.75	0.57	0.74	0.56	0.79							
UT	0.08	0.67	0.73	0.86	0.70	0.64	0.77	0.55	0.77	0.64						
VT	0.03	0.22	0.67	0.73	0.30	0.39	0.67	0.42	0.57	0.41	0.60					
VA	0.08	0.89	0.53	0.61	0.95	0.84	0.85	0.56	0.85	0.77	0.75	0.41				
WA	0.19	0.84	0.60	0.67	0.80	0.57	0.77	0.56	0.79	0.80	0.81	0.35	0.81			
WV	0.13	0.63	0.11	0.25	0.60	0.51	0.56	0.47	0.68	0.51	0.27	0.13	0.63	0.58		
WI	0.03	0.77	0.64	0.87	0.86	0.79	0.91	0.71	0.89	0.65	0.90	0.63	0.85	0.78	0.48	
WY	0.16	0.52	0.87	0.78	0.68	0.61	0.81	0.70	0.70	0.61	0.78	0.70	0.68	0.62	0.24	0.83

Table 4: **The Housing Wealth Effect in Historical Data.** This table presents the results of panel data regressions of annual aggregated non-housing log-consumption growth (Δc) on the growth of log-housing wealth (Δw^H), log of non-housing tradable wealth (Δw^{TR}), and log income (Δy). State-level fixed effects are included in all models. β_{w^H}, $\beta_{w^{TR}}$ and β_y are the coefficients of the terms Δw^H, Δw^{TR} and Δy, respectively. α is the average of the fixed effect. The value in parentheses below the coefficient is its T-statistic. Overall R^2 (in %) values are reported in the last row. The sample contains observations at annual frequency for the period 1976–2012.

	(1)	(2)	(3)	(4)	(5)
β_{w^H}	0.2077			0.1258	0.1266
	(12.16)			(7.27)	(7.28)
β_y		0.7603		0.6416	0.6406
		(16.99)		(13.65)	(13.61)
$\beta_{w^{TR}}$			0.0007		-0.0040
			(0.07)		(-0.47)
α	0.0137	0.0053	0.0160	0.0055	0.0057
	(11.75)	(4.11)	(12.52)	(4.40)	(4.33)
R^2	8.26	14.50	0.00	17.25	17.26

Table 5: **Model Parameters Common to All States.** This table presents the parameters common to all states in the model calibration.

Parameter	Symbol	Value
House flow services	b	0.100
Rate of depreciation of housing stock	δ	0.013
Time preference	ρ	0.020
Curvature of the utility function	γ	1.200
Productivity of the housing sector	X	0.033

Table 6: **Simulated Data Mean and Standard Deviation.** This table contains the means and standard deviations (Std. Dev.) of the log growth of annual aggregate consumption (Δc) and of housing wealth (Δw^H) averaged over 500 simulations of these variables. For each state in each simulation, the numerical solution to the structural model with the parameters α, σ and ω_0 appropriate to that state is used to generate the evolution of Δc and Δw^H over 30 years. The correlation of shocks to K between states is set equal to the correlation of consumption growth between the corresponding states observed in historical data. The parameters α and σ for each state i are chosen to match the historical mean and volatility of Δc_i. The parameter ω_0 in Panel A (B) is chosen for each state i to match the historical mean (volatility) of Δw_i^H.

	Panel A: ω_0 to match mean housing wealth growth							Panel B: ω_0 to match housing wealth volatility						
	Δc		Δw^H		α	σ	ω_0	Δc		Δw^H		α	σ	ω_0
	Mean	Std. Dev.	Mean	Std. Dev.				Mean	Std. Dev.	Mean	Std. Dev.			
AL	1.25	2.56	0.57	1.03	3.53	2.69	1.34	1.27	2.64	2.56	2.64	3.53	2.69	-0.60
AK	2.04	1.82	1.04	1.22	4.47	1.92	1.48	2.04	1.88	3.17	1.81	4.47	1.92	-0.55
AZ	0.50	4.61	1.05	3.19	2.59	4.97	1.70	0.39	4.83	1.80	5.18	2.59	4.97	-0.56
AR	1.08	3.37	0.47	1.20	3.34	3.62	1.29	1.04	3.53	2.36	3.58	3.34	3.62	-0.60
CA	1.54	3.75	2.33	3.19	3.82	3.84	2.27	1.47	3.79	2.72	3.76	3.82	3.84	-0.56
CO	1.63	4.15	1.50	2.62	4.02	4.40	1.76	1.62	4.28	2.82	4.17	4.02	4.40	-0.57
CT	2.89	8.34	1.85	5.10	5.38	8.68	1.91	2.61	8.38	3.33	7.58	5.38	8.68	-0.60
DE	1.52	1.33	1.41	1.07	3.79	1.39	1.70	1.49	1.36	2.75	1.35	3.79	1.39	-0.56
DC	2.96	5.52	3.47	4.71	5.85	5.71	2.67	3.06	5.53	3.72	4.91	5.85	5.71	-0.59
FL	1.06	3.38	0.58	1.35	3.41	3.52	1.34	1.11	3.44	2.42	3.48	3.41	3.52	-0.58
GA	1.16	3.45	0.01	0.21	3.55	3.79	0.81	1.20	3.67	2.49	3.69	3.55	3.79	-0.58
HI	2.28	5.11	3.29	4.78	4.82	5.27	2.86	2.21	5.10	3.23	4.78	4.82	5.27	-0.56
ID	0.78	3.89	0.57	1.62	2.95	4.16	1.34	0.77	4.02	2.14	4.20	2.95	4.16	-0.55
IL	0.47	3.51	0.71	1.80	2.64	3.78	1.48	0.49	3.70	1.90	3.94	2.64	3.78	-0.58
IN	0.49	5.11	0.31	1.75	2.92	5.36	1.21	0.62	5.11	1.07	3.43	2.92	5.36	-1.73
IA	1.05	4.08	0.29	1.13	3.21	4.39	1.18	0.98	4.33	2.31	4.42	3.21	4.39	-0.58
KS	1.41	4.01	0.05	0.42	3.66	4.38	0.89	1.38	4.17	2.19	3.56	3.66	4.38	-1.17
KY	2.40	4.19	0.66	1.51	5.01	4.36	1.29	2.41	4.21	2.83	3.43	5.01	4.36	-1.06
LA	1.63	5.13	0.77	2.20	4.15	5.41	1.43	1.66	5.19	2.42	4.45	4.15	5.41	-1.07
ME	2.16	4.28	2.01	2.95	4.70	4.51	1.98	2.16	4.37	3.19	4.09	4.70	4.51	-0.59
MD	1.54	4.88	1.70	3.36	3.92	5.07	1.91	1.47	4.94	2.68	4.84	3.92	5.07	-0.59
MA	3.21	6.07	2.74	4.45	6.07	6.39	2.27	3.29	6.12	3.79	5.34	6.07	6.39	-0.60
MI	1.29	5.95	0.52	2.25	3.77	6.34	1.29	1.28	6.17	2.51	6.11	3.77	6.34	-0.58
MN	1.62	5.86	1.10	3.08	4.05	6.18	1.58	1.61	5.97	2.39	5.14	4.05	6.18	-1.06
MS	0.80	3.03	0.10	0.41	3.00	3.24	1.04	0.81	3.14	2.17	3.25	3.00	3.24	-0.60
MO	0.33	3.76	0.45	1.55	2.52	4.02	1.34	0.34	3.95	1.75	4.25	2.52	4.02	-0.58
MT	2.33	1.46	1.82	1.37	4.85	1.53	1.83	2.36	1.47	3.39	1.41	4.85	1.53	-0.56
NE	1.01	6.13	0.13	1.50	3.53	6.51	1.04	1.04	6.16	1.07	3.71	3.53	6.51	-1.80
NV	0.93	2.71	0.10	0.36	3.27	2.90	0.95	1.00	2.85	2.36	2.93	3.27	2.90	-0.52
NH	1.92	1.39	2.18	1.19	4.28	1.47	2.07	1.91	1.42	3.04	1.37	4.28	1.47	-0.60
NJ	1.59	3.57	2.02	2.73	3.98	3.79	2.07	1.59	3.66	2.79	3.56	3.98	3.79	-0.60
NM	1.56	4.79	1.04	2.47	4.12	5.06	1.53	1.67	4.90	2.84	4.77	4.12	5.06	-0.56
NY	1.36	2.84	1.99	2.24	3.59	3.02	2.07	1.29	2.92	2.57	2.92	3.59	3.02	-0.58
NC	2.17	4.87	0.72	1.88	4.78	5.11	1.34	2.21	4.87	2.20	3.54	4.78	5.11	-1.37
ND	1.80	4.86	1.12	2.53	4.21	5.18	1.58	1.74	5.03	2.89	4.84	4.21	5.18	-0.59
OH	2.65	3.18	0.26	0.70	5.22	3.46	1.01	2.65	3.35	3.54	3.07	5.22	3.46	-0.58
OK	1.57	4.11	0.13	0.63	3.93	4.52	0.98	1.52	4.36	2.74	4.28	3.93	4.52	-0.58
OR	1.32	2.21	1.76	1.64	3.72	2.32	1.91	1.38	2.25	2.65	2.24	3.72	2.32	-0.57
PA	2.10	3.80	1.16	2.03	4.48	3.99	1.58	2.01	3.87	3.10	3.67	4.48	3.99	-0.59
RI	1.45	4.69	2.08	3.78	3.89	4.93	2.17	1.46	4.75	2.68	4.67	3.89	4.93	-0.59
SC	1.85	5.85	0.94	2.77	4.29	6.14	1.48	1.70	5.82	1.23	3.27	4.29	6.14	-1.81
SD	2.40	3.92	0.99	1.85	4.90	4.12	1.48	2.37	3.99	3.34	3.70	4.90	4.12	-0.59
TN	1.32	3.82	0.43	1.22	3.56	4.04	1.25	1.27	3.91	2.24	3.49	3.56	4.04	-1.06
TX	1.31	3.45	0.11	0.50	3.59	3.61	0.98	1.27	3.52	2.55	3.53	3.59	3.61	-0.57
UT	2.72	9.17	0.90	4.01	6.06	9.56	1.38	3.02	9.11	2.31	6.19	6.06	9.56	-1.33
VT	2.61	5.25	2.69	3.95	5.30	5.41	2.27	2.62	5.25	3.47	4.75	5.30	5.41	-0.60
VA	1.27	3.33	1.51	2.30	3.62	3.46	1.83	1.30	3.37	2.57	3.36	3.62	3.46	-0.59
WA	1.63	5.25	2.16	4.20	4.20	5.46	2.17	1.78	5.34	2.93	5.17	4.20	5.46	-0.57
WV	1.22	7.48	0.15	2.01	3.90	8.02	1.04	1.26	7.80	2.45	7.70	3.90	8.02	-0.59
WI	1.86	5.43	0.78	2.23	4.35	5.69	1.38	1.85	5.55	2.83	5.11	4.35	5.69	-0.77
WY	1.03	6.68	1.05	3.97	3.55	7.03	1.64	1.12	6.83	2.05	6.14	3.55	7.03	-1.05

Table 7: **Wealth Effect Regressions in Data Simulated to Match the Mean Housing Wealth Growth.** This table displays the results of regressions estimated on 500 panels of simulated data. For each state in each simulation, 30 years of data are generated using the calibrated theoretical model. The data are simulated with the theoretical model calibrated to match the mean of housing wealth growth in each state. Panel A of Table 6 presents details of this calibration. The dependent variable of the regressions under the column labeled "Dep. var. Δw^H" is the log growth of housing wealth (Δw^H). The dependent variable of the regressions under the column labeled "Dep. var. Δc" is the log growth of non-housing consumption. The independent variables are Δw^H and the log growth of non-housing capital (Δk). All the variables are assumed to have mean-zero normally distributed measurement errors that are independent of each other and independent of the shocks to non-housing capital. The results in Panels A, B, C and D are based on different levels of the noise-to-signal ratio. That is, in Panel A (B, C, D), for each state in each simulation, the variance of the measurement error is equal to 0% (50%, 100%, 150%) of the variance of each of the error-free simulated variables—Δc, Δw^H and Δk—obtained in that simulation. All panels have state-level fixed effects. β_{w^H}, β_k and α are the average across all simulated panels of the estimated coefficients on Δw^H, Δk and state-level fixed effects. The value in parentheses below the coefficient is the average T-statistic. The last row of each panel contains the average of the overall R^2 (in %) of the simulated regressions.

	Dep var Δw^H	Dep var Δc		
		(1)	(2)	(3)
Panel A: No measurement errors				
β_{w^H}		1.3842		0.0120
		(55.10)		(6.15)
β_k	0.4547		0.9606	0.9541
	(18.87)		(759.89)	(761.88)
α	0.0057	-0.0018	-0.0002	-0.0003
	(0.52)	(-0.24)	(-0.83)	(-0.91)
R^2	60.96	60.94	99.74	99.75
Panel B: 50% noise-to-signal ratio				
β_{w^H}		0.9204		0.4370
		(24.27)		(13.61)
β_k	0.3044		0.6389	0.5043
	(8.19)		(33.64)	(27.74)
α	0.0081	0.0042	0.0053	0.0017
	(0.74)	(0.34)	(0.67)	(0.20)
R^2	28.01	27.92	44.28	48.71
Panel C: 100% noise-to-signal ratio				
β_{w^H}		0.6901		0.4145
		(16.71)		(10.97)
β_k	0.2286		0.4783	0.3830
	(5.64)		(21.69)	(17.97)
α	0.0093	0.0072	0.0080	0.0042
	(0.78)	(0.57)	(0.76)	(0.39)
R^2	16.07	15.98	24.86	29.71
Panel D: 150% noise-to-signal ratio				
β_{w^H}		0.5521		0.3712
		(12.91)		(9.20)
β_k	0.1831		0.3819	0.3137
	(4.36)		(16.37)	(13.80)
α	0.0101	0.0090	0.0097	0.0059
	(0.76)	(0.66)	(0.78)	(0.48)
R^2	10.44	10.36	15.89	20.12

Table 8: **Wealth Effect Regressions in Data Simulated to Match the Volatility of Housing Wealth Growth.** This table displays the results of regressions estimated on 500 panels of simulated data. For each state in each simulation, 30 years of data are generated using the calibrated theoretical model. The data are simulated with the theoretical model calibrated to match the volatility of housing wealth growth in each state. Panel B of Table 6 presents details of this calibration. The dependent variable of the regressions under the column labeled "Dep. var. Δw^H" is the log growth of housing wealth (Δw^H). The dependent variable of the regressions under the column labeled "Dep. var. Δc" is the log growth of non-housing consumption. The independent variables are Δw^H and the log growth of non-housing capital (Δk). All the variables are assumed to have mean-zero normally distributed measurement errors that are independent of each other and independent of the shocks to non-housing capital. The results in Panels A, B, C and D are based on different levels of the noise-to-signal ratio. That is, in Panel A (B, C, D), for each state in each simulation, the variance of the measurement error is equal to 0% (50%, 100%, 150%) of the variance of each of the error-free simulated variables—Δc, Δw^H and Δk—obtained in that simulation. All panels have state-level fixed effects. β_{w^H}, β_k and α are the average across all simulated panels of the estimated coefficients on Δw^H, Δk and state-level fixed effects. The value in parentheses below the coefficient is the average T-statistic. The last row of each panel contains the average of the overall R^2 (in %) of the simulated regressions.

	Dep var Δw^H	Dep var Δc (1)	(2)	(3)
	Panel A: No measurement errors			
β_{w^H}		1.0512		0.1104
		(211.58)		(95.20)
β_k	0.8858		0.9758	0.8759
	(182.96)		(822.45)	(813.66)
α	0.0124	-0.0123	-0.0002	-0.0016
	(3.96)	(-4.03)	(-1.24)	(-7.86)
R^2	94.04	94.61	99.78	99.82
	Panel B: 50% noise-to-signal ratio			
β_{w^H}		0.6996		0.4078
		(32.49)		(20.87)
β_k	0.5924		0.6490	0.4074
	(27.62)		(33.66)	(22.91)
α	0.0173	-0.0028	0.0053	-0.0018
	(1.94)	(-0.35)	(0.67)	(-0.24)
R^2	41.94	42.06	44.29	52.51
	Panel C: 100% noise-to-signal ratio			
β_{w^H}		0.5246		0.3461
		(21.18)		(14.87)
β_k	0.4449		0.4859	0.3320
	(18.03)		(21.70)	(15.68)
α	0.0197	0.0020	0.0080	0.0012
	(1.75)	(0.16)	(0.75)	(0.11)
R^2	23.68	23.68	24.86	32.72
	Panel D: 150% noise-to-signal ratio			
β_{w^H}		0.4196		0.2983
		(16.06)		(11.93)
β_k	0.3563		0.3880	0.2818
	(13.69)		(16.37)	(12.39)
α	0.0212	0.0048	0.0097	0.0033
	(1.62)	(0.36)	(0.77)	(0.27)
R^2	15.22	15.18	15.89	22.41

Table 9: **Wealth Effect Regressions in Data Simulated to Match the Mean Housing Wealth Growth and with Errors in Independent Variables.** This table displays the results of regressions estimated on 500 panels of simulated data. For each state in each simulation, 30 years of data are generated using the calibrated theoretical model. The data are simulated with the theoretical model calibrated to match the mean housing wealth growth in each state. Panel A of Table 6 presents details of this calibration. The dependent variable of the panels is the log growth of non-housing consumption (Δc). The independent variables in these panels are the log growth of housing wealth (Δw^H) and the log growth of non-housing capital (Δk). The independent variables are assumed to have mean-zero normally distributed measurement errors that are independent of each other and independent of the shocks to non-housing capital. Each model and panel displays results with different noise-to-signal ratios in Δw^H and Δk. Each model contains the results when the variance of the measurement error of Δw^H is equal to 5%, 10% or 30% of the variance of the error-free Δw^H in that simulation. Panel A (B and C) contains the results when the variance of the measurement error of Δk is equal to 5% (10% and 30%) of the variance of the error-free series of Δk obtained in that simulation. All estimated models have state-level fixed effects. β_{w^H}, β_k and α are the average across all simulated panels of the estimated coefficients on Δw^H, Δk and state-level fixed effects. The value in parentheses below the coefficient is the average T-statisic. The last row of each panel contains the average of the overall R^2 (in %) of the simulated regressions.

	Noise-to-signal ratio in Δw^H								
	5%			10%			30%		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	Panel A: Noise-to-signal ratio in Δk equals 5%								
β_{w^H}	1.2576		0.1513	1.0640		0.1035	0.9222		0.0790
	(47.40)		(16.74)	(38.71)		(12.17)	(33.61)		(9.87)
β_k		0.9151	0.8466		0.9151	0.8687		0.9151	0.8799
		(164.86)	(158.62)		(164.86)	(160.65)		(164.86)	(161.68)
α	-0.0002	0.0006	-0.0004	0.0023	0.0006	-0.0001	0.0041	0.0006	0.0001
	(-0.10)	(0.29)	(-0.18)	(0.16)	(0.29)	(-0.05)	(0.38)	(0.29)	(0.03)
R^2	55.84	95.02	95.33	47.85	95.02	95.24	41.88	95.02	95.19
	Panel B: Noise-to-signal ratio in Δk equals 10%								
β_{w^H}	1.3177		0.2961	1.2576		0.2640	1.0640		0.1851
	(50.77)		(24.55)	(47.40)		(22.07)	(38.71)		(16.27)
β_k		0.8736	0.7462		0.8736	0.7604		0.8736	0.7949
		(118.04)	(109.07)		(118.04)	(110.11)		(118.04)	(112.60)
α	-0.0010	0.0013	-0.0007	-0.0002	0.0013	-0.0004	0.0023	0.0013	0.0001
	(-0.17)	(0.48)	(-0.20)	(-0.10)	(0.48)	(-0.15)	(0.16)	(0.48)	(0.01)
R^2	58.28	90.72	91.85	55.84	90.72	91.75	47.85	90.72	91.47
	Panel C: Noise-to-signal ratio in Δk equals 30%								
β_{w^H}	1.3177		0.6015	1.2576		0.5487	1.0640		0.4071
	(50.77)		(34.80)	(47.40)		(31.68)	(38.71)		(24.09)
β_k		0.7395	0.5233		0.7395	0.5426		0.7395	0.5942
		(68.74)	(57.70)		(68.74)	(58.78)		(68.74)	(61.57)
α	-0.0010	0.0035	-0.0009	-0.0002	0.0035	-0.0005	0.0023	0.0035	0.0005
	(-0.17)	(0.86)	(-0.18)	(-0.10)	(0.86)	(-0.12)	(0.16)	(0.86)	(0.09)
R^2	58.28	76.81	82.71	55.84	76.81	82.26	47.85	76.81	80.98

Table 10: **Wealth Effect Regressions in Data Simulated to Match the Volatility of Housing Wealth Growth and with Errors in Independent Variables.** This table displays the results of regressions estimated on 500 panels of simulated data. For each state in each simulation, 30 years of data are generated using the calibrated theoretical model. The data are simulated with the theoretical model calibrated to match the volatility of housing wealth growth in each state. Panel B of Table 6 presents details of this calibration. The dependent variable of the panels is the log growth of non-housing consumption (Δc). The independent variables in these panels are the log growth of housing wealth (Δw^H) and the log growth of non-housing capital (Δk). The independent variables are assumed to have mean-zero normally distributed measurement errors that are independent of each other and independent of the shocks to non-housing capital. Each model and panel displays results with different noise-to-signal ratios in Δw^H and Δk. Each model contains the results when the variance of the measurement error of Δw^H is equal to 5%, 10% or 30% of the variance of the error-free Δw^H in that simulation. Panel A (B and C) contains the results when the variance of the measurement error of Δk is equal to 5% (10% and 30%) of the variance of the error-free series of Δk obtained in that simulation. All estimated models have state-level fixed effects. β_{w^H}, β_k and α are the average across all simulated panels of the estimated coefficients on Δw^H, Δk and state-level fixed effects. The value in parentheses below the coefficient is the average T-statisic. The last row of each panel contains the average of the overall R^2 (in %) of the simulated regressions.

	Noise-to-Signal ratio in Δw^H								
	5%			10%			30%		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	Panel A: Noise-to-signal ratio in Δk equals 5%								
β_{w^H}	1.0010		0.3834	0.9555		0.2807	0.8085		0.1365
	(124.62)		(79.13)	(98.79)		(54.65)	(63.19)		(26.38)
β_k		0.9295	0.6033		0.9295	0.6912		0.9295	0.8139
		(165.51)	(134.27)		(165.51)	(143.44)		(165.51)	(155.23)
α	-0.0110	0.0006	-0.0045	-0.0098	0.0006	-0.0031	-0.0058	0.0006	-0.0012
	(-2.81)	(0.30)	(-2.42)	(-2.24)	(0.30)	(-1.72)	(-1.09)	(0.30)	(-0.69)
R^2	90.11	95.06	96.76	86.01	95.06	96.32	72.78	95.06	95.68
	Panel B: Noise-to-signal ratio in Δk equals 10%								
β_{w^H}	1.0010		0.5421	0.9555		0.4241	0.8085		0.2276
	(124.62)		(93.26)	(98.79)		(66.65)	(63.19)		(33.81)
β_k		0.8874	0.4478		0.8874	0.5439		0.8874	0.7035
		(118.30)	(84.45)		(118.30)	(93.01)		(118.30)	(105.55)
α	-0.0110	0.0013	-0.0062	-0.0098	0.0013	-0.0046	-0.0058	0.0013	-0.0019
	(-2.81)	(0.49)	(-2.57)	(-2.24)	(0.49)	(-1.89)	(-1.09)	(0.49)	(-0.77)
R^2	90.11	90.76	95.23	86.01	90.76	94.27	72.78	90.76	92.66
	Panel C: Noise-to-signal ratio in Δk equals 30%								
β_{w^H}	1.0010		0.7726	0.9555		0.6671	0.8085		0.4316
	(124.62)		(110.36)	(98.79)		(83.03)	(63.19)		(46.33)
β_k		0.7513	0.2225		0.7513	0.2949		0.7513	0.4562
		(68.80)	(37.46)		(68.80)	(43.20)		(68.80)	(53.70)
α	-0.0110	0.0035	-0.0086	-0.0098	0.0035	-0.0069	-0.0058	0.0035	-0.0033
	(-2.81)	(0.86)	(-2.72)	(-2.24)	(0.86)	(-2.09)	(-1.09)	(0.86)	(-0.92)
R^2	90.11	76.85	92.81	86.01	76.85	90.65	72.78	76.85	85.82

Figure 1: **Illustration of the model.** This figure presents the model solution using the parameter values in Table 5 as well as $\alpha = 4.05\%$, $\sigma = 6.18\%$, and $\omega_0 = 1.58\%$. Panel A shows house prices (P) and consumption to non-housing capital ratio (C/K) as functions of the log of the ratio of housing to non-housing capital (ω). Panel B shows the log of house prices (p) and of consumption (c) as functions of the log of non-housing capital (k).

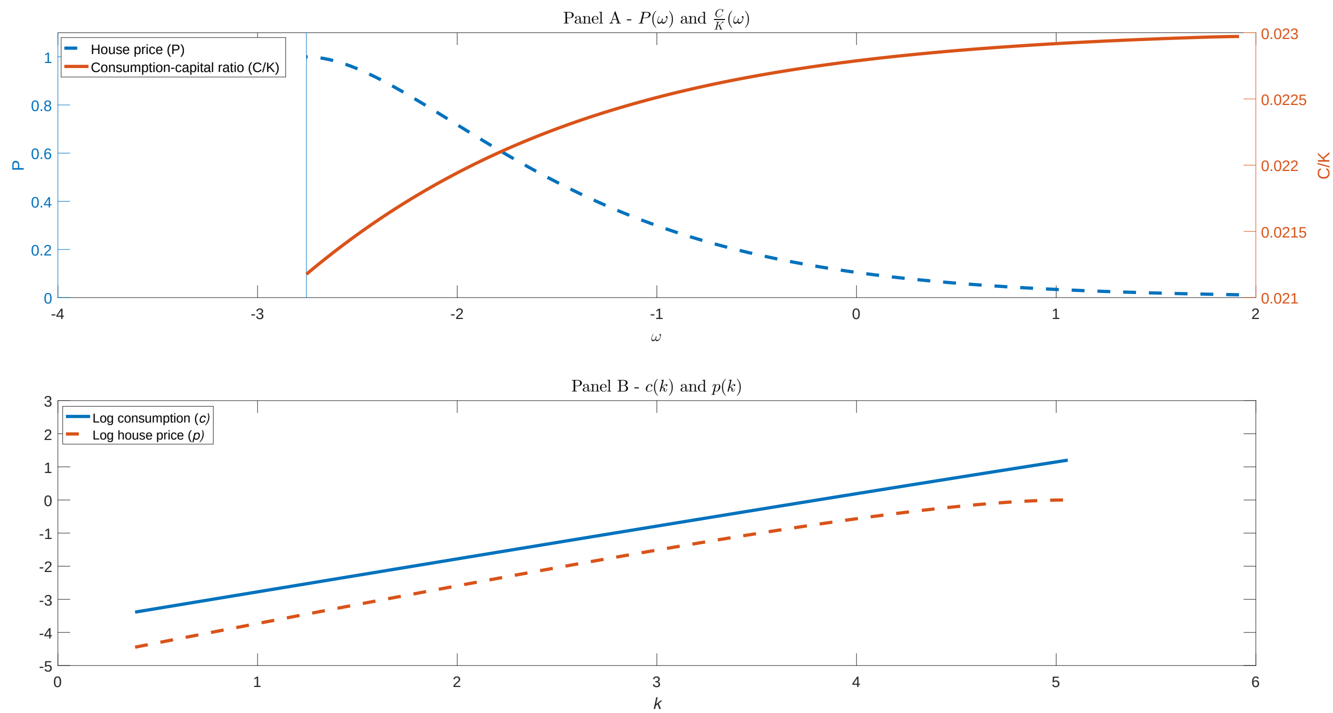

Figure 2: **Housing wealth effect as a function of errors in variables.** This figure plots the mean estimated housing wealth effect β_{w^H} in fixed-effect regressions across 500 panels of data simulated for each level of the noise-to-signal ratio in the dependent and independent variables. The dependent variable of the panels is the log growth of non-housing consumption (Δc). The independent variables in these panels are the log growth of housing wealth (Δw^H) and the log growth of non-housing capital (Δk). For each state in each simulation, 30 years of data are generated using the calibrated theoretical model. The data are simulated with the theoretical model calibrated to match the mean of housing wealth growth in each state. All the variables are assumed to have mean-zero normally distributed measurement errors that are independent of each other and independent of the shocks to non-housing capital. 500 simulations are generated for each of the chosen levels of the noise-to-signal ratio between 1% and 300%. For example, for the case of a noise-to-signal ratio of 10%, for each state in each simulation, the variance of the measurement error is equal to 10% of the variance of each of the error-free simulated variables Δc, Δw^H and Δk obtained in that simulation. All panels have state-level fixed effects. The dotted lines indicate the 95% confidence interval bands for the parameter estimates. The inset figure magnifies the section of the graph between 0% and 5% noise-to-signal ratio.