What Can Fifty-Two Collateralizable Wealth Measures Tell Us About Future Housing Market Returns? Evidence from U.S. State-Level Data

Mehmet Balcilar

Eastern Mediterranian University

mehmet@mbalcilar.net

Rangan Gupta

University of Pretoria

Rangan.Gupta@up.ac.za

Ricardo M. Sousa

University of Minho, NIPE and LSE Alumni Association

rjsousa@eeg.uminho.pt; rjsousa@alumni.lse.ac.uk

Mark E. Wohar*

University of Nebraska-Omaha and Loughborough University

mwohar@unomaha.edu

Abstract

We use a novel U.S. state-level database to evaluate the role of housing wealth as a provider of collateral services. First, we estimate the cointegrating relationship between housing wealth and labour income for all 50 states, as well as the District of Columbia (D.C.), and overall U.S. Then, we assess the predictive ability of the housing wealth-to-income ratios (labelled by *hwy*) for state-level future real housing returns. We uncover: (i) positive estimates for the elasticity of housing wealth with respect to labour income, which are also largely heterogeneous across U.S. states; and (ii) a negative link between the housing wealth-to-income ratios and future housing returns, albeit the forecasting power of *hwy* also varies considerably across states. We conclude that country-level regressions typically "mask" this diversity of features surrounding the usefulness of housing in collateral provision and unfavourable labour income shock smoothing that state-level frameworks are able to recover.

Keywords: housing wealth-to-income ratio, housing returns, forecasting regression.

JEL Codes: C22, R31.

* Corresponding author.

Introduction

There is a well-known and established body of research looking at house price determinants (Leung 2004; Hwang and Quigley 2006), housing wealth effects on consumption (Lettau and Ludvigson 2004; Case et al. 2005, 2013; Sousa 2010a) and the dual role of housing as an investment asset and a consumption good (Henderson and Ioannides 1987).

Housing is also an important driver of business cycles (Leamer 2015; Balcilar et al. 2014; Agnello et al. 2015, 2018) [1] and households' collateral constraints (Chen and Leung 2007; Jin et al. 2012; Ren and Yuan 2014), thus, deserving a special attention by policymakers in the design of (housing) policy (Zhou and Haurin 2010; Agnello et al. forthcoming).

In the run-up to the Great Recession, academics from the empirical finance literature have started to formalize asset pricing models that incorporate specific characteristics of housing assets or the housing sector functioning to match the time-varying dynamics of equity risk premium that one observes in the data. In particular, Lustig and van Nieuwerburgh (2005) show that changes in the housing collateral ratio track variation in the exposure of investors to labour income risk, thus, changes in the joint distribution of equity prices and consumption growth. In the same vein, Sousa (2010b) investigates how the dynamics of collateralizable wealth elps explain equity and bond risk premia, and finds that the residuals of the trend relationship among housing wealth and labour income, labelled by *hwy*, predict future expected returns. The economic rationale is that, in a world with idiosyncratisk risk emerging from labour income, negative shocks lead to a fall in the housing wealth-to-labour income ratio and increase investors' vulnerability to risk. As a result, when such decline occurs, they demand a higher premium to hold risky assets.[2]

Despite these advances in asset pricing theory and the empirical studies aimed at forecasting equity risk premium, the literature on housing return predictability is not so extensively documented even though and housing risk is one of most important components of economic risk (Shiller 1998).[3] From a theoretical point of view, Spiegel and Strange (1992) develop a model where the value of a house is a function of owner's actions, but affects the wealth of both the owner and the lender responsible for the mortgage that finances the house purchase. Thus, the buyer's exposure to moral hazard can lead to sub-optimal maintenance and generate predictable home ownership excess returns. Leung (2007) builds a theoretical model that rationalizes the serial correlation between housing prices and equity returns and derives the optimal housing weight in asset portfolios. In this framework, economic shock persistence and investors' time horizon length are crucial.

From an empirical perspective, Case and Shiller (1990) use city-level data for Atlanta, Chicago, Dallas, and San Francisco, and show that housing returns in a given year are correlated with construction costs, per real income growth and demographic changes of the previous year, thus, casting doubts about the efficiency of the U.S. housing market. Such inefficiency is also witnessed in the observed house price dispersion (Leung et al. 2006). He (2015) constructs an endurance index of housing investor sentiment that tracks investors' reactions to all relevant news and is able to predict an important fraction of the variation in housing stock returns. Using data for 15 OECD countries, Rocha Armada and Sousa (2012) argue that when hit by a negative shock to their labour income that generates a fall in their asset wealth-to-income ratio, investors will demand a higher (lower) housing risk premium if housing and financial assets perceived as complements (substitutes). Caporale et al. (forthcoming) show that transitory deviations of consumption from its common trend with aggregate wealth and labour income, denoted by *cay*, forecast housing risk premium. They also find that if financial and housing assets are seen as complements (substitutes), investors will temporarily allow consumption to rise (fall) when they expect a rise in future housing returns. Caporale and Sousa (2016) provide similar evidence for 31 emerging market economies. Balcilar et al. (2017) use a nonparametric causality-in-quantiles test and find evidence of nonlinearity and regime changes in the relationship between housing returns (and its volatility) and the consumption-wealth ratio.

In this paper, we assess the predictive power of collateralizable wealth (as expressed by the ratio of housing wealth to labour income) for future housing returns through the lens of a novel dataset containing U.S. state-level information over the period of 1975: Q1–2012:Q2. This is both the key contribution of this work to the existing literature and its main goal. Thus, instead of focusing on country-level aggregates, we exploit the granularity of state-level data to obtain important insights about the dynamics of housing returns. In this respect, the current paper is inspired by the work of Balcilar et al. (2019), who use the same dataset to investigate the forecasting power of different consumption-wealth ratios. By looking at the housing wealth-to-income ratio instead, we place the attention on the role of housing wealth as a provider of collateral services.

We start by estimating the long-run equilibrium relationship between housing wealth and labour income for all 50 states, as well as the District of Columbia (D.C.), and the overall U.S. economy. Our empirical evince supports the view of a stable link between the two variables that is not contaminated by the presence of structural breaks due to the occurrence of economic recessions or financial crises.

Despite being positive, the elasticity of housing wealth with respect to labour income displays large cross-state heterogeneity: our parameter estimates stand above 3 in 16 states, and below unity in 5 states. For the U.S. as a whole, our time-series and panel estimates are 1.54 and 1.66, respectively.

Next, we show that deviations of housing wealth from its trend relationship with labour income, labelled by *hwy*, measured at the state-level are able to forecast state-level real housing returns. More specifically, a fall in the housing wealth-to-income ratio is associated with a fall in future housing returns. Yet, the predictive power of this empirical proxy also varies considerably across states: at the eight quarter-ahead horizon, *hwy* forecasts more than 30% of the variation of real housing returns in 15 states, but less than 10% of that variation in 19 states. For the country as a whole, different estimation methods suggest that *hwy* predicts a fraction of between 10.5% and 19.4% of the dynamics of future real housing returns.

All in all, our empirical evidence lends support to the view about the usefulness of housing in collateral provision (Sousa 2010b), as well as its ability to smooth unfavourable labour income shocks and capture time-variation in risk premium (Sousa 2015a). However, we also show that country-level estimates typically "mask" a large amount of heterogeneity that state-level estimates are able to track, as suggested also by other housing studies (Apergis and Payne 2012; Miles 2015).

The remainder of the paper is as follows. Section 2 describes the data. Section 3 estimates state-level housing wealth-to-income ratios and analyses the results. Section 4 forecasts state-level housing returns using state-level *hwy* as the predictor and discusses the main findings. Finally, Section 5 concludes.

Data

The ratio of housing wealth to labour income, *hwy*, is computed using unique information (gathered by Case et al. (2005, 2013)) about owner-occupied housing wealth and personal income for each of the 50 U.S. states plus D.C. over the period 1975:Q1–2012:Q2. For the U.S. as a whole, we aggregate state-level information.

As highlighted by Ashley and Li (2014), Case et al. (2005, 2013) assemble virtually the only dataset that includes both financial wealth and housing wealth information disaggregated at the state-level and the quarterly frequency over a significantly long time frame. Among its advantages, it allows one: (i) to explore the differences in the distribution of both forms of wealth across geographic units given that variable definitions are uniform; (ii); to assess the empirical relationship between the level (and not just the growth rate) of housing wealth and labour income (and housing returns) across different states; and (iii) to benefit from the fact that the sample spans over almost 40 years, that is, 150 quarterly observations per state or a total of 7650 observations in our panel. Its main disadvantages are: (i) the approximation of state-level per capita consumption by state-level total retail sales, albeit the two variables tend to be strongly correlated at the country-level; and (ii) the fact that the growth rate of household financial wealth is restricted to be the same as the growth rate of households' holdings of mutual funds due to data availability. In this last case, to the extent that the correlation between the two variables is low, the implicit omitted variable bias is small; by contrast, if the correlation between the two variables is high, then, the imputed computation will minimize the potential measurement error.

Both housing wealth and labour income are expressed in logs of per capita, real terms, with the time-series being deflated using the Consumer Price Index (CPI) - All Urban Consumers (with the base year of 1982–1984) obtained from the Bureau of Labor Statistics (BLS) via the FRED database of the Federal Reserve Bank of St. Louis.

Real housing returns (*rhr*) are computed as the difference between the continuously compounded log of (nominal) housing returns and the CPI inflation rate. Nominal housing returns are calculated as the first-difference of logs of the housing price index, that is, excluding the rental yield (i.e. the rent-to price ratio) component, as this information is not available at the state-level. Despite this, it is important to emphasize that, when computed at the country-level, rental yields are typically a small fraction of housing returns given that most of the dynamics accrues to housing price variation. Moreover, they are measured from imputed rents, thus, being prone to measurement error. Therefore, we collect data on all-transactions single-family house price indices from the Federal Housing Finance Agency (FHFA). These indices measure average price changes and are based on repeated mortgage transactions on single-family properties whose mortgages have been purchased or securitized by either Fannie Mae or Freddie Mac. They can be downloaded from: https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx#qat. House price data are seasonally adjusted using the X-13 approach of the U.S. Census Bureau.

Housing Wealth-to-Income Ratio: U.S. State-Level Evidence

Following Sousa (2010b), we estimate the cointegrating relationship between housing wealth and labour income using the dynamic ordinary least squares (DOLS) estimator of Stock and Watson (1993) with Newey and West (1987) standard errors, which enables us to control for potential regressor's endogeneity. Thus, we regress

$$hwy_t = \chi + \varpi y_t + \vartheta t + \sum_{i=-k}^{k} \varpi_i \Delta y_{t-i} + \zeta_t \qquad (1)$$

where hw_t is the log of real housing wealth, y is the log of real labour income, the parameter ϖ pins down the long-run elasticity of housing wealth with respect to labour income, t is a time trend and ϑ is the associated parameter, χ is a constant, Δ denotes the first-difference operator, and ζ_t is the error term. The cointegrating vector eliminates the deterministic trends, such that the housing wealth-to-income ratio is stationary. Moreover, as noted by Stock and Watson (1993), the inclusion of the sum of leads and lags of the first-differences of the regressors eliminates the effects of regressor's endogeneity on the distribution of the ordinary least squares (OLS) estimator.

The housing wealth-to-income ratio ($\widehat{hwy_t}$) is then expressed as the deviation of housing wealth from its equilibrium relationship with labour income, that is:

$$\widehat{hwy_t} = hw_t - \widehat{hw_t} = hw_t - \hat{\chi} - \hat{\varpi} y_t - \hat{\vartheta} t \qquad (2)$$

Table 1 summarises the point coefficient estimates associated with state-level *hwy*, and shows that housing wealth and labour income share a positive relationship in all states. Moreover, with the exception of South Carolina and Tennessee, such long-term equilibrium link is statistically significant. The time trend is also statistically significant for all states except Alabama, Delaware, Florida, Georgia, Hawaii, New Jersey, North Carolina, Oregon, Pennsylvania, South Carolina, Tennessee and Vermont. This confirms the importance of the inclusion of a deterministic trend in the cointegrating vector to ensure stationarity.[4]

Table 1 State-level cointegration between housing wealth and labour income: Time-series DOLS estimator

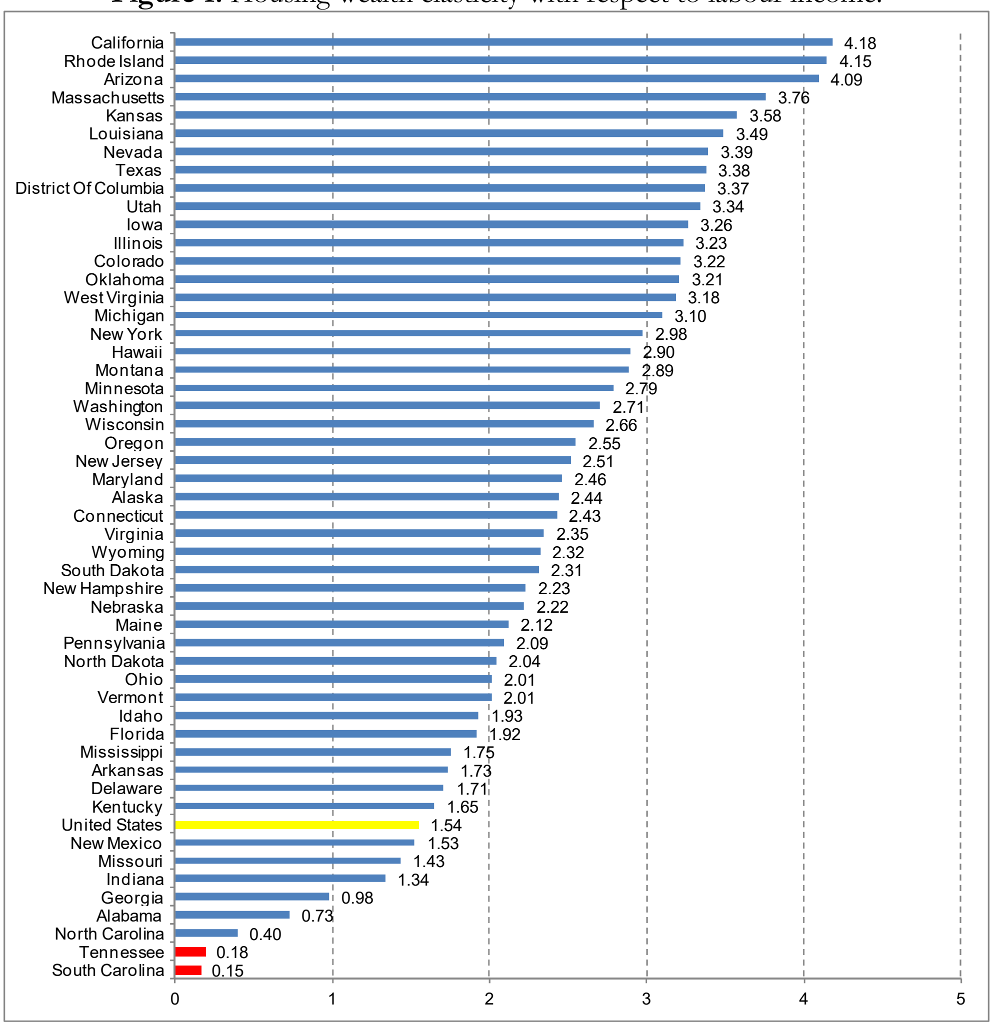
Variable	*hwy*	Variable	*Hwy*
Alabama		Indiana	
Labour income	0.7263*	Labour income	1.3354***
Time trend	−0.0011	Time trend	−0.0033***
Constant	3.0767	Constant	−2.9133**
Alaska		Iowa	
Labour income	2.4399***	Labour income	3.2642***
Time trend	0.0008*	Time trend	−0.0095***
Constant	−14.8231***	Constant	−22.0263***
Arizona		Kansas	
Labour income	4.0920***	Labour income	3.5764***
Time trend	−0.0104***	Time trend	−0.0119***
Constant	−29.9154***	Constant	−25.1245***
Arkansas		Kentucky	
Labour income	1.7337***	Labour income	1.6488***
Time trend	−0.0069***	Time trend	−0.0038***
Constant	−6.5434	Constant	−6.0005***
California		Louisiana	
Labour income	4.1799***	Labour income	3.4900***
Time trend	−0.0070***	Time trend	−0.0127***
Constant	−31.4955***	Constant	−23.7402***
Colorado		Maine	
Labour income	3.2188***	Labour income	2.1212***
Time trend	−0.0091***	Time trend	−0.0031*
Constant	−21.5256***	Constant	−10.5886***
Connecticut		Maryland	
Labour income	2.4275***	Labour income	2.4628***
Time trend	−0.0049**	Time trend	−0.0054***
Constant	−14.1064***	Constant	−14.0188***

Delaware		Massachusetts	
Labour income	1.7110***	Labour income	3.7570***
Time trend	−0.0003	Time trend	−0.0097***
Constant	−6.8697**	Constant	−27.3448***
DC		Michigan	
Labour income	3.3710***	Labour income	3.0989***
Time trend	−0.0089**	Time trend	−0.0053***
Constant	−24.1261***	Constant	−20.6808***
Florida		Minnesota	
Labour income	1.9172**	Labour income	2.7864***
Time trend	−0.0039	Time trend	−0.0081***
Constant	−8.6190	Constant	−17.2853***
Georgia		Mississippi	
Labour income	0.9800***	Labour income	1.7522***
Time trend	−0.0022	Time trend	−0.0076***
Constant	0.6172	Constant	−6.6117*
Hawaii		Missouri	
Labour income	2.8980***	Labour income	1.4340***
Time trend	0.0015	Time trend	−0.0031***
Constant	−18.8695***	Constant	−3.9243
Idaho		Montana	
Labour income	1.9315***	Labour income	2.8910***
Time trend	−0.0044***	Time trend	−0.0045***
Constant	−8.4835***	Constant	−18.1148***
Illinois		Nebraska	
Labour income	3.2309***	Labour income	2.2223***
Time trend	3.2309***	Time trend	−0.0075***
Constant	3.2309***	Constant	−11.7574***
Nevada		South Carolina	
Labour income	3.3931***	Labour income	0.1547
Time trend	−0.0068***	Time trend	0.0023
Constant	−23.6176***	Constant	8.5359***
New Hampshire		South Dakota	
Labour income	2.2333***	Labour income	2.3134***
Time trend	−0.0051**	Time trend	−0.0084***
Constant	−11.8436***	Constant	−12.5472***
New Jersey		Tennessee	
Labour income	2.5144***	Labour income	0.1844
Time trend	−0.0034	Time trend	0.0002
Constant	−15.0294**	Constant	8.4813***
New Mexico		Texas	
Labour income	1.5252***	Labour income	3.3770***
Time trend	−0.0036**	Time trend	−0.0128***
Constant	−4.5071	Constant	−22.9713***
New York		Utah	
Labour income	2.9768***	Labour income	3.3394***
Time trend	−0.0043**	Time trend	−0.0092***
Constant	−19.8481***	Constant	−22.1520***
North Carolina		Vermont	
Labour income	0.3952**	Labour income	2.0112***
Time trend	0.0012	Time trend	−0.0028
Constant	6.2908***	Constant	−9.2966**
North Dakota		Virginia	
Labour income	2.0448***	Labour income	2.3493***
Time trend	−0.0076***	Time trend	−0.0046*
Constant	−9.9355***	Constant	−12.9991**

Ohio		Washington	
Labour income	2.0143***	Labour income	2.7071***
Time trend	−0.0044***	Time trend	−0.0047**
Constant	−9.7316***	Constant	−16.6102***
Oklahoma		West Virginia	
Labour income	3.2086***	Labour income	3.1837***
Time trend	−0.0119***	Time trend	−0.0106***
Constant	−21.1374***	Constant	−20.5487***
Oregon		Wisconsin	
Labour income	2.5528***	Labour income	2.6600***
Time trend	−0.0030	Time trend	−0.0053***
Constant	−14.9861***	Constant	−16.1627***
Pennsylvania		Wyoming	
Labour income	2.0926**	Labour income	2.3218***
Time trend	−0.0021	Time trend	−0.0065***
Constant	−10.6941	Constant	−12.6361***
Rhode Island			
Labour income	4.1493***		
Time trend	−0.0102***		
Constant	−30.8359***		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 1. Housing wealth elasticity with respect to labour income.



Note: Red bars indicate that the coefficient is not statistically significant. Blue bars denote significant coefficients. The yellow bar reports the coefficient for the U.S. as a whole.

Concerning the elasticitiy of housing wealth with respect to labour income, Fig. 1 shows that it is particularly large for California (4.18), Rhode Island (4.15), Arizona (4.09), Massachusetts (3.76), Kansas (3.58) or Louisiana (3.49), and small for South Carolina (0.15), Tennessee (0.18), North Carolina (0.40), Alabama (0.73) or Georgia (0.98). Thus, there is substantial heterogeneity in the housing wealth-to-income ratio across U.S. states.

To further investigate this issue, Table 2 reports the results of the estimation of the cointegrating vector using either: (i) the DOLS estimator and applying it to the U.S. as a whole (i.e. a time-series approach); or (ii) a panel fixed-effects (FE) estimator, where we pool all state-level observations and account for potential cross-state unobserved heterogeneity.

Table 2 Country-level cointegrating relationship between housing wealth and labour income: Time-series DOLS and panel FE estimators

US (time-series DOLS estimator)	*hwy*	US (panel FE estimator)	*hwy*
Labour income	1.5448***	Labour income	1.6589***
Time trend	−0.0016	Time trend	−0.0027***
Constant	−5.1112	constant	−6.1754***
# Obs.	141		7650

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As can be seen, the elasticity of housing wealth with respect to labour income is positive and statistically significant in both cases. Both point coefficient estimates are also close to unity, i.e. 1.54 (DOLS estimator) and 1.66 (FE estimator). Combined with the information presented in Table 1, this means that, with the exception of the states already mentioned with a low elasticity of housing wealth with respect to labour income and the states of Indiana (1.34), Missouri (1.43), New Mexico (1.53), the elasticity estimates for other states are larger than the average for the U.S..

All in all, we conclude that average (country-level) estimations of the housing wealth-to-income ratio mask important state-level heterogeneity.

The results presented so far reveal that, despite the variation at the state-level in the point coefficient estimates associated with labour income in the housing wealth equation, the two variables display a positive and significant long-term link. However, has this long-run relationship remained stable over time? Is it immune to the presence of economic recessions? Did the occurrence of financial crises affect the cointegrating vector between housing wealth and labour income?

To provide an answer to this question, we begin by dating: (i) economic recessions; and (ii) financial crisis episodes. U.S. economic recessions are identified by the NBER's Business Cycle Dating Committee as starting at the peak of a business cycle and ending at the trough (see: http://www.nber.org/cycles/cyclesmain.html). Our sample period encompasses six recession episodes: 1) 1973:Q4–1975:Q1[5]; 2) 1980:Q1–1980:Q3; 3) 1981:Q3–1982:Q4; 4) 1990:Q3–1991:Q1; 5) 2001:Q1–2001:Q4; and 6) 2007:Q4-2009Q2. Similarly, U.S. systemic banking crises are dated by the Federal Reserve Bank of St. Louis (https://fraser.stlouisfed.org/timeline/financial-crisis), the U.S. Council on Foreign Relations (https://www.cfr.org/timeline/us-financial-crisis) and Laeven and Valencia (2018). Our sample period includes two financial crisis episodes: 1) 1998:Q1–1988:Q4; and 2) 2007:Q1–2011:Q2.

Next, we create two dummy variables. The first one, labelled $Recession_t$, takes the value of one in the case of the occurrence of an economic recession at time t, and zero, otherwise. The second dummy variable, labelled $Fin.\ Crisis_t$, takes the value of one in the presence of a financial crisis at time t, and zero, otherwise.

After the construction of the two above mentioned dummy variables, we extend our baseline model expressed by eq. (1) and estimate:

$$hw_t = \chi + \varpi y_t + \varpi^{Recession} y_t \times Recession_t + \vartheta t + \zeta_t \tag{1i}$$

$$hw_t = \chi + \varpi y_t + \varpi^{Fin.Crisis} y_t \times Fin.\,Crisis_t + \vartheta t + \zeta_t \tag{1ii}$$

where $\varpi^{Recession}$ and $\varpi^{Fin.\ Crisis}$ pin down the impact of recessions and financial crises, respectively, on the long-run elasticity of housing wealth with respect to labour income. For brevity, the sum of leads and lags of the first-differences of the regressors are omitted from eqs. (1i) and (1ii) even though these terms are included in the estimation.

The same econometric exercise is considered in a panel framework and, thus, we regress:

$$hw_{i,t} = \chi_i + \varpi y_{i,t} + \varpi^{Recession} y_{i,t} \times Recession_t + \vartheta t + \zeta_{i,t} \tag{1iii}$$

$$hw_{i,t} = \chi_i + \varpi y_{i,t} + \varpi^{Fin.Crisis} y_{i,t} \times Fin.\,Crisis_t + \vartheta t + \zeta_{i,t} \tag{1v}$$

where χ_i captures state-level fixed-effects.

Tables 3 and 4 summarise the empirical evidence for the inclusion of economic recessions in the baseline model, while Tables 5 and 6 present the results associated with financial crises. In the case of economic recessions, Table 3 shows that the point coefficient estimates associated with the interaction term ($y_t \times Recession_t$) is significant at the 1% level for Arizona, Arkansas, Florida and Utah only and at the 5% level for Nevada, Nebraska and Washington only. Moreover, while being positive - thus, implying that housing wealth becomes more sensitive to changes in labour income during recessions -, their magnitude is very close to zero. For the U.S. as a whole, Table 4 reveals that the interaction term is not statistically significant in the case of the DOLS framework, and significant in the case of the panel FE estimator but near nil.

Table 3 State-level cointegration between housing wealth and labour income: Time-series DOLS estimator - presence of economic recessions

Variable	*Hwy*	Variable	*hwy*
Alabama		Indiana	
Labour income	0.8236	Labour income	1.3594***
Lab. income x Recession	0 .0057	Lab. income x Recession	0.0005
constant	2.1206	constant	−3.1483***
Alaska		Iowa	
Labour income	2.5548***	Labour income	3.2618***
Lab. income x Recession	−0.0075	Lab. income x Recession	0.0042
constant	−15.9869***	constant	−22.0101***
Arizona		Kansas	
Labour income	3.7125***	Labour income	3.4435***
Lab. income x Recession	0.0443***	Lab. income x Recession	0.0102*
constant	−26.3280***	constant	−23.8340***
Arkansas		Kentucky	
Labour income	2.0988***	Labour income	1.6533***
Lab. income x Recession	0.0126***	Lab. income x Recession	0.0034
constant	−10.0789**	constant	−6.0542***
California		Louisiana	
Labour income	4.2088***	Labour income	3.5885***
Lab. income x Recession	−0.0098	Lab. income x Recession	−0.0034
constant	−31.7543***	constant	−24.6863***
Colorado		Maine	
Labour income	3.1795***	Labour income	2.1958***
Lab. income x Recession	0.0109	Lab. income x Recession	0.0038
Constant	−21.1659***	constant	−11.3195**
Connecticut		Maryland	
Labour income	2.3696***	Labour income	2.4083***
Lab. income x Recession	−0.0035	Lab. income x Recession	−0.0007
constant	−13.5061**	constant	−13.4743***
Delaware		Massachusetts	
Labour income	1.7182***	Labour income	3.6915***
Lab. income x Recession	−0.0007	Lab. income x Recession	−0.0047
constant	−6.9368**	constant	−26.6799***
DC		Michigan	
Labour income	3.2987***	Labour income	3.2453***
Lab. income x Recession	0.0155	Lab. income x Recession	0.0092
constant	−23.4284***	constant	−22.1600***
Florida		Minnesota	
Labour income	2.1475***	Labour income	2.8735***
Lab. income x Recession	0.0494***	Lab. income x Recession	0.0087
constant	−11.0686	constant	−18.1694***
Georgia		Mississippi	
Labour income	1.0045***	Labour income	1.8374***
Lab. income x Recession	0.0054	Lab. income x Recession	0.0078
constant	0.3560	constant	−7.4409**
Hawaii		Missouri	
Labour income	3.1753***	Labour income	1.4714***
Lab. income x Recession	0.0277***	Lab. income x Recession	0.0040
constant	−21.7028***	constant	−4.3019
Idaho		Montana	
Labour income	2.0144***	Labour income	2.9477***
Lab. income x Recession	0.0024	Lab. income x Recession	−0.0057
constant	−9.2914***	Constant	−18.6562***
Illinois		Nebraska	
Labour income	3.0195***	Labour income	2.4211***
Lab. income x Recession	−0.0053	Lab. income x Recession	0.0106**
constant	−20.0622***	constant	−13.7302***

Nevada		South Carolina	
Labour income	3.285742***	Labour income	0.24175
Lab. income x Recession	0.0473**	Lab. income x Recession	0.0087
Constant	−22.6807**	constant	7.6662**
New Hampshire		South Dakota	
Labour income	2.2064***	Labour income	2.3288***
Lab. income x Recession	−0.0035	Lab. income x Recession	0.0075*
Constant	−11.5640**	constant	−12.7067***
New Jersey		Tennessee	
Labour income	2.4083***	Labour income	0.0401
Lab. income x Recession	−0.0039	Lab. income x Recession	−0.0013
Constant	−13.9494**	constant	9.8756***
New Mexico		Texas	
Labour income	1.3149***	Labour income	3.3120***
Lab. income x Recession	0.0089*	Lab. income x Recession	0.0080
Constant	−2.4895	constant	−22.3522***
New York		Utah	
Labour income	3.0879***	Labour income	3.2250***
Lab. income x Recession	0.0072	Lab. income x Recession	0.0187***
Constant	−20.9798***	constant	−21.0871***
North Carolina		Vermont	
Labour income	0.3233	Labour income	1.7882***
Lab. income x Recession	−0.0011	Lab. income x Recession	−0.0107
Constant	6.9868***	constant	−7.0993*
North Dakota		Virginia	
Labour income	2.0756***	Labour income	2.34438***
Lab. income x Recession	0.0042	Lab. income x Recession	0.0029
Constant	−10.2470***	constant	−12.9562**
Ohio		Washington	
Labour income	1.9605***	Labour income	2.3563***
Lab. income x Recession	−0.0013	Lab. income x Recession	0.0165**
Constant	−9.19372***	constant	−13.1710**
Oklahoma		West Virginia	
Labour income	3.4070***	Labour income	3.0838***
Lab. income x Recession	−0.0047	Lab. income x Recession	0.0057
Constant	−23.0750***	constant	−19.5972***
Oregon		Wisconsin	
Labour income	2.7055***	Labour income	2.7468***
Lab. income x Recession	0.0164	Lab. income x Recession	0.0003
Constant	−16.5359**	constant	−17.01309***
Pennsylvania		Wyoming	
Labour income	1.8330*	Labour income	2.4977***
Lab. income x Recession	−0.0065	Lab. income x Recession	−0.0158*
Constant	−8.1067	constant	−14.3487***
Rhode Island			
Labour income	4.2519***		
Lab. income x Recession	0.0044		
Constant	−31.8526***		

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. In accordance with the baseline model expressed by eq. (1), all specifications also include a deterministic trend. However, for brevity, its point coefficient estimates are not reported in the Table.

Table 4 Country-level cointegrating relationship between housing wealth and labour income: Time-series DOLS and panel FE estimators - presence of economic recessions

US (time-series DOLS estimator)	*hwy*	US (panel FE estimator)	*hwy*
Labour income	1.5261***	Labour income	1.6658***
Lab. income x Recession	0.0081	Lab. income x Recession	0.0027***
Constant	−4.9513	constant	−6.2469***
# Obs.	141		7650

Note: *** p < 0.01, ** $p < 0.05$, * $p < 0.1$. In accordance with the baseline model expressed by eq. (1), all specifications also include a deterministic trend. However, for brevity, its point coefficient estimates are not reported in the Table.

Table 5 State-level cointegration between housing wealth and labour income: Time-series DOLS estimator - presence of financial crises

Variable	*hwy*	Variable	*hwy*
Alabama		Indiana	
Labour income	0.4555	Labour income	1.0499***
Lab. income x Fin. Crisis	0.0020	Lab. income x Fin. Crisis	−0.0060**
constant	5.6880*	constant	−0.1110
Alaska		Iowa	
Labour income	2.6779***	Labour income	3.3855***
Lab. income x Fin. Crisis	−0.0143***	Lab. income x Fin. Crisis	−0.0096***
constant	−17.3103***	constant	−23.2336***
Arizona		Kansas	
Labour income	3.3362***	Labour income	3.5390***
Lab. income x Fin. Crisis	−0.0051	Lab. income x Fin. Crisis	0.0032
constant	−22.4948***	constant	−24.7538***
Arkansas		Kentucky	
Labour income	1.1857**	Labour income	1.6356***
Lab. income x Fin. Crisis	0.0040	Lab. income x Fin. Crisis	0.0009
constant	−1.2724	constant	−5.8696**
California		Louisiana	
Labour income	3.8416***	Labour income	3.8320***
Lab. income x Fin. Crisis	−0.0214*	Lab. income x Fin. Crisis	−0.0102*
constant	−28.1036***	constant	−27.0583***
Colorado		Maine	
Labour income	3.5074***	Labour income	2.3394***
Lab. income x Fin. Crisis	0.0091	Lab. income x Fin. Crisis	0.0152**
Constant	−24.3851***	constant	−12.6774***
Connecticut		Maryland	
Labour income	2.6365***	Labour income	2.1434***
Lab. income x Fin. Crisis	0.0163*	Lab. income x Fin. Crisis	−0.0153***
constant	−16.1951***	constant	−10.8263**
Delaware		Massachusetts	
Labour income	1.9308***	Labour income	3.7236***
Lab. income x Fin. Crisis	0.0151***	Lab. income x Fin. Crisis	0.0030
constant	−9.0551***	constant	−27.0040***
DC		Michigan	
Labour income	3.4435***	Labour income	1.6336***
Lab. income x Fin. Crisis	−0.0044	Lab. income x Fin. Crisis	−0.0349***
constant	−24.8593***	constant	−6.1470*
Florida		Minnesota	
Labour income	0.7777	Labour income	1.9574***
Lab. income x Fin. Crisis	0.0060	Lab. income x Fin. Crisis	−0.0143
constant	2.6322	constant	−9.0929
Georgia		Mississippi	
Labour income	0.4814*	Labour income	1.6706***
Lab. income x Fin. Crisis	−0.0129**	Lab. income x Fin. Crisis	0.0084***
constant	5.4686	constant	−5.8259*

Hawaii		Missouri	
Labour income	2.9768***	Labour income	0.9831**
Lab. income x Fin. Crisis	−0.0066	Lab. income x Fin. Crisis	−0.0015
constant	−19.6676***	constant	0.5159
Idaho		Montana	
Labour income	1.8261***	Labour income	2.9026***
Lab. income x Fin. Crisis	0.0076	Lab. income x Fin. Crisis	−0.0051***
constant	−7.4512**	Constant	−18.2313***
Illinois		Nebraska	
Labour income	2.5698***	Labour income	2.0198***
Lab. income x Fin. Crisis	−0.0103	Lab. income x Fin. Crisis	−0.0044
constant	−15.5866***	Constant	−9.7712
Nevada		South Carolina	
Labour income	2.1146**	Labour income	−0.0358
Lab. income x Fin. Crisis	−0.0112	Lab. income x Fin. Crisis	−0.0010
Constant	−10.8070	constant	10.3735***
New Hampshire		South Dakota	
Labour income	2.3421***	Labour income	2.2706***
Lab. income x Fin. Crisis	0.0156	Lab. income x Fin. Crisis	−0.0002
Constant	−12.8897***	constant	−12.1327***
New Jersey		Tennessee	
Labour income	2.6953***	Labour income	−0.0922
Lab. income x Fin. Crisis	0.0165	Lab. income x Fin. Crisis	−0.0040
Constant	−16.8166**	constant	11.1627***
New Mexico		Texas	
Labour income	0.9381*	Labour income	3.3991***
Lab. income x Fin. Crisis	0.0046	Lab. income x Fin. Crisis	0.0139***
Constant	1.1804	constant	−23.1795***
New York		Utah	
Labour income	2.7792***	Labour income	3.2954***
Lab. income x Fin. Crisis	0.0071	Lab. income x Fin. Crisis	0.0057
Constant	−17.8569***	constant	−21.7220***
North Carolina		Vermont	
Labour income	0.3643***	Labour income	1.9611***
Lab. income x Fin. Crisis	0.0012	Lab. income x Fin. Crisis	0.0114**
Constant	6.5965***	constant	−8.7900**
North Dakota		Virginia	
Labour income	2.0743***	Labour income	1.9775***
Lab. income x Fin. Crisis	−0.0005	Lab. income x Fin. Crisis	0.0006
Constant	−10.2226***	constant	−9.3155
Ohio		Washington	
Labour income	1.2881***	Labour income	2.3650***
Lab. income x Fin. Crisis	−0.0128***	Lab. income x Fin. Crisis	0.0027
Constant	−2.5548	constant	−13.2099**
Oklahoma		West Virginia	
Labour income	3.5346***	Labour income	3.1285***
Lab. income x Fin. Crisis	−0.0077*	Lab. income x Fin. Crisis	0.0069*
Constant	−24.3362***	constant	−20.0044***
Oregon		Wisconsin	
Labour income	2.5540***	Labour income	2.7507***
Lab. income x Fin. Crisis	0.0080	Lab. income x Fin. Crisis	0.0055
Constant	−14.9863**	constant	−17.0525***
Pennsylvania		Wyoming	
Labour income	2.4173***	Labour income	2.4356***
Lab. income x Fin. Crisis	0.0144*	Lab. income x Fin. Crisis	−0.0083
Constant	−13.8858	constant	−13.7725***
Rhode Island			
Labour income	3.9471***		
Lab. income x Fin. Crisis	0.0081		
Constant	−28.8207***		

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. In accordance with the baseline model expressed by eq. (1), all specifications also include a deterministic trend. However, for brevity, its point coefficient estimates are not reported in the Table.

Table 6 Country-level cointegrating relationship between housing wealth and labour income: Time-series DOLS and panel FE estimators - presence of financial crises

US (time-series DOLS estimator)	*hwy*	US (panel FE estimator)	*hwy*
Labour income	1.0602**	Labour income	1.6653***
Lab. income x Fin. Crisis	0.0026	Lab. income x Fin. Crisis	0.0033***
Constant	−0.3097	Constant	−6.2335***
# Obs.	141		7650

Note: *** p < 0.01, ** $p < 0.05$, * $p < 0.1$. In accordance with the baseline model expressed by eq. (1), all specifications also include a deterministic trend. However, for brevity, its point coefficient estimates are not reported in the Table.

Regarding financial crises, the results displayed in Table 5 show that the interaction term ($y_t \times$ *Fin. Crisis*$_t$) is: (i) negative and significant at either the 1% (Alaska, Iowa, Maryland, Michigan, Montana and Ohio) or 5% level (Indiana and Georgia); and (ii) positive and significant at either the 1% (Delaware, Mississippi and Texas) or the 5% level (Vermont). Consequently, in the former group of states, housing wealth appears to be more responsive to labour income variation during periods of financial crises, while, for the second group of states, it is less responsive. Despite this, point coefficient estimates associated with the interaction term is much smaller (in the order of one hundredth or less) than those associated with labour income. As in the case of Table 4, the empirical evidence for the U.S. as a whole reported in Table 6 reveals that the interaction term is not statistically significant under the DOLS estimator, and significant but roughly nil in the panel FE framework.

Summing up, we do not find evidence of a structural break in the cointegrating relationship between housing wealth and labour income attributed to the presence of economic recessions or financial crises. Thus, we proceed with the assessment of the forecasting power of *hwy* on the basis of model specifications (1) and (2).

Housing Return Forecasting Regressions: U.S. State-Level Evidence

In this Section, we evaluate the predictive ability of *hwy* estimated using state-level data for future real housing returns over different time horizons. Thus, we estimate the following equation

$$\sum_{h=1}^{H} rhr_{t+h} = \kappa + \gamma hwy_{t-1} + \varsigma_t \quad (3)$$

where the H-period real housing return, $rhr_{t+1} + \ldots + rhr_{t+H}$, is regressed on the lag of the housing wealth-to-income ratio, hwy_{t-1}, $\varkappa$ is a constant, and ς_t is the error term.

Table 7 presents the results from OLS forecasting regressions over horizons from one quarter-ahead up to eight quarters-ahead. The point coefficient estimates of hwy_t are negative for all states, that is, a fall in the housing wealth-to-income ratio makes investors more exposed to labour income shocks, leading them to demand a higher risk premium on housing.

Table 7 Forecasting state-level real housing returns: Time-series DOLS estimator

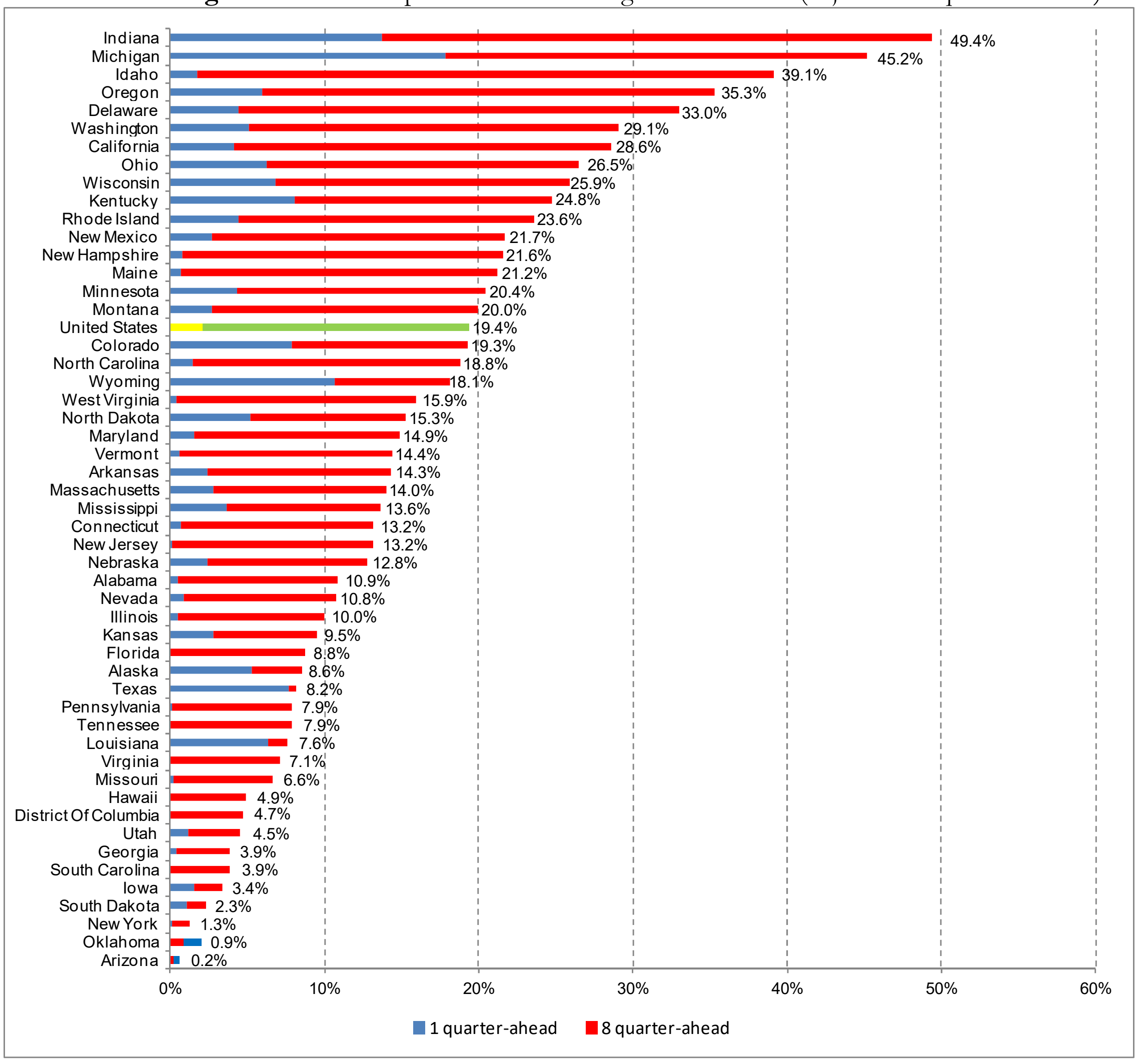
	Forecast horizon H				
State	**1**	**2**	**3**	**4**	**8**
Alabama	−0.0222 (0.027) [0.005]	−0.0413 (0.033) [0.010]	−0.0772** (0.037) [0.028]	−0.1102** (0.046) [0.038]	−0.3001*** (0.071) [0.109]
Alaska	−0.1005*** (0.035) [0.053]	−0.1623*** (0.047) [0.076]	−0.2659*** (0.056) [0.134]	−0.3202*** (0.067) [0.136]	−0.3150*** (0.085) [0.086]
Arizona	0.0155 (0.017) [0.006]	0.0232 (0.028) [0.005]	0.0216 (0.038) [0.002]	0.0109 (0.049) [0.000]	−0.0514 (0.088) [0.002]
Arkansas	−0.0362* (0.019) [0.024]	−0.0844*** (0.027) [0.061]	−0.1340*** (0.034) [0.097]	−0.1732*** (0.040) [0.113]	−0.3029*** (0.061) [0.143]
California	−0.0307** (0.012) [0.042]	−0.0779*** (0.023) [0.075]	−0.1365*** (0.032) [0.109]	−0.2020*** (0.041) [0.141]	−0.5287*** (0.069) [0.286]
Colorado	−0.0391*** (0.011) [0.079]	−0.0834*** (0.017) [0.135]	−0.1292*** (0.023) [0.177]	−0.1663*** (0.029) [0.181]	−0.3081*** (0.052) [0.193]
Connecticut	−0.0171 (0.017) [0.007]	−0.0493* (0.029) [0.019]	−0.0931** (0.041) [0.034]	−0.1428*** (0.053) [0.048]	−0.4274*** (0.090) [0.132]
Delaware	−0.0947*** (0.036) [0.044]	−0.1260*** (0.037) [0.073]	−0.2142*** (0.039) [0.172]	−0.2748*** (0.051) [0.163]	−0.5900*** (0.069) [0.330]
DC	−0.0038 (0.019) [0.000]	−0.0184 (0.023) [0.004]	−0.0394 (0.032) [0.010]	−0.0652 (0.041) [0.017]	−0.1925*** (0.072) [0.047]
Florida	0.0030 (0.013) [0.000]	−0.0054 (0.021) [0.000]	−0.0241 (0.029) [0.005]	−0.0542 (0.036) [0.015]	−0.2441*** (0.065) [0.088]
Georgia	0.0113 (0.015) [0.004]	0.0098 (0.023) [0.001]	0.0018 (0.030) [0.000]	−0.0082 (0.036) [0.000]	−0.1541** (0.063) [0.039]
Hawaii	0.0101 (0.046) [0.000]	−0.0005 (0.052) [0.000]	−0.0414 (0.060) [0.003]	−0.0785 (0.066) [0.010]	−0.2633*** (0.096) [0.049]
Idaho	−0.0412 (0.025) [0.018]	−0.1119*** (0.027) [0.103]	−0.1970*** (0.034) [0.189]	−0.2566*** (0.041) [0.209]	−0.5910*** (0.061) [0.391]
Illinois	−0.0134 (0.015) [0.005]	−0.0350 (0.024) [0.014]	−0.0648* (0.033) [0.025]	−0.0947** (0.042) [0.034]	−0.2858*** (0.071) [0.100]
Indiana	−0.0958*** (0.020) [0.137]	−0.2008*** (0.028) [0.258]	−0.2980*** (0.034) [0.342]	−0.3810*** (0.041) [0.371]	−0.7503*** (0.063) [0.494]
Iowa	−0.0295 (0.019) [0.016]	−0.0761*** (0.025) [0.059]	−0.0951*** (0.033) [0.054]	−0.1065*** (0.039) [0.048]	−0.1509** (0.066) [0.034]
Kansas	−0.0218** (0.011) [0.028]	−0.0547*** (0.016) [0.073]	−0.0811*** (0.022) [0.088]	−0.0980*** (0.027) [0.082]	−0.1846*** (0.047) [0.095]
Kentucky	−0.0639*** (0.018) [0.081]	−0.1409*** (0.028) [0.151]	−0.2134*** (0.035) [0.198]	−0.2806*** (0.042) [0.231]	−0.4769*** (0.069) [0.248]
Louisiana	−0.0466*** (0.015) [0.064]	−0.0912*** (0.023) [0.097]	−0.1383*** (0.031) [0.121]	−0.1739*** (0.039) [0.121]	−0.2399*** (0.069) [0.076]
Maine	−0.0387 (0.039) [0.007]	−0.0963** (0.042) [0.035]	−0.1560*** (0.043) [0.082]	−0.1501*** (0.054) [0.050]	−0.4686*** (0.075) [0.212]
Maryland	−0.0250 (0.016) [0.016]	−0.0690** (0.028) [0.039]	−0.1191*** (0.040) [0.058]	−0.1752*** (0.051) [0.075]	−0.4569*** (0.090) [0.149]
Massachusetts	−0.0304** (0.015) [0.028]	−0.0743*** (0.026) [0.053]	−0.1233*** (0.037) [0.070]	−0.1761*** (0.048) [0.084]	−0.4232*** (0.087) [0.140]
Michigan	−0.0605*** (0.011) [0.179]	−0.1277*** (0.017) [0.287]	−0.1913*** (0.022) [0.344]	−0.2539*** (0.026) [0.388]	−0.4943*** (0.045) [0.452]
Minnesota	−0.0274** (0.011) [0.043]	−0.0599*** (0.018) [0.071]	−0.0940*** (0.023) [0.101]	−0.1282*** (0.028) [0.124]	−0.2977*** (0.048) [0.204]
Mississippi	−0.0390** (0.016) [0.037]	−0.0842*** (0.027) [0.064]	−0.1366*** (0.036) [0.090]	−0.1870*** (0.044) [0.110]	−0.3678*** (0.076) [0.136]

Missouri	−0.0191 (0.032) [0.002]	−0.0702** (0.035) [0.026]	−0.0818** (0.040) [0.028]	−0.1279*** (0.046) [0.050]	−0.2156*** (0.067) [0.066]
Montana	−0.0644** (0.032) [0.027]	−0.1270*** (0.036) [0.078]	−0.2109*** (0.040) [0.158]	−0.2386*** (0.051) [0.129]	−0.4624*** (0.076) [0.200]
Nebraska	−0.0276* (0.015) [0.024]	−0.0644*** (0.020) [0.067]	−0.0957*** (0.024) [0.099]	−0.1267*** (0.029) [0.118]	−0.2186*** (0.047) [0.128]
Nevada	−0.0170 (0.014) [0.009]	−0.0429* (0.025) [0.019]	−0.0773** (0.035) [0.031]	−0.1185** (0.046) [0.043]	−0.3453*** (0.082) [0.108]
New Hampshire	−0.0238 (0.022) [0.008]	−0.0651** (0.026) [0.042]	−0.1190*** (0.033) [0.081]	−0.1626*** (0.042) [0.092]	−0.4365*** (0.069) [0.216]
New Jersey	−0.0045 (0.012) [0.001]	−0.0231 (0.022) [0.007]	−0.0527* (0.031) [0.019]	−0.0911** (0.040) [0.034]	−0.3319*** (0.070) [0.132]
New Mexico	−0.0533** (0.027) [0.027]	−0.1372*** (0.035) [0.094]	−0.2265*** (0.044) [0.154]	−0.3008*** (0.055) [0.168]	−0.5705*** (0.089) [0.217]
New York	0.0062 (0.017) [0.001]	0.0081 (0.026) [0.001]	0.0025 (0.033) [0.000]	0.0001 (0.041) [0.000]	−0.1008 (0.072) [0.013]
North Carolina	−0.0320 (0.022) [0.015]	−0.0677** (0.033) [0.027]	−0.1156*** (0.043) [0.048]	−0.1696*** (0.053) [0.066]	−0.4939*** (0.085) [0.188]
North Dakota	−0.0775*** (0.027) [0.052]	−0.0880** (0.037) [0.037]	−0.1219*** (0.044) [0.049]	−0.1415*** (0.046) [0.060]	−0.2913*** (0.056) [0.153]
Ohio	−0.0438*** (0.014) [0.063]	−0.1026*** (0.023) [0.117]	−0.1633*** (0.030) [0.167]	−0.2160*** (0.037) [0.188]	−0.4474*** (0.061) [0.265]
Oklahoma	−0.0302* (0.018) [0.020]	−0.0715*** (0.026) [0.048]	−0.0930** (0.036) [0.044]	−0.0990** (0.045) [0.032]	−0.0912 (0.077) [0.009]
Oregon	−0.0451*** (0.015) [0.060]	−0.0977*** (0.022) [0.122]	−0.1633*** (0.028) [0.187]	−0.2294*** (0.036) [0.217]	−0.5204*** (0.058) [0.353]
Pennsylvania	−0.0048 (0.014) [0.001]	−0.0189 (0.022) [0.005]	−0.0345 (0.028) [0.010]	−0.0563 (0.036) [0.017]	−0.2188*** (0.062) [0.079]
Rhode Island	−0.0392*** (0.015) [0.044]	−0.0875*** (0.026) [0.071]	−0.1438*** (0.036) [0.099]	−0.2100*** (0.046) [0.125]	−0.5340*** (0.079) [0.236]
South Carolina	−0.0001 (0.022) [0.000]	0.0075 (0.030) [0.000]	−0.0030 (0.035) [0.000]	−0.0200 (0.042) [0.002]	−0.1722** (0.070) [0.039]
South Dakota	−0.0509 (0.041) [0.011]	−0.1170*** (0.043) [0.047]	−0.1116** (0.052) [0.030]	−0.1487*** (0.053) [0.051]	−0.1252* (0.067) [0.023]
Tennessee	−0.0055 (0.024) [0.000]	−0.0273 (0.030) [0.005]	−0.0519 (0.038) [0.013]	−0.0762* (0.046) [0.019]	−0.2579*** (0.073) [0.079]
Texas	−0.0399*** (0.011) [0.077]	−0.0796*** (0.018) [0.121]	−0.1128*** (0.023) [0.144]	−0.1356*** (0.029) [0.133]	−0.1830*** (0.050) [0.082]
Utah	−0.0265 (0.020) [0.012]	−0.0660** (0.032) [0.028]	−0.1025** (0.044) [0.036]	−0.1320** (0.056) [0.037]	−0.2563*** (0.098) [0.045]
Vermont	−0.0666 (0.068) [0.006]	−0.1632** (0.075) [0.031]	−0.1975** (0.080) [0.040]	−0.1489* (0.083) [0.021]	−0.4475*** (0.090) [0.144]
Virginia	0.0005 (0.010) [0.000]	−0.0105 (0.017) [0.003]	−0.0229 (0.023) [0.006]	−0.0396 (0.029) [0.012]	−0.1741*** (0.052) [0.071]
Washington	−0.0437*** (0.016) [0.051]	−0.1059*** (0.027) [0.096]	−0.1752*** (0.036) [0.137]	−0.2457*** (0.046) [0.165]	−0.5829*** (0.075) [0.291]
West Virginia	−0.0350 (0.046) [0.004]	−0.0074 (0.050) [0.000]	−0.1471*** (0.044) [0.071]	−0.1726*** (0.059) [0.055]	−0.3467*** (0.066) [0.159]
Wisconsin	−0.0573*** (0.018) [0.068]	−0.1269*** (0.026) [0.136]	−0.1862*** (0.034) [0.172]	−0.2377*** (0.041) [0.186]	−0.4509*** (0.063) [0.259]
Wyoming	−0.0844*** (0.020) [0.107]	−0.1600*** (0.028) [0.178]	−0.2317*** (0.037) [0.212]	−0.2778*** (0.047) [0.191]	−0.4618*** (0.081) [0.181]

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors appear in parenthesis. Adjusted R-square is reported in square brackets.

The coefficients associated with hwy_t are also statistically significant for the vast majority of states. The main exceptions are: Arizona and New York, where the housing wealth-to-income ratio does not forecast real housing returns regardless of the forecasting horizon considered; D.C., Florida, Georgia, Hawaii, Pennsylvania, South Carolina and Virginia, where there is evidence of predictability at the eight quarter-ahead horizon; and, to some extent, Tennessee, where hwy_t is statistically significant at the same forecasting horizon and only weakly significant at the four quarter-ahead horizon. In all other states, the housing wealth-to-income ratio significantly predicts future housing returns across a range of forecasting horizons.

Figure 2. Predictive power of the housing collateral ratio (adjusted R-square statistics).



Note: Blue bars indicate the adjusted R-square of 1 quarter-ahead forecasting regressions. Red bars report the different between the adjusted R-square of 8 quarter-ahead forecasting regressions and the adjusted R-square of 1 quarter-ahead forecasting regressions or the opposite for Arizona and Oklahoma. The yellow bar reports the adjusted R-square of the 1 quarter-ahead forecasting regression for the U.S. as a whole and the green bar corresponds to the different between the adjusted R-square of the 8 quarter-ahead forecasting regression and the adjusted R-square of the 1 quarter-ahead forecasting regression for the U.S. as a whole.

Figure 2 allows one to better visualize the amount of information condensed in Table 7. It plots the adjusted R-square statistics associated with one quarter-ahead and eight quarter-ahead forecasting regressions (blue and red bars, respectively). Two major observations strike: 1) the predictive power of the housing wealth-to-income ratio varies substantially across U.S. states;

and 2) the ratio displays stronger forecasting ability at long horizons than short horizons. Indeed, red bars are longer than blue bars.

More specifically, at the eight quarter-ahead horizon, the best performance of hwy_t is registered for Indiana (49%), Michigan (45%), Idaho (39%), Oregon (35%), Delaware (33%), California and Washington (both 29%), Ohio (27%), Wisconsin (26%) and Kentucky (25%). By contrast, the worst performances are observed in the case of Arizona and Oklahoma (both 0%), New York (1%), South Dakota (2%), Iowa (3%), South Carolina and Georgia (both 4%), Utah and D.C. (both 5%) and Hawaii (5%). For all other states, the adjusted R-statistics range between 5% and 25%.

As before, we also present evidence for the U.S. as a whole. We start by considering a time-series approach, where we regress eq. (3) and estimate it by DOLS using U.S. aggregates. Then, we exploit the panel structure, and make use of nearly 7600 data point observations to estimate the following equation using a fixed-effects (FE) regressor:

$$\sum_{h=1}^{H} rhr_{i,t+h} = \kappa_i + \gamma hwy_{i,t-1} + \varsigma_{i,t} \qquad (4)$$

where the H-period real housing return of state i, $rhr_{i,t+1} + \ldots + rhr_{i,t+H}$, is regressed on the lag of the housing wealth-to-income ratio, $hwy_{i,t-1}$ of state i, $\varkappa_i$ is a constant, and ς_t is the error term.

Table 8 provides a summary of the findings. In both econometric frameworks, the coefficient associated with the housing wealth-to-income ratio is negative and statistically significant at the 1% level. Moreover, *hwy* explains an important fraction of the variation in future real housing returns at different forecasting horizons: in the DOLS framework, the housing wealth-to-income ratio predicts between 2.1% and 19.4% of the variation of housing returns; and, in the panel FE framework, it forecasts between 0.5% and 10.5% of future housing returns at horizons ranging between one quarter-ahead and eight quarters-ahead. Point coefficient estimates associated with *hwy* are larger in magnitude in the DOLS framework compared to the panel FE model, ranging between −0.02 and − 0.35 and − 0.01 and − 0.21, respectively. Adjusted R-square statistics are also larger at longer horizons (e.g. four quarter-ahead or eight quarter-ahead) relative to shorter horizons (e.g. one quarter-ahead or two quarter-ahead).

Table 8 Forecasting country-level real housing returns: Time-series DOLS and panel FE estimators

	Forecast horizon H				
State	**1**	**2**	**3**	**4**	**8**
U.S. (time-series DOLS estimator); # obs.: 149	−0.0206* (0.012) [0.021]	−0.0513** (0.020) [0.042]	−0.0880*** (0.027) [0.066]	−0.1291*** (0.034) [0.088]	−0.3499*** (0.059) [0.194]
U.S. (panel FE estimator); # obs.: 7599	−0.0146*** (0.002) [0.005]	−0.0339*** (0.003) [0.017]	−0.0589*** (0.004) [0.032]	−0.0827*** (0.005) [0.042]	−0.2146*** (0.007) [0.105]

Note: *** p < 0.01, ** p < 0.05, * p < 0.1. Standard errors appear in parenthesis. Adjusted R-square is reported in square brackets.

In sum, time-series and panel econometric methods confirm the predictive ability of the housing wealth-to-income ratio for future real housing returns. They also show that state-level regressions are able to portray the large heterogeneity in the forecasting power of *hwy* that country-level estimations are unable to capture.

Conclusion

Our paper estimates the long-term equilibrium relationship between housing wealth and labour income using a novel database of U.S. state-level information over the period of 1975:Q1–2012:Q2. We find the such link is stable over time and is not affected by the occurrence of economic recessions or financial crises.

Next, we investigate the forecasting ability of the deviations of housing wealth from its cointegrating link with labour income (i.e. the housing wealth-to-income ratio labelled by *hwy*) for future real housing returns.

We find that: (i) albeit positive, there is a large degree of heterogeneity in the estimates of the elasticity of housing wealth with respect to labour income across U.S. states; and (ii) despite the fact that a rise in the housing wealth-to-income ratio is associated with a fall in future housing returns, the predictive power of *hwy* also varies considerably across states.

More specifically, the elasticity of housing wealth with respect to labour income is larger than 3 for California, Rhode Island, Arizona, Massachusetts, Kansas, Louisiana, Nevada, Texas, D.C., Utah, Iowa, Illinois, Colorado, Oklahoma, West Virginia and Michigan, but lower than unity for South Carolina, Tennessee, North Carolina, Alabama and Georgia. For the U.S. as a whole, time-series and panel econometric methods provide estimates of 1.54 and 1.66, respectively. In the same vein, at the eight quarter-ahead horizon, the housing wealth-to-income ratio predicts less than 10% of the variation of real housing returns in 19 states and more than 30% of that variation in 15 states. For the country as a whole, our estimates of the forecasting power of *hwy* stand at 10.5% and 19.4%.

The empirical evidence provided in this paper can be particularly relevant for investors and practitioners, as it gives support to the usefulness of the housing wealth-to-income ratio as a predictor of real housing returns. From a policy perspective, it is also of utmost importance, especially, if one takes into account that consumers derive both utility and collateral services from the housing assets that they own. And private consumption is the largest component of GDP, so housing market fluctuations play a key role in shaping the business cycle.

Notes

[1.]See also Nyakabawo et al. (2015) and Emirmahmutoglu et al. (2016).

[2.]In the same spirit, Yogo (2006) and Piazzesi et al. (2007) exploit the role of non-separability between durable (housing) and nondurable (non-housing) consumption in investors' preferences, and highlight the importance of consumption composition risk. Pakos (2011) argues that durable goods generate a bias in intratemporal and intertemporal substitution parameter estimates and suggests that preferences display non-homotheticity. Other studies like Fernandez-Corugedo et al. (2007) and Sousa (2010a) emphasize the relevance of the dynamics of durable goods' relative prices and the wealth composition risk, respectively. And while Sousa (2015a) investigates the predictive power of the ratio of asset wealth to labour income for stock returns and sovereign bond risk premium, Blenman (1990) and Sousa (2015b) provide compelling evidence supporting the view that housing delivers collateral services used by investors as a hedge against inflation risk or unfavourable wealth fluctuations.

[3.]Another related strand of research has focused on the predictability of equity real estate investment trust (REIT) returns instead. Liu and Mei (1992) find that REITs are more predictable than other financial assets, because they embed information about general economic risk conditions, and this is particularly true in countries with developed and mature REIT systems (Serrano and Hoesli 2010; Karolyi and Sanders 1998) show that the predictable variation in REIT portfolios is captured by both equity and bond risk premia. Ling et al. (2000) highlight that transaction costs can erase excess returns of active-trading strategies on equity REITs compared to buy-and-hold strategies. Ghysels et al. (2013) show that housing returns are particularly sensitive to leverage and monetary policy, while Akinsomi et al. (2016) stress the importance of sentiment and uncertainty indicators, especially, during periods of financial turmoil. Bianchi and Guidolin (2014) note that REIT returns display abrupt bull-bear dynamic regime shifts.

[4].Our empirical proxies typically pass standard time-series and numerous panel cointegration tests, such as Dickey and Fuller (1979), Phillips and Perron (1988), MacKinnon (1994), Fuller (1996), Harris and Tzavalis (1999), Breitung (2000), Hadri (2000), Choi (2001), Levin et al. (2002), Im et al. (2003) and Breitung and Das (2005). In the same tradition of the work of Engle and Granger (1987), Table A of the Appendix reports a summary of the panel cointegration tests based on the assessment of the stationarity of the housing wealth-to-income ratio estimated using the time-series DOLS framework (hwy_t) and the panel FE method ($hwy_{i,t}$). They provide strong evidence supporting the rejection of the null hypothesis of a unit root in both empirical proxies, thus, corroborating cointegration among housing wealth and labour income.

[5].1975: Q1 is the first observation of our sample period.

References

Agnello, L., Castro, V., & Sousa, R. M. (2015). Booms, busts and normal times in the housing market. *Journal of Business & Economic Statistics, 33*(1), 25–45.

Agnello, L., Castro, V., & Sousa, R. M. (2018). Economic activity, credit market conditions and the housing market. *Macroeconomic Dynamics, 22*(7), 1769–1789.

Agnello, L., Castro, V., & Sousa, R. M. (forthcoming). The housing cycle: What role for mortgage market development and housing finance? *Journal of Real Estate Finance and Economics*. https://doi-org.uplib.idm.oclc.org/10.1007/s11146-019-09705-z.

Akinsomi, K., Aye, G. C., Babalos, V., Economou, F., & Gupta, R. (2016). Real estate returns predictability revisited: Novel evidence from the US REITs market. *Empirical Economics, 51*(3), 1165–1190.

Apergis, N., & Payne, J. E. (2012). Convergence in U.S. housing prices by state: Evidence from the club convergence and clustering procedure. *Letters in Spatial and Resource Sciences, 5*(2), 103–111.

Ashley, R., & Li, G. (2014). Re-examining the impact of housing wealth and stock wealth on retail sales: Does persistence in wealth changes matter? *Journal of Housing Economics, 26*, 109–118.

Balcilar, M., Gupta, R., & Miller, S. M. (2014). Housing and the great depression. *Applied Economics, 46*(24), 2966–2981.

Balcilar, M., Gupta, R., Sousa, R. M., & Wohar, M. E. (2017). The predictability of *hwy* and hwy^{MS} for stock and housing returns: A nonparametric causality in quantile test. *International Review of Economics and Finance, 48*(1), 269–279.

Balcilar, M., Gupta, R., Sousa, R. M., & Wohar, M. E. (2019). *Housing market returns and the consumption-(dis)aggregate wealth ratio: Evidence from U.S. state-level data.* University of Pretoria, Department of Economics Working Paper no. 42.

Bianchi, D., & Guidolin, M. (2014). Can linear predictability models time bull and bear real estate markets? Out-of-sample evidence from REIT portfolios. *Journal of Real Estate Finance and Economics, 49*(1), 116–164.

Blenman, L.P. (1990). Price Forecasts and Interest Rate Forecasts: An Extension of Levy's Hypothesis. *The Journal of Futures Markets, 10*(6), 605-610.

Breitung, J. (2000). The local power of some unit root tests for panel data. In B. H. Baltagi (Ed.), *Advances in econometrics: Nonstationary panels, panel cointegration, and dynamic panels* (Vol. 15, pp. 161–178). Amsterdam: JAI Press.

Breitung, J., & Das, S. (2005). Panel unit root tests under cross-sectional dependence. *Statistica Neerlandica, 59*, 414–433.

Caporale, G. M., & Sousa, R. M. (2016). Consumption, wealth, stock and housing returns: Evidence from emerging markets. *Research in International Business and Finance, 36*, 562–578.

Caporale, G. M., Sousa, R. M., & Wohar, M. E. (Forthcoming). Can the consumption-wealth ratio predict housing returns? Evidence from OECD countries. *Real Estate Economics.* Available at: https://doi-org.uplib.idm.oclc.org/10.1111/1540-6229.12135.

Case, K. E., & Shiller, R. J. (1990). *Forecasting prices and excess returns in the housing market.* National Bureau of Economic Research, NBER working paper no. 3368.

Case, K. E., Quigley, J. M., & Shiller, R. J. (2005). Comparing wealth effects: The stock market versus the housing market. *B.E. Journal of Macroeconomics, 5*(1), 1.

Case, K. E., Quigley, J. M., & Shiller, R. J. (2013). Wealth effects revisited: 1975-2012. *Critical Finance Review, 2*(1), 101–128.

Chen, N.-K., & Leung, C. K. Y. (2007). Asset price spillover, collateral and crises: With an application to property market policy. *Journal of Real Estate Finance and Economics, 37*(4), 351–385.

Choi, I. (2001). Unit root tests for panel data. *Journal of International Money and Finance, 20*, 249–272.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*, 427–431.

Emirmahmutoglu, F., Balcilar, M., Apergis, N., Simo-Kengne, B. D., Chang, T., & Gupta, R. (2016). Causal relationship between asset prices and output in the US: Evidence from state-level panel Granger causality test. *Regional Studies, 50*(10), 1728–1741.

Engle, R., & Granger, C. (1987). Co-integration and error-correction: Representation, estimation and testing. *Econometrica, 55*, 251–276.

Fernandez-Corugedo, E., Price, S., & Blake, A. (2007). The dynamics of consumers' expenditure: The UK consumption ECM redux. *Economic Modelling, 24*, 453–469.

Fuller, W. A. (1996). *Introduction to statistical time series* (2nd ed.). New York: Wiley.

Ghysels, E., Plazzi, A., Valkanov, R., & Torous, W. (2013). Forecasting real estate prices. In *Handbook of economic forecasting*. Amsterdam: Elsevier.

Hadri, K. (2000). Testing for stationarity in heterogeneous panel data. *The Econometrics Journal, 3*, 148–161.

Harris, R. D. F., & Tzavalis, E. (1999). Inference for unit roots in dynamic panels where the time dimension is fixed. *Journal of Econometrics, 91*, 201–226.

He, L. T. (2015). Forecasting of housing stock returns and housing prices: Evidence from the endurance index of housing investor sentiment. *Journal of Financial Economic Policy, 7*(2), 90–103.

Henderson, J. V., & Ioannides, Y. (1987). Owner occupancy: Consumption vs. investment demand. *Journal of Urban Economics, 21*(2), 228–241.

Hwang, M., & Quigley, J. (2006). Economic fundamentals in local housing markets: Evidence from US metropolitan regions. *Journal of Regional Science, 46*(3), 425–453.

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics, 115*, 53–74.

Jin, Y., Leung, C. K. Y., & Zeng, Z. (2012). Real estate, the external finance premium and business investment: A quantitative dynamic general equilibrium analysis. *Real Estate Economics, 40*(1), 167–195.

Karolyi, G. A., & Sanders, A. B. (1998). The variation of economic risk premiums in real estate returns. *Journal of Real Estate Finance and Economics, 17*(3), 245–262.

Laeven, L., & Valencia, F. (2018). *Systemic banking crises revisited*. International Monetary Fund, IMF working paper no. 206.

Leamer, E. E. (2015). Housing really is the business cycle: What survives the lessons of 2008-09? *Journal of Money, Credit and Banking, 47*(S1), 43–50.

Lettau, M., & Ludvigson, S. (2004). Understanding trend and cycle in asset values: Reevaluating the wealth effect on consumption. *American Economic Review, 94*, 276–299.

Leung, C. K. Y. (2004). Macroeconomics and housing: A review of the literature. *Journal of Housing Economics, 13*, 249–267.

Leung, C. K. Y. (2007). Equilibrium correlation of asset price and return. *Journal of Real Estate Finance and Economics, 34*(2), 233–256.

Leung, C. K. Y., Leong, Y., & Wong, S. (2006). Housing price dispersion: An empirical investigation. *Journal of Real Estate Finance and Economics, 32*(3), 357–385.

Levin, A., Lin, C.-F., & Chu, C.-S. J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. *Journal of Econometrics, 108*, 1–24.

Ling, D. C., Naranjo, A., & Ryngaert, M. D. (2000). The predictability of equity REIT returns: Time variation and economic significance. *Journal of Real Estate Finance and Economics, 20*(2), 117–136.

Liu, C. H., & Mei, J. (1992). The predictability of returns on equity REITs and their co-movement with other assets. *Journal of Real Estate Finance and Economics, 5*(4), 401–418.

Lustig, H., & van Nieuwerburgh, S. (2005). Housing collateral, consumption insurance, and risk premia: An empirical perspective. *Journal of Finance, 60*, 1167–1219.

MacKinnon, J. G. (1994). Approximate asymptotic distribution functions for unit-root and cointegration tests. *Journal of Business and Economic Statistics, 12*, 167–176.

Miles, W. (2015). Regional house price segmentation and convergence in the US: A new approach. *Journal of Real Estate Finance and Economics, 50*(1), 113–128.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, 55*(3), 703–708.

Nyakabawo, W. V., Miller, S. M., Balcilar, M., Das, S., & Gupta, R. (2015). Temporal causality between house prices and output in the U.S.: A bootstrap rolling-window approach. *North American Journal of Economics and Finance, 33*(1), 55–73.

Pakos, M. (2011). Estimating intertemporal and intratemporal substitutions when both income and substitution effects are present: The role of durable goods. *Journal of Business and Economic Statistics, 29*(3), 439–454.

Phillips, P. C. B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika, 75*, 335–346.

Piazzesi, M., Schneider, M., & Tuzel, S. (2007). Housing, consumption and asset pricing. *Journal of Financial Economics, 83*, 531–569.

Ren, Y., & Yuan, Y. (2014). Why the housing sector leads the whole economy: The importance of collateral constraints and news shocks. *Journal of Real Estate Finance and Economics, 48*(2), 323–341.

Rocha Armada, M. J., & Sousa, R. M. (2012). Can the wealth-to-income ratio be a useful predictor in alternative finance? Evidence from the housing risk premium. In W. A. Barnett & F. Jawadi (Eds.), *Recent developments in alternative finance: Empirical assessments and economic implications* (International Symposia in Economic Theory and Econometrics, 22) (pp. 67–79). Bingley: Emerald Group Publishing.

Serrano, C., & Hoesli, M. (2010). Are securitized real estate returns more predictable than stock returns? *Journal of Real Estate Finance and Economics, 41*(2), 170–192.

Shiller, R. J. (1998). *Macro markets: Creating institutions for managing society's largest economic risks*. New York: Oxford University Press.

Sousa, R. M. (2010a). Consumption, (dis)aggregate wealth and asset returns. *Journal of Empirical Finance, 17*(4), 606–622.

Sousa, R. M. (2010b). Collateralizable wealth, asset returns and systemic risk: International evidence. In W. A. Barnett & F. Jawadi (Eds.), *Nonlinear modeling of economic and financial time-series* (International symposia in economic theory and econometrics, 20) (pp. 1–27). London: Emerald Group Publishing.

Sousa, R. M. (2015a). Linking wealth and labour income with stock returns and government bond yields. *European Journal of Finance, 21*(10/11), 806–825.

Sousa, R. M. (2015b). What is the impact of wealth shocks on asset allocation? *Quantitative Finance, 15*(3), 493–508.

Spiegel, M., & Strange, W. (1992). A theory of predictable excess returns in real estate. *Journal of Real Estate Finance and Economics, 5*(4), 375–392.

Stock, J. H., & Watson, M. W. (1993). A simple estimator of cointegrating vectors in higher order integrated systems. *Econometrica, 61*(4), 783–820.

Yogo, M. (2006). A consumption-based explanation of expected stock returns. *Journal of Finance, 61*(2), 539–580.

Zhou, Y., & Haurin, D. R. (2010). On the determinants of house value volatility. *Journal of Real Estate Research, 32*(4), 377–396.

Appendix

Table 9 Cointegration tests

Test	Time-series DOLS estimator (hwy_t)	Panel FE estimator (hwy_{it})
Levin et al. (2002)		
LLC unadjusted test statistic, t_δ	−18.0598	−17.2233
LLC bias-adjusted test statistic, t^*_δ (*p value*)	−2.2413*** (0.0125)	−2.2238*** (0.0131)
Harris and Tzavalis (1999)		
HT ρ estimate	0.9075	0.9408
HT test statistic, *z* (*p value*)	−9.3326*** (0.0000)	−2.1206** (0.0170)
Breitung (2000) and Breitung and Das (2005)		
Breitung (2000) test statistic, λ (*p value*)	−3.9865*** (0.0000)	−3.6315*** (0.0001)
Im et al. (2003)		
IPS test statistic, *Wt*-bar	−5.8396*** (0.0000)	−3.0384*** (0.0012)
Choi (2001)		
ADF Fisher-type test:		
Inverse χ^2(102) *P* statistic	330.4974*** (0.0000)	146.3108*** (0.0027)
Inverse ℵ z statistic	−11.0623*** (0.0000)	−3.4302*** (0.0003)
Inverse logit t(259) L^* statistic	−12.0702*** (0.0000)	−3.3984*** (0.0004)
Modified Inverse χ^2 P_m statistic	15.9980*** (0.0000)	3.1024*** (0.0010)
Choi (2001)		
PP Fisher-type test:		
Inverse χ^2(102) *P* statistic	346.2906*** (0.0000)	119.6391 (0.1119)
Inverse ℵ *Z* statistic	−10.6643*** (0.0000)	−2.2602*** (0.0119)
Inverse logit t(259) L^* statistic	−12.5861*** (0.0000)	−2.2899*** (0.0114)
Modified Inverse χ^2 P_m statistic	17.1038*** (0.0000)	1.2350 (0.1084)
Hadri (2000)		
LM *z* statistic	172.9247*** (0.0000)	200.8191*** (0.0000)

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *p* values appear in parenthesis.