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+Absolute Income Inequality and Rising House Prices

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Abstract

Income inequality and house prices have risen sharply in developed countries during the last three decades. We argue that this co-movement is no coincidence but that inequality has driven up house prices on the grounds that it raises the total demand for houses, which inflates their prices considering supply restrictions. To test this hypothesis, we conduct cointegration tests for a panel of 18 OECD countries for the period 1975-2010. The results suggest that income inequality and house prices in most OECD countries are positively correlated and cointegrated, and that in the majority of cases absolute inequality Granger-causes house prices when measured in absolute terms. Relative inequality, on the other hand, is not cointegrated with house prices, which is expected given that total house demand depends on the absolute amount of investible income.

Key Words: Personal Income Inequality, Absolute Inequality, House Prices, Asset Price Inflation, Asset Bubbles

JEL Classification: D31; G12; R21

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1. Introduction

Variations in house prices can have important macroeconomic effects. Rising house prices stimulate consumption expenditure and economic growth when they increase the security feeling of homeowners and ease access to credit—so called wealth and collateral effects (Case *et al.*, 2005a; 2005b, 2013; Iacoviello, 2004). However, at the same time, easier access to credit can foster unsustainable debt-driven growth models, and declining house prices can lead to large reductions in household consumption and prolonged recessions. Indeed, all of these effects have been observed prior to and after the Great Recession (Mian *et al.*, 2013; Jordá *et al.,* 2014; Mian and Sufi, 2015; Goda *et al.*, 2016).

Moreover, starkly rising prices can make housing unaffordable. This especially concerns the most productive urban areas and low income households (Dewilde and Lancee, 2013; Gyourko *et al.*, 2013)[1]. Finally, house price inflation can translate in to retail price inflation (Stroebel and Vavra, 2014), which can have important implications for monetary policy and is also seen to affect mainly low income households (see Easterly and Fischer (2001) on the latter).

Considering these potential socio-economic effects, it is not surprising that a vast literature on the dynamics of house prices exist (especially in the aftermath of the US Subprime Crisis). Typically, income growth is identified as an important long-run determinant of house prices (Case and Shiller, 2003; ECB, 2003). However, in developed countries "in the past two decades preceding the 2008 global financial crisis, real house price growth outpaced income growth by a substantial margin" (Knoll *et al.*, 2014: 23). Recent literature suggests that this phenomenon is mainly explained by low real interest rates coupled with credit expansion (Taylor, 2007; Goodhart and Hofman, 2008; Gerdesmeier *et al.*, 2010; Agnello and Schuknecht, 2011).

[1] In the UK, for example, "Homes in popular towns and London boroughs have risen to 10 and 20 times local incomes, while rents account for up to 78% of earnings" (Collinson, 2015).

Other studies also consider financial innovation and deregulation (Dokko et al., 2011; Bordo and London-Lane, 2013), and global liquidity (Sá et al., 2014; Cesa-Bianchi et al., 2015) as explanatory factors. All of these determinants have in common that they are seen to increase the total demand for houses, which leads to increasing prices taking into account that house supply is restricted. However, they also have in common that they mostly took place in the first decade of the twentieth first century.

The aim of the present paper is to assess rising income inequality as an alternative contributing factor for an increase in demand for houses during the period 1975-2010. It is well established that houses are mainly bought by the upper part of the distribution (although houses are more evenly distributed than financial assets). The top 10% percentage share in house ownership in OECD countries typically is between 40% (Italy) and 60% (US) and the Gini coefficient ranges between 0.6 and 0.7 (Cowell *et al.*, 2012), even rising to above 0.9 when only non-primary residences are considered (Bonesmo Fredriksen, 2012). It is also well established that income inequality increased starkly in most developed countries after 1980, especially due to income concentration at the top (OECD, 2015).

Our hypothesis is therefore that the co-movement of income inequality and house prices is no coincidence and that the increase in inequality has driven up house demand and, in turn, their prices. This supposition is in line with theoretical models that provide two potential mechanisms that are in play: (i) with rising inequality the number of households increases that are willing to pay higher prices for their homes (Gyourko *et al.*, 2013); (ii) houses are an investment good for the upper part of the income distribution and in more unequal countries the investment demand is higher (Nakajima, 2005; Zhang, 2016). In both cases, the change in demand is expected to drive up house prices when supply restrictions are considered.

To our best knowledge, so far no study has tested empirically if the stark increase in real house prices in OECD countries during the last decades was partly driven by rising income inequality. To close this gap in the literature and test our hypothesis, the present study conducts cointegration tests for a panel of 18 OECD countries for the period 1975-2010.

Given the evident nonstationarity of house prices and inequality we use cointegration based methods to avoid problems of spurious regression. Additionally, our interest is centered in the existence of a long-term relationship between both variables.

A second novelty of our study is that we will use both absolute and relative inequality measures to test our hypothesis.[2] The difference between relative and absolute inequality measures is that the former report proportional income differences (e.g. the Gini coefficient), while the latter refer to income differences in monetary terms (e.g. the variance).[3] Studies that investigate the impact of inequality on socio-economic variables like growth and crime typically only account for relative inequality measures. However, in view of the investment demand for houses depending on the absolute amount of investible income and that "it is the absolute level of resources, not their relative distribution, that affects access to housing" (Dewilde and Lancee, 2013: 1189), we expect that absolute inequality measures are more suitable for our purpose.

Indeed, we find that absolute income inequality and house prices in OECD countries are positively correlated and cointegrated (with the notable exception of Germany, Japan, and Korea), whereas the relative inequality measures are not cointegrated. Importantly, we find that in the majority of cases absolute inequality Granger-causes house prices, whereas house prices do not Granger-cause income inequality. In other words, the increase in absolute income inequality has driven up house prices, whereas in most countries the increase in house price seemingly has not contributed to the observed inequality increase.

Moreover, the results confirm previous findings that decreasing real short-term interest rates also have contributed to the long-term increase in real house prices (at least in some countries). Real GDP, on the contrary, shows no signs of cointegration with OECD house

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[2] Our measures for overall inequality changes are the Gini coefficient and the variance, while our measures for changes in the concentration of income are the top 5% income share and the top 5% market income.

[3] Absolute and relative inequality trends can be quite different. If, for example, the income of the whole population increases by the same percentage, the Gini and Theil coefficients remain constant, even though the absolute income gap increases.

prices, which is in line with Knoll *et al.*'s (2014) observation that real house price growth in OECD countries has been much higher than income growth.

The layout of this paper is as follows. Section Two details the theoretical link between inequality and house prices. Section Three gives an overview of the research design. Section Four presents the results concerning the impact of (absolute) inequality on house prices. Section Five concludes the paper.

2. The theoretical link between (absolute) inequality and house prices

The models that examine whether inequality affects house prices are typically general equilibrium models that have three main conditions in common: First, the existence of heterogeneous agents, so that inequalities can be analysed. Second, house supply is assumed to be at least very inelastic, so that the house market adjusts to demand shocks by price changes. Third, the presence of frictions that limit the access to the house market.

According to these models, inequality can affect house prices via two demand mechanisms: (i) when houses are considered as consumption goods, an increase in income inequality raises the amount of people that are willing to pay high prices in order to access to certain areas; and (ii) when houses are considered as rent generating assets, inequality is expected to increase the absolute amount of savings (assuming that the propensity to consume decreases with higher incomes), which in turn raises the total demand for houses.

Regarding the first mechanism, Gyourko *et al.* (2013) presents a model in which two types of houses exist. The first type has an elastic supply, whereas the second type has an inelastic supply and is preferred by households. The model also differentiates between low and high wage earners. When the wage distribution changes in favour of high wage earners, more people desire to live in (and can pay for) the preferred houses that have an inelastic supply. As a result, the price of preferred houses increase and thus also the average house price, given that the houses with elastic supply experience a quantitative adjustment.

Määttänen and Terviö (2014) present a related model but differentiate houses according to their quality. The quality is defined as a continuous spectrum, which implies that the supply is perfectly inelastic for each quality type of house. Agents are assumed to maximize their utility choosing between goods consumption and the quality of their residence.[4] With increasing inequality low income households' willingness to pay for the quality of houses decreases, whereas the willingness of high income households to pay for the quality of houses increases. The outcome is that rising inequality leads to lower prices for low quality houses and to higher prices for high quality houses. The overall effect on house prices depends on which of these opposing effects dominates.

The second line of research considers houses as assets. Nakajima (2005) uses a life-cycle general equilibrium model with portfolio allocation between housing and a financial asset to explain changes in the demand for houses. The return of each asset is determined by the ratio of the total return in terms of the available quantity. Houses are assumed to be inelastic, whereas the financial asset is assumed to be elastic with a decreasing marginal productivity. Rising income inequality increases savings, assuming an increasing marginal propensity to save with increasing incomes. The additional savings are first invested in the financial asset. However, the increase in demand decreases the return of these assets (assuming elastic supply and decreasing marginal productivity). Consequently, investors will switch their investment to the house market. The increasing demand for houses increase their price on the grounds that their supply is assumed to be inelastic.

Zhang (2016), on the other hand, proposes an incomplete market model with heterogeneous households and an exogenously given house supply. In the same vein as Nakajima (2005), Zhang treats houses as an asset that competes against an alternative asset (i.e. bonds) but in his model houses have a higher rate of return than the investment alternative. The reason why the return is higher is that houses are assumed to be a risk-free

[4] The model assumes that each household only owns one house and that it chooses the quality level according to its income.

investment and that entry barriers to the market exist. Given its relatively high return, households always want to invest in the house market. However, the poor have not enough income to enter the market and middle-income households can only hold a minimum amount of houses. Top income households, on the other hand, are not constrained and increase investment income in the house market. Rising inequality thus leads to increasing house demand and, in turn, to an increase in their prices.

Finally, Matlack and Vigdor (2008) present a model that considers the importance of land as a production factor and of houses as consumption goods (land that can be transformed into houses without any cost). The model assumes that the quantity of land is constant, that workers are divided according to their skills (high- and low-skilled), that wages equal marginal productivity, and production has a neoclassical function production.[5] Considering this setting, rising wage inequality leads to an increase in house prices when the marginal productivity of land is constant. This is the case because house demand of high-skilled workers increases by more than the demand from low-skilled workers decreases given that the amount of land available for households is unchanged.

All of these potential mechanisms have in common that an increase of the absolute level of income at the top leads to an increase house demand. It therefore seems important to distinguish between relative and absolute income inequality when empirically studying the impact of income inequality on house prices. The most widely used relative inequality index is the Gini coefficient (1), whereas the variance is typically used when measuring absolute income differences (2) (see Goda and Torres García, 2016). The main difference between these two indices is that the Gini coefficient normalizes the sum of income differences with the mean income (μ), whereas the variance subtracts μ from individual incomes.

[5] More specifically, the authors assume the following production function: $Y = H^{\alpha} L^{\beta} A^{\varphi} K^{1-\alpha-\beta-\varphi}$, where H are high-skilled workers, L are low-skilled workers and A is land. Changes in α, β or φ, not only change the marginal productivity of each factor, but also the participation in total income. Hence, a variation in the values of these parameters changes the distribution of income.

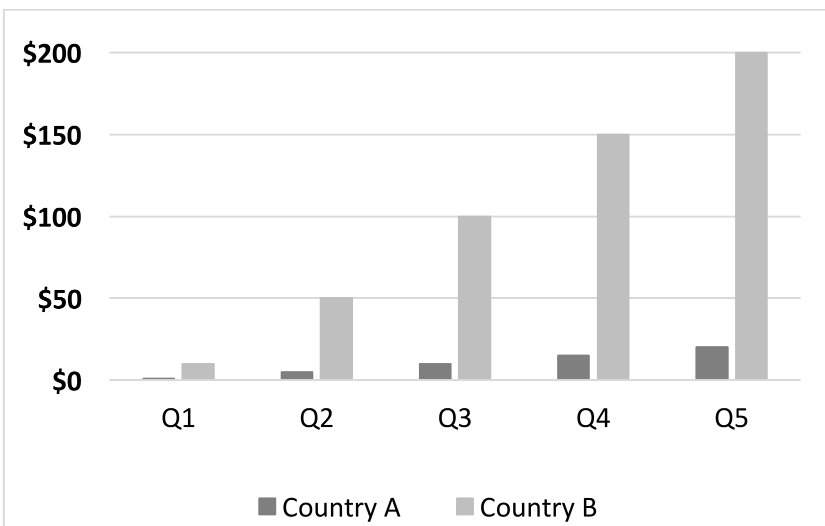
$$\text{Gini} = \frac{1}{\mu}\frac{1}{N^2}\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left|\gamma_j - \gamma_i\right| \tag{1}$$

$$\text{Variance} = \frac{1}{N}\sum_{i=1}^{N}(\gamma_i - \mu)^2 \tag{2}$$

where *N* is population size, μ is mean income, γ_i is income of the *i-th* individual, and γ_j is the income of the *j-th* individual.

An important property of the Gini coefficient is that its value is independent of overall income, whereas the opposite is true for the variance. To make this more palpable, Figure 1 shows the income distribution of two countries, which are both assumed to have a population size of five. Although the income per capita of Country B is much higher than that of Country A, the Gini coefficient of both countries is identical (0.38). On the contrary, the value of the variance of both countries is quite distinct: the variance of Country B is 4,616, while that of Country A is only 46.

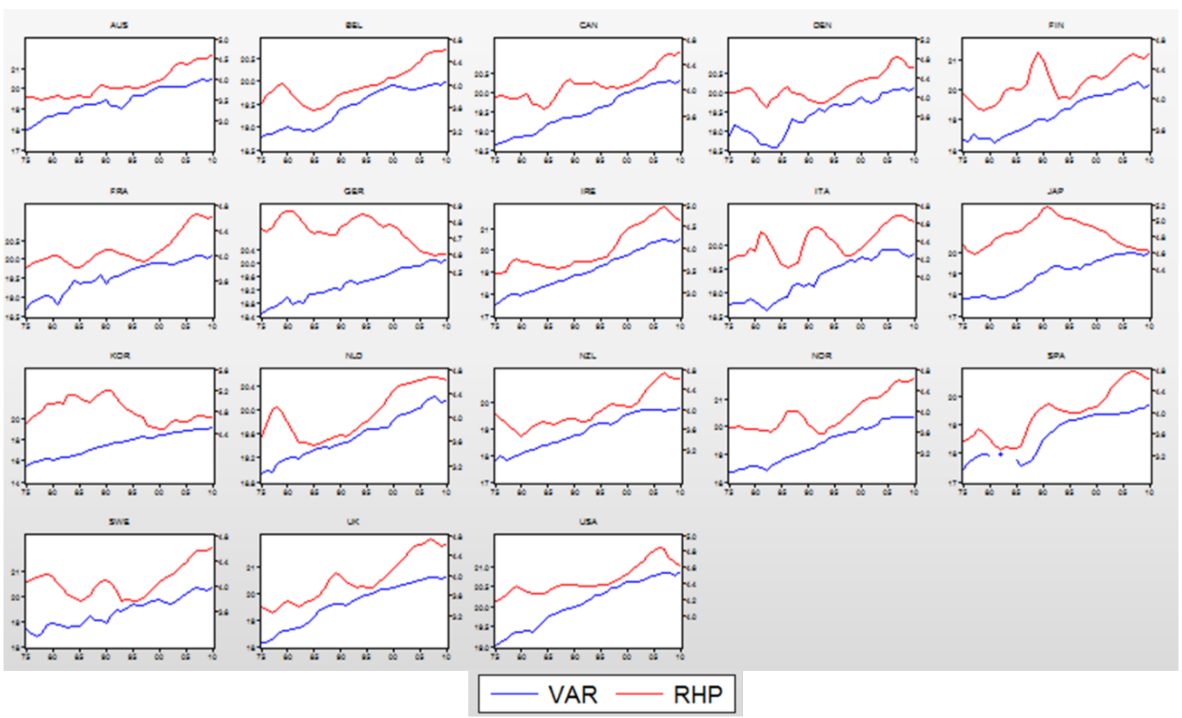
Figure 1: Relative vs. Absolute Inequality



As well as overall inequality the absolute amount of investible income of the upper part of the distribution in Country B is much higher than that of Country A. According to the above discussed theories, one would therefore expect that, that households in Country B would pay higher prices for houses as consumption goods and also would have a higher demand for houses as an investment good. As a result house prices in Country B should be higher than in Country A (everything else equal). Similarly, when the Gini coefficient in both countries would increase by the same amount, the absolute amount of income at the upper part of the distribution would increase by more in Country B than in Country A, and consequently also house prices in Country B should increase by more than in Country A.

Figure 2 suggests that in most OECD countries real house prices and absolute income inequality are positively correlated and nonstationary. To deal with nonstationarity and avoid the associated problem of spurious regression we use cointegration based methods. The remainder of this paper tests whether income inequality and house prices in OECD countries are cointegrated with a positive correlation in the long-run and with the direction of causation running from inequality to house prices.

Figure 2: Real house prices and absolute inequality in OECD countries, 1975-2010



Note: This graphs shows the evolution of the logarithm of the income variance (VAR, left axis) and the logarithm of real house prices (RHP, right axis) in 18 selected OECD countries during the period 1975-2010.

3. Research design

3.1 General specification and data

Consider the following potential cointegrating equation of interest:

$$ln(HP_t) = \beta_1 + \beta_2 INEQ_t + u_t \quad (3)$$

where $ln(HP_t)$ is the natural logarithm of real house prices and $INEQ_t$ are different income inequality measures. The house price data are yearly averages of the OECD real house price index. The four inequality measures considered are (i) the Gini coefficient ($Gini_t$), (ii) the top income share ($Top5\%_t$), (iii) the income variance in constant PPP ($ln(variance_t)$), and (iv) the market income of the top 5% income earners in constant US$ ($ln(Top5\$_t)$).

The market Gini coefficient is retrieved from Solt's Standardized World Income Inequality Database (SWIID, V5.0). The SWIID combines and adjusts Gini coefficients from different sources and currently is the most extensive publicly available database of income Gini coefficients that are comparable across countries and time. SWIID data have been widely used in previous studies concerned with income inequality.[6]

Data on real house prices and Gini coefficients are available on a yearly basis for 18 countries: Australia (AUS), Belgium (BEL), Canada (CAN), Denmark (DEN), Finland (FIN), France (FRA), Germany (GER), Ireland (IRE), Italy (ITA), Japan (JAP), the Netherlands (NET), New Zealand (NEW), Norway (NOR), South Korea (KOR), Spain (SPA), Sweden (SWE), the UK (UKD) and the USA (USA).

Following Goda and Torres García (2016), the retrieved Gini coefficients are used to estimate the other three inequality measures. Income shares are not readily available on a frequent basis, so first ventile income shares are obtained.[7] Supposing a lognormal

[6] See, for example, Bergh and Nilsson (2010), Fox and Hoelscher (2012), Agnello and Soussa (2014), Herzer *et al.* (2014), Chon (2015) and Goda and Torres García (2016).

[7] Ventile shares are frequently used in the literature (the lowest ventile represents the poorest 5% of the population, etc.) because they allow for relatively exact inequality estimates when differences within income groups are not taken into account (see Davies and Shorrocks, 1989; Milanovic, 2012).

distribution, the relationship between the Gini coefficient and the Lorenz curve can be expressed as follows (Aitchison and Brown, 1966):

$$L(p) = \Phi(\Phi^{-1}(p) - \sigma_i), \tag{4}$$

where Φ is the lognormal cumulative distribution function of income, p is the percentile of the distribution, and σ_i is the standard deviation, which is associated with the Gini coefficient of each country and year under study as is shown by the following expression:

$$\sigma_i = \sqrt{2}\Phi^{-1}\left(\frac{1+G_i}{2}\right), \tag{5}$$

where G_i is the Gini coefficient of the *i-th* country. Hence, changes in the Gini coefficient affect the estimation of the standard deviation and, consequently, of the Lorenz curve and the income share of the p-th percent of the population. It is important to note that a higher Gini coefficient leads to a higher standard deviation, which implies that the population at the bottom (top) has a lower (higher) income share.

The obtained income shares are then used to calculate the income variance:

$$Var = \sum_{i=1}^{k} \frac{n_i}{n}\left(\frac{1}{20}\sum_{p=1}^{20}\left((x_{ip} * GDP_i) - GDPpc_i\right)^2\right) \tag{6}$$

where n_i denotes the population size of the *i-th* country, GDP_{pci} is the mean per capita income of the *i-th* country, x_{ip} is the income share of the *p-th* population ventile of the *i-th* country, and GDP_i is the total income of the *i-th* country.

3.2 Determining stationary, trend stationary and nonstationary series

After having derived these data, we test for each of these variables' order of integration and then consider whether their (log) ratios are stationary (cointegrate with a unit coefficient). To establish if the necessary condition for cointegration between real house prices ($ln(HP_t)$)

and the inequality measures ($INEQ_t$) is satisfied, first Pesaran's (2007) panel unit root test is applied to the natural log of real house prices and the four inequality variables. Pesaran's (2007) test assumes linear adjustment, can deal with cross-sectional dependence and is based upon the following time-series regression estimated for each i:

$$\Delta y_{i,t} = a_i^P + \alpha_i^P t + b_i^P y_{i,t-1} + c_{i,0}^P \bar{y}_{t-1} + \sum_{j=1}^{p_i} c_{i,j}^P \Delta y_{i,t} + \sum_{j=0}^{p_i} d_{i,j}^P \Delta \bar{y}_{t-j} + u_{i,t}^P \quad (7)$$

where, $i = 1, 2, \dots, N$; $t = 1, 2, \dots, T$, $\Delta \bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{i,t}$ and $\bar{y}_{t-1} = \frac{1}{N}\sum_{i=1}^{N} y_{i,t-1}$.

The null hypothesis is that there is a unit root for all cross-sectional units, $b_i^P = 0 \; \forall \; i$ while the alternative is that $y_{i,t}$ is stationary for at least one cross-section, $b_i^P < 0$ for *at least* one i. The CADF statistic for each cross-section is the OLS t-ratio corresponding to b_i^P, denoted $t_i^P(N,T) = \frac{\hat{b}_i^P}{s_{\hat{b}_i^P}}$. The panel test statistic, $CIPS$, is:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} t_i^P(N,T) \quad (8)$$

The version of the test that we use is based upon truncated CADF statistics, following the scheme given in Pesaran (2007) and denoted $t_i^{P^*}(N,T)$, thus:

$$CIPS^* = \frac{1}{N}\sum_{i=1}^{N} t_i^{P^*}(N,T) \quad (9)$$

To corrobate the obtained results, in a second step Cerrato *et al.*'s (2009, 2011) heterogeneous nonlinear panel unit root tests are used. Cerrato et al's test assumes a stationary common factor across individual units to account for cross-sectional dependence. It involves estimating the following nonlinear auxiliary regression by ordinary least squares (OLS):

$$\Delta y_{i,t} = a_i^C + \alpha_i^C t + b_i^C y_{i,t-1}^3 + c_{i,0}^C \overline{y_{t-1}^3} + \sum_{j=1}^{p_i} c_{i,j}^C \Delta y_{i,t} + \sum_{j=0}^{p_i} d_{i,j}^C \Delta \bar{y}_{t-j} + u_{i,t}^C \quad (10)$$

where, $\overline{y_{t-1}^3} = \frac{1}{N}\sum_{i=1}^{N} y_{i,t-1}^3$. A time trend, t, is included following Cerrato et al (2013) and the lag length, p_i, can be determined using information criteria.

The null hypothesis is $b_i^C = 0 \; \forall \; i$, while the alternative is $b_i^C < 0$ for *at least* one i. The t-ratios for each cross-section, denoted $t_i^C(N,T) = \frac{\hat{b}_i^C}{s_{\hat{b}_i^C}}$, where $\hat{b}_i^C$ is the OLS estimate of b_i^C and $s_{\hat{b}_i^C}$ is the corresponding OLS coefficient standard error, are used to calculate the panel test statistic:

$$\bar{t}(N,T) = \frac{1}{N}\sum_{i=1}^{N} t_i^C(N,T) \qquad (11)$$

If the test statistic is not more negative than the critical value, reported in Cerrato et al (2009 and 2011), the null hypothesis cannot be rejected. Simulations indicate that this test has superior size and power than Pesaran's (2007) test when the data generating process is nonlinear.

For both panel unit root tests the sequential panel selection method (SPSM), proposed by Chortareas and Kapetanios (2009), is applied to identify which cross-sections (countries) are stationary and which are nonstationary (the procedure is explained within the context of Cerrato et al's (2009, 2011) test)[8]. The null hypothesis is that all countries' series are I(1) and the alternative is that at least one country's series is I(0).

The SPSM essentially involves applying the panel unit root test, $\bar{t}(N,T)$, to all N countries and if the null cannot be rejected the procedure stops and all countries' series I(1). However, if the null hypothesis is rejected at least one country's series is I(0) and we exclude the country that that rejects the I(1) null the most, which is the one that has the smallest (most negative) individual country test statistic, $min\{t_i^C(N,T)\}$. The panel unit root test statistic, $\bar{t}(N-1,T)$, is calculated for the remaining $N-1$ countries.

If the null cannot be rejected the procedure stops and the $N-1$ countries' series included in this panel unit root test are all I(1) and the 1 country's series that was excluded from this test is I(0). However, if the null hypothesis is rejected at least one of these $N-1$ countries'

[8] Chortareas and Kapetanios (2009) apply the SPSM procedure to the Im *et al* (2003) panel unit root test that does not account for cross-sectional dependence.

series is I(0) and we exclude the country that has the smallest individual country test statistic, $min\{t_i^C(N-1,T)\}$, and the panel unit root test, $\bar{t}(N-2,T)$, is calculated for the remaining $N-2$ countries. This process continues until the panel unit root test cannot reject the null. All countries' series included in this last test are I(1) and all countries' series excluded from this last test are I(0).

To finally determine which series is stationary, trend-stationary or nonstationary we use the following procedure: if the unit root null is rejected using the test including only an intercept as a deterministic term the series is stationary. However, if the null is not rejected, the unit root test including both an intercept and trend is considered. If the null of this test is rejected the series is trend stationary, whereas if the null is not rejected the series has a unit root.

The Cerrato et al (2009 and 2011) test assumes nonlinear adjustment (possibly approximating structural breaks) whereas the Pesaran (2007) test assumes linear adjustment. Since each test is most powerful for the adjustment it is designed for we infer stationarity if either test indicates stationary. Further, if either test suggests trend stationarity and neither indicates stationarity we will infer trend stationarity. Otherwise, we infer a unit root.

3.3 Determining cointegration and causality

We then proceed to test for cointegration between $ln(HP_t)$ and $INEQ_t$ by applying Westerlund's (2007) panel cointegration test. We use the `xtwest` command, provided by Persyn and Westerlund (2008), with the Stata program, to produce all of the reported results associated with Westerlund's (2007) method. Westerlund's (2007) tests use the following model assuming a single cointegrating vector:[9]

$$\Delta y_{i,t} = \delta_{1,i} + \delta_{2,i}t + \alpha_i y_{i,t-1} + \boldsymbol{\lambda}_i'\boldsymbol{x}_{i,t-1} + \sum_{j=1}^{p_i}\alpha_{ij}\Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i}\boldsymbol{\gamma}_{ij}'\Delta\boldsymbol{x}_{i,t-j} + e_{i,t} \qquad (12)$$

[9] Pedroni's (1999, 2004) tests also assume a single cointegrating equation.

where, $\boldsymbol{x}'_{i,t} = (x_{1,i,t} \quad x_{2,i,t} \quad \cdots \quad x_{K,i,t})$ is a vector containing K explanatory variables that are assumed to be weakly exogenous while the inclusion of q_i lead values prevents the violation of strict exogeneity. The number of leads and lags is chosen to minimise Akaike's information criterion (AIC) as implemented with Persyn and Westerlund's (2008) Stata program.

The null of no cointegration for any cross-sectional unit, $H_0\colon \alpha_i = 0 \ \forall \ i$, is tested against two different alternative hypotheses. The two group mean statistics, denoted G_τ and G_α, specify the alternative as cointegration *for at least one cross-sectional unit*: $H_1^G\colon \alpha_i < 0$ *for at least one* i. G_α utilises a heteroscedasticity and autocorrelation consistent (HAC) adjustment where we set the bandwidth parameter using: $M_i = 4\left(\frac{T}{100}\right)^{2/9}$, giving $M_i = 3$.[10] The two panel statistics, denoted P_τ and P_α,[11] specify the alternative hypothesis that there is cointegration *for all cross-sectional units*, that is, $H_1^P\colon \alpha_i < 0 \ \forall \ i$.[12]

The 4 panel cointegration statistics are normalised using the asymptotic moments reported in Table 1 of Westerlund (2007) and have an asymptotic standard normal distribution. Any normalised statistic that is less negative (greater) than the left-tail critical value implies that the no cointegration null should not be rejected. We report bootstrapped probability values (using 600 replications), that are robust to very general forms of cross-sectional dependence, as produced by Persyn and Westerlund's (2008) program.[13]

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[10] We set the maximum number of lead and lags in (12) to 3.

[11] The G_α and P_α statistics may reject the null too often in small samples (though not asymptotically). Westerlund (2007) suggests that "[g]iven their faster rate of divergence, it is probable that the coefficient tests G_α and P_α have higher power than G_τ and P_τ in samples where T is substantially larger than N". This suggests that G_α should be favoured when T is large relative to N (as in our case). However, Westerlund's (2007) simulation results for smaller sample sizes (with $T = 100$ and $T = 200$ as well as $N = 10$ and $N = 20$) suggest that G_τ has slightly better size and power compared to G_α, hence G_τ may be more appropriate for our analysis where T is not large.

[12] We find that when cointegration is supported it is based on at least one of the panel statistics suggesting cointegration for the whole panel of countries.

[13] Pedroni's (1999 and 2004) panel cointegration tests assume cross-sectional independence although Pedroni (2004) applies them using cross-sectionally demeaned data to address cross-sectional dependence. However, cross-sectional demeaning only addresses the common time effects form of cross-sectional dependence.

Unlike the residual based tests of Pedroni (1999 and 2004) that are most commonly employed in panel cointegration analysis, Westerlund's (2007) method does not assume that common factor restrictions hold. Residual based tests have substantially lower power (especially in small samples) compared to Westerlund's (2007) error-correction method when the common factor restrictions do not hold – see Persyn and Westurlund (2008). As Westerlund (2007) notes, "[i]f weak exogeneity fails, then the error correction test may have low power, while if the common factor restriction fails, then the residual based tests may have low power." The power of Pedroni's (1999, 2004) tests are also adversely affected when weak exogeneity is violated, if not as much as Westerlund's (2007) tests can be.

Westerlund (2007) concludes that, "… under the maintained assumption of weak exogeneity, the new tests perform well with good size and power in most panels. In particular, we find that the error correction tests have both better size accuracy and vastly superior power in comparison with residual based tests. We also find that the bootstrapped versions of the new tests are very effective in eliminating the effects of the cross-sectional dependence without sacrificing power." Westerlund continues, "We further show that this difference in power arises mainly because the residual-based tests ignore potentially valuable information by imposing a possibly invalid common factor restriction." These conclusions are robust to different sample sizes and deterministic components. However, when weak exogeneity is violated, while the size of Westerlund's (2007) tests are broadly correct the power can be low. Nevertheless, Westerlund's (2007) tests have good power when the adjustment coefficient in the differenced equation of a regressor is positive (although not when this coefficient is negative). "Zivot (2000) also presents several reasons for why weak exogeneity may not be too much of a problem in practice. One reason is that it can be readily tested as a restriction on the unconditional model, which in the current panel data setting corresponds to the panel vector error correction model studied by Larsson *et al.* (2001). Another reason is that there appears to be strong support for the weak exogeneity assumption in many applications, see Zivot (2000) and the references therein." Westerlund (2007).

While we first assess the weak exogeneity assumption by applying the Westerlund (2007) test to the reverse regression of inequality on house prices the use of the Westerlund (2007) cointegration test for weak exogeneity in this way is only suggestive. The reasons for this include the following. First, the cointegrating equations in the autiregressive distributed lag (ADL) models are different when the difference of $ln(HP_t)$ is the dependent variable and when the difference of inequality is the dependent variable. Second, leads and lags of the differenced regressors (and not the dependent variable) are included in the ADL model. A more typical test for weak exogeneity is based on the error-correction form of a vector autoregression (VAR), typically referred to as the *restricted* vector error correction model (VECM) or VEC.[14] The VEC, assuming 1 cointegrating equation with (unrestricted) intercept and no trend, in this two variable system would be specified as follows for country i:

$$\begin{aligned} \Delta ln(HP_t) &= \gamma_{11} + \textstyle\sum_{j=1}^{p} \gamma_{12j} \Delta\, INEQ_{t-j} + \sum_{j=1}^{p} \gamma_{13j} \Delta ln\left(HP_{t-j}\right) + \alpha_1 [ln(HP_{t-1}) - \beta_2\, INEQ_{t-1}] \\ \Delta INEQ &= \gamma_{21} + \textstyle\sum_{j=1}^{p} \gamma_{22j} \Delta\, INEQ_{t-j} + \sum_{j=1}^{p} \gamma_{23j} \Delta ln\left(HP_{t-j}\right) + \alpha_2 [ln(HP_{t-1}) - \beta_2\, INEQ_{t-1}] \end{aligned} \tag{13}$$

The t-tests for weak exogeneity, and long-run Granger non-causality (LRGNC), are based on the following hypotheses:

- H_0^1: $\alpha_1 = 0$, implies that $ln(HP_t)$ is weakly exogenous with respect to the parameters in the equation for $\Delta INEQ$ and $INEQ$ does not Granger-cause $ln(HP_t)$ in the long-run. Whereas H_A^1: $\alpha_1 \neq 0$ implies that $ln(HP_t)$ is not weakly exogenous with respect to the parameters in the equation for $\Delta INEQ$ and $INEQ$ Granger-causes $ln(HP_t)$ in the long-run.
- H_0^2: $\alpha_2 = 0$, implies that $INEQ$ is weakly exogenous with respect to the parameters in the equation for $\Delta ln(HP_t)$ and that $ln(HP_t)$ does not Granger-cause $INEQ$ in the long-

[14] The restricted VECM, or VEC, imposes the number and form of cointegrating equations on the unrestricted VECM.

run. Whereas $H_A^2\colon \alpha_2 \neq 0$ implies that $INEQ$ is not weakly exogenous with respect to the equation for $\Delta ln(HP_t)$ and that $ln(HP_t)$ Granger-causes $INEQ$ in the long-run.

In applying the Granger non-causality (GNC) tests we estimate the system (13) for each country with time-series regressions using previously defined cointegrating equations to define the error-correction terms. We subtract the mean of these error-correction terms to produce new zero mean error-correction terms to be used in a slightly modified version of (13) when applying the GNC tests. An unrestricted intercept is included in this modified version of (13). The lag lengths for each country are determined using the AIC with a maximum lag of ($p =$) 3.

3.4 Robustness checks

Finally, we conduct two robustness checks. The first is a bivariate cointegration analysis that tests if income growth (real GDP, retrieved from AMECO) is a determinant of $ln(HP_t)$:

$$ln(HP_t) = \beta_1 + \beta_2 \ln{(GDP)_t} + u_t \tag{14}$$

As mentioned in the introduction, income growth is found to be an important house price diver. Moreover, Figure 1 shows that absolute inequality is strongly related to overall income. Hence, it might be that income growth rather than absolute inequality growth was the main driver behind the growth in OECD house prices.

The second robustness check involves two trivariate cointegration models that account for monetary policy (r) as potential omitted variable:

$$ln(HP_t) = \beta_1 + \beta_2 INEQ_t + \beta_3 \mathrm{r}_t + u_t \tag{15}$$

$$ln(HP_t) = \beta_1 + \beta_2 \ln{(GDP)_t} + \beta_3 \mathrm{r}_t + u_t \tag{16}$$

Loose monetary policy is the most mentioned potential driver behind the recent upsurge in OECD house prices and interest rate data are readily available. The monetary proxy used is the nominal 3-month nominal interbank interest rate from OECD.stat and the St. Louis Fed (Germany and Ireland), adjusted with consumer price inflation.

4. The impact of (absolute) income inequality on house prices

4.1 Are real house prices and income inequality cointegrated?

Pesaran's (2007) and Cerrato *et al.*'s (2011) unit root tests (allowing for both linear and nonlinear adjustment) suggest that $ln(HP_t)$ and our four inequality measures are at least I(1) for the vast majority of the 18 sample countries. To be more precise, the number of countries that are found to be I(1) according to at least one of the two test are: 13 for the logged real house price index ($ln(HP_t)$), 16 for the Gini coefficient ($Gini_t$), 15 for the top 5% income share ($Top5\%_t$), 17 for the logged income variance ($ln(Var_t)$), and 16 for the logged market income of the top 5% ($ln(Top5\$_t)$).[15]

That not all countries' variables are I(1) may be due to factors such as Type I errors. Hence, we treat all series as if they are I(1), satisfying the necessary condition for cointegration, and proceed to conduct tests of cointegration.[16] If the assumption that the necessary condition for cointegration being satisfied is incorrect this may manifest itself in the rejection of cointegration.

We therefore proceed to test for cointegration between $ln(HP_t)$ and $INEQ_t$ by applying Westerlund's (2007) panel cointegration test. For the two relative inequality measures, $Gini_t$ and $Top5\%_t$, all four tests for both sets of deterministic terms cannot reject the null hypothesis. Hence, it is unambiguous that there is no evidence of cointegration between $ln(HP_t)$ and $Gini_t$ and $ln(HP_t)$ and $Top5\%_t$. For $ln(Var_t)$ all four tests indicate cointegration at the 5% level when the intercept is the only deterministic term included in the

[15] Details about the unit root tests and their results are available on request.
[16] If some of the series are I(0) this should not be an issue because the ADL method can identify error-correction relationships when some series are I(1) and others are I(0) – although the critical values reported in Westerlund (2007) assume I(1) variables.

model (when both an intercept and trend are included in the model cointegration is only indicated at the 5% level by 2 tests). For $ln(Top5\$_t)$ three tests reject the no cointegration null at the 1% level while the other test, G_α, rejects it at the 10% level when only an intercept is included in the model. When both an intercept and trend are included in the model one test, G_τ indicates cointegration at the 5% level.

Table 1: Robust p-values for Westerlund's (2007) panel cointegration tests of $ln(HP_t)$ on $INEQ_t$

	$GINI_t$		$Top5\%_t$		$ln(VAR_t)$		$ln(Top5\$_t)$	
Det	*Int*	*Trend*	*Int*	*Trend*	*Int*	*Trend*	*Int*	*Trend*
G_τ	0.898	0.315	0.902	0.293	**0.002*****	**0.007*****	**0.003*****	**0.030****
G_α	0.782	0.277	0.813	0.168	**0.025****	0.052*	0.058*	0.268
P_τ	0.325	0.200	0.328	0.145	**0.000*****	**0.005*****	**0.002*****	0.063**
P_α	0.305	0.335	0.295	0.252	**0.010****	0.053*	**0.002*****	0.105
Leads	1.28	1.28	1.28	1.28	1.22	1.50	1.22	1.61
Lags	1.00	1.00	1.06	1.00	1.11	1.22	1.11	1.28

Table 1 notes. The row labelled $INEQ_t$ denotes the inequality measure involved in the potential cointegrating equation with $ln(HP_t)$ as the dependent variable and the row labelled Det specifies the deterministic terms included in the cointegration equation as Int when only an intercept is included and Trend when both an intercept and trend are included. G_τ and G_α denote the tests when the alternative hypothesis is that there is cointegration for at least one country in the panel, based on OLS and heteroscedasticity and autocorrelation consistent (HAC) coefficient standard errors, respectively. P_τ and P_α denote the tests when the alternative hypothesis is that there is cointegration for all 18 countries in the panel, based on OLS and HAC coefficient standard errors, respectively. The null hypothesis for all four tests is that there is no cointegration for any of the 18 countries in the panel. The reported statistics are the bootstrapped probability values (using 600 replications) that are robust to cross-sectional dependence. The average number of leads and lags (selected with the AIC) used in the 18 countries' error-correction models are specified in the rows labelled Leads and Lags, respectively. A maximum of 3 leads and lags are allowed. *, ** and *** denote rejection of the non-cointegration null at the 10%, 5% and 1% levels, respectively. All results reported in this table are produced with Stata 14 IC using the `xtwest` command provided by Persyn and Westerlund (2008).

In summary, there is no evidence of cointegration between $ln(HP_t)$ and the two relative inequality measures, $GINI_t$ and $Top5\%_t$. In contrast, there is strong evidence supporting cointegration between $ln(HP_t)$ and the two absolute inequality measures $ln(VAR_t)$ and $ln(Top5\$_t)$), especially when only an intercept is included in the model. Because both of the panel statistics, P_τ and P_α, support cointegration at least at the 5% level for both absolute inequality measures when only an intercept is included in the model this suggests that this is the case for all 18 countries in the panel with homogeneous long-run coefficients.

4.2 The long-run relationship between house prices and absolute inequality

Given the general evidence in favour of cointegration with homogeneous long-run coefficients across all 18 countries for both absolute measures of inequality we report the implied estimated homogeneous long-run relationships for these measures in Table 2. When both an intercept and trend are included in the model the trend term is insignificant at the 1% level for both absolute inequality measures. This suggests that the trend term can be excluded from the long-run equation and that cointegrating equations including a trend should not be favoured. This is consistent with the model including both intercept and trend providing less support for cointegration than the model where the intercept is the only deterministic term (as reported in Table 1). Hence, we favour inference from the models where the intercept is the only deterministic term. This also suggests that there are no omitted variables from the long-run equations that approximately follow a linear trend.

Table 2: Estimated panel long-run relationship and short-run adjustment for $ln(HP_t)$

	$ln(Var_t)$		$ln(Top5\$_t)$	
	Int	*Trend*	*Int*	*Trend*
$INEQ_t$	**0.387***** (4.41)	0.209 (0.70)	**0.783***** (4.57)	0.131 (0.21)
Intercept	-3.380* (-1.93)	-10.992 (-0.28)	-5.078** (-2.47)	-29.656 (-0.82)
Trend		0.006 (0.25)		0.016 (0.75)
Adjustment	-0.164*** (-6.61)	-0.251*** (-6.32)	-0.158*** (-6.44)	-0.246*** (-8.22)

Table 2 notes. The estimated long-run coefficients, with t-ratios given in parentheses, are reported for each measure of inequality, $INEQ_t$, specified in the top row, where $ln(HP_t)$ is the dependent variable. The column headed Int indicates that the only deterministic term included is an intercept while the column headed Trend indicates that both an intercept and trend are included as deterministic terms. *, ** and *** denote rejection of the zero coefficient null at the 10%, 5% and 1% levels, respectively. All results reported in this table are the estimated long-run relationships with short-run adjustment produced with Stata 14 IC using the `mg` option with the `xtwest` command provided by Persyn and Westerlund (2008).

In the two long-run models where the only deterministic term included is an intercept the inequality measures are both significant at the 1% level and exhibit the expected positive coefficient sign. Because both cointegrating equations that include absolute inequality measures have double log specifications, the coefficients can be interpreted as elasticities. According to the overall absolute inequality measure (Var_t) a 1% rise in absolute inequality leads to around a 0.39% increase in real house prices whereas a 1% rise in the top 5% market income ($Top5\$_t$) leads to an approximate 0.78% increase in real house prices.

Table 3 reports panel dynamic OLS (DOLS) estimates of the long-run relationships assuming homogeneous coefficients across countries and with only an intercept included as a deterministic term in the model for both inequality measures where cointegration was found. Both inequality measures are significant at the 1% level and the estimated elasticities are around 0.30 for Var_t and 0.61 for $Top5\$_t$. Whilst slightly lower than the estimates implied by the Westerlund (2007) model they are not too dissimilar. This suggests that the results are broadly robust in the sense of positive and significant coefficients on the inequality measures as well as the coefficient on $Top5\$_t$ being around twice as large as that on the other inequality measures.

Table 3: Estimated panel DOLS long-run relationship

	$\boldsymbol{ln(Var_t)}$	$\boldsymbol{ln(Top5\$_t)}$
$INEQ_t$	**0.302***** (10.613)	**0.612***** (10.991)

Table 3 notes. The DOLS estimated long-run coefficients, with t-ratios based on HAC standard errors given in parentheses, are reported for each measure of inequality, $INEQ_t$, specified in the top row, where $ln(HP_t)$ is the dependent variable. Leads and lags are chosen using the AIC with a maximum of 3 leads and 3 lags with only an intercept included as a deterministic term.

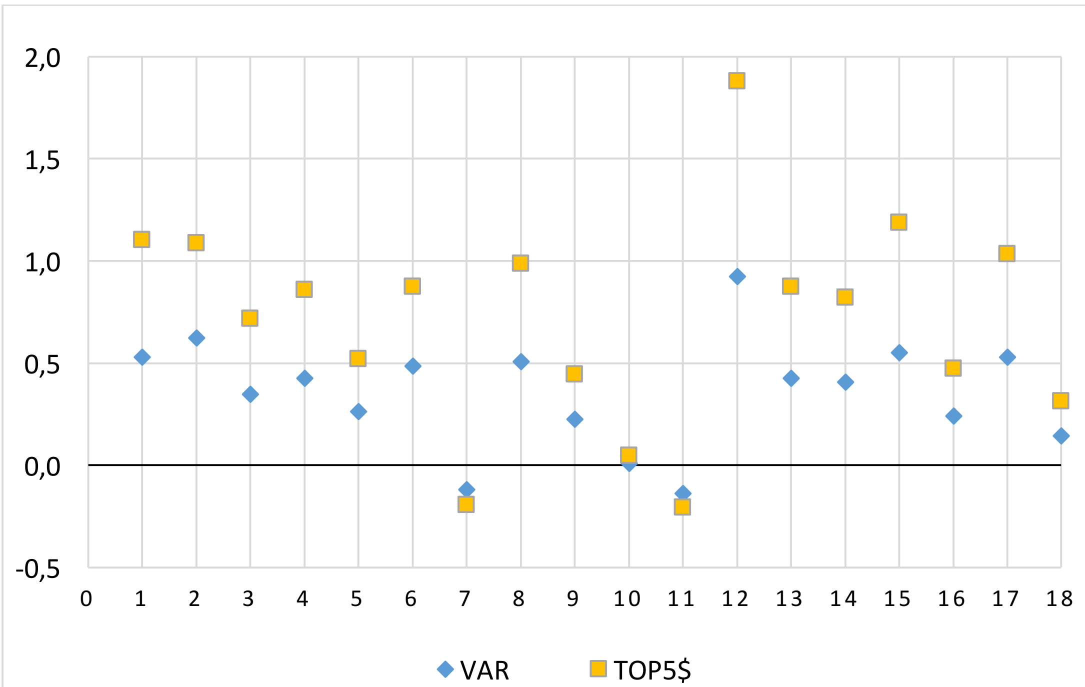
Whilst our tests suggest that the cointegrating equations are homogeneous across all 18 countries we report DOLS estimates of the long-run equations for each of the individual countries in Table 4 (these are plotted in Figure 3). The general results are robust across both absolute inequality measures in the following ways. First, for 14 countries the coefficient on absolute inequality (however measured) is positive and significant at the 1% level. Second, for one country (SWE) this coefficient is positive and only significant at the 10% level. Third, for one country (JAP) this coefficient is positive if insignificant. Fourth, for two countries (GER and KOR) the coefficient on inequality is negative and significant. Hence, while these results may be arguably interpreted as supporting the homogeneity of the coefficient on inequality for 15 of the countries (in the sense that it is positive and significant) there are doubts that this homogeneity extends to three of the countries in the panel.

Table 4: Estimated individual country DOLS long-run relationships

	Var	Top5$
AUS	0.531***	1.103***
	(7.575)	(7.732)
BEL	0.624***	1.089***
	(5.640)	(4.403)
CAN	0.348***	0.720***
	(12.053)	(10.475)
DEN	0.427***	0.861***
	(3.968)	(4.171)
FIN	0.263***	0.522***
	(5.689)	(5.640)
FRA	0.486***	0.874***
	(3.012)	(2.905)
GER	-0.117***	-0.193***
	(-3.481)	(-3.169)
IRE	0.508***	0.989***
	(8.302)	(9.916)
ITA	0.227***	0.446***
	(3.528)	(3.765)
JAP	0.011	0.047
	(0.228)	(0.483)
KOR	-0.136***	-0.204***
	(-4.724)	(-3.481)
NET	0.924***	1.881***
	(5.207)	(6.327)
NEW	0.428***	0.874***
	(12.808)	(11.177)
NOR	0.409***	0.822***
	(7.268)	(7.193)
SPA	0.554***	1.188***
	(7.153)	(7.197)
SWE	0.242*	0.473*
	(1.914)	(1.837)
UKD	0.531***	1.035***
	(8.427)	(7.633)

USA	0.147*** (4.906)	0.315*** (5.236)

Figure 3: Individual country DOLS estimates



4.3 Direction of causation

The Westerlund (2007) panel cointegration tests on the reverse regression with inequality as the dependent variable regressed on $ln(HP_t)$ reject cointegration for all four inequality measures regardless of the deterministic specification (Table 5). Hence, for all measures of inequality this is suggestive that inequality is weakly exogenous with respect to $ln(HP_t)$ and that the cointegration results reported in Table 1 are not subject to lower power due to the violation of weak exogeneity. This is particularly the case for the two absolute inequality measures ($ln(Var_t)$ and $ln(Top5\$_t)$) where cointegration is evident in Table 1. A further implication of the suggestion of the two absolute measures of inequality ($ln(Var_t)$ and

$ln(Top5\$_t)$) being weakly exogenous with respect to $ln(HP_t)$ is that there is uni-directional long-run Granger-causality from absolute inequality to $ln(HP_t)$ and no reverse causality in the opposite direction.

Table 5: Robust p-values for Westerlund's (2007) panel cointegration tests of $\boldsymbol{INEQ_t}$ on $\boldsymbol{ln(HP_t)}$

	$GINI_t$		$Top5\%_t$		$ln(Var_t)$		$ln(Top5\$_t)$	
	Int	Trend	Int	Trend	Int	Trend	Int	Trend
G_τ	0.747	0.247	0.818	0.487	1.000	0.462	1.000	0.267
G_α	0.930	0.565	0.963	0.777	1.000	0.458	1.000	0.187
P_τ	0.595	0.517	0.618	0.483	0.985	0.938	0.970	0.792
P_α	0.550	0.567	0.597	0.570	0.987	0.862	0.975	0.713
Leads	1.06	1.00	1.06	1.00	1.39	1.50	1.17	1.33
Lags	0.56	0.50	0.39	0.33	0.89	0.72	0.44	0.61

Table 5 notes. See notes to Table 1 except the row labelled $INEQ_t$ denotes the inequality measure that is as the dependent variable in the potential cointegrating equation with $ln(HP_t)$ as the regressor.

The individual country probability values of t-tests for long-run GNC based on time-series regressions (Tabe 6) confirm the above finding that for the overwhelming majority of countries there is no evident violation of the weak exogeneity assumption, which implies that the cointegration results from the Westerlund (2007) tests reported above are valid. The columns headed INEQ to LHP" refer to tests of the null hypothesis, $H_0^1: \alpha_1 = 0$, that is, that $INEQ$ does not Granger-cause $ln(HP_t)$ in the long-run, whereas the columns headed "LHP to INEQ" refer to tests of the null hypothesis, $H_0^2: \alpha_2 = 0$, that is, whether $INEQ$ is weakly exogenous with respect to the parameters in the equation for $\Delta ln(HP_t)$.

To interpret our results we use a 5% level of significance in all cases. For 13 countries there is evidence that, in the long-run, $ln(Var_t)$ Granger-causes $ln(HP_t)$ and that $ln(HP_t)$ does not Granger-cause $ln(VAR_t)$. For two countries (CAN and NEW) there is bi-directional long-run Granger-causality, for three countries (IRE, JAP and SPA) there is evidence of no long-run Granger-causality in either direction, and for no country is there evidence of uni-directional long-run Granger-causality from $ln(HP_t)$ to $ln(VAR_t)$.

Table 6: Time-series long-run GNC tests

Country	$\boldsymbol{ln(VAR_t)}$			$\boldsymbol{ln(Top5\$_t)}$		
	Lag AIC	Pt(ecm) INEQ to LHP	Pt(ecm) LHP to INEQ	Lag AIC	Pt(ecm) INEQ to LHP	Pt(ecm) LHP to INEQ
AUS	2	0.033**	0.142	3	0.072*	0.438
BEL	1	0.007***	0.425	1	0.007***	0.270
CAN	3	0.002***	0.033**	3	0.001***	0.066*
DEN	1	0.014**	0.987	1	0.013**	0.850
FIN	1	0.003***	0.805	1	0.003***	0.628
FRA	1	0.008***	0.445	1	0.011**	0.479
GER	3	0.043**	0.296	3	0.092*	0.898
IRE	2	0.058*	0.075*	2	0.059*	0.062*
ITA	2	0.000***	0.644	2	0.000***	0.632
JAP	2	0.146	0.766	2	0.167	0.827
KOR	2	0.000***	0.412	2	0.000***	0.397
NET	1	0.006***	0.082*	1	0.003***	0.105
NEW	1	0.013**	0.009***	1	0.023**	0.003***
NOR	1	0.015**	0.083*	1	0.017**	0.050*
SPA	1	0.112	0.050*	1	0.079*	0.046**
SWE	1	0.003***	0.470	3	0.139	0.840
UKD	1	0.021**	0.438	1	0.020**	0.539
USA	3	0.014**	0.982	3	0.008***	0.804

Table 6 note. Pt(ecm) denotes the probability value of a t-test on the error-correction term (the time-series tests of LR GNC). Lag AIC denotes the VAR lag length chosen according to AIC criterion. INEQ to LHP refers to tests of the measure of inequality Granger-causing LHP while LHP to INEQ refers to tests of LHP Granger-causing inequality.

For the $ln(Top5\$_t)$ measure of inequality there is evidence of uni-directional long-run Granger causality to $ln(HP_t)$ for 11 countries. For one country (NEW) there is evidence of bi-directional long-run Granger-causality, for five countries (AUS, GER, IRE, JAP and SWE) there is no long-run Granger causality in either direction and for one country (SPA) there is evident uni-directional long-run Granger causality from $ln(HP_t)$ to $ln(Top5\$_t)$.

Overall, the time-series Granger-causality test results from Table 6 show that for the vast majority of countries in our sample the direction of Granger-causality is from $INEQ$ to

$ln(HP_t)$. The anomalies found may be due to small (time-series) sample effects, Type I errors and questionable cointegrating equations in the case of GER and JAP (as reported in Table 4).[17]

4.4 Is it inequality or income growth that drives house prices?

In section 4.1 it was established that the two absolute inequality measures cointegrated with $ln(HP_t)$ on their own. We next consider whether the natural logarithm of real GDP (denoted $ln(GDP_t)$) also cointegrates with $ln(HP_t)$. This analysis is restricted to 16 countries (the two countries excluded are NEW and KOR).

First of all, it is important to note that $ln(GDP_t)$ is I(1) for 12 countries (AUS, BEL, CAN, DEN, FIN, GER, ITA, NET, NOR, SPA, SWE and the USA), I(1) around a linear trend in 1 country (JAP) and at least I(2) for the other 3 countries according to at least one of the two panel unit root tests. Therefore, it is in principle possible that the GDP variable cointegrates on its own with $ln(HP_t)$ given that they generally have the same orders of integration.

Table 7 reports the bivariate Westurlund (2007) statistics for null of no cointegration between $ln(HP_t)$ and $ln(GDP_t)$, and shows that there is no evidence of cointegration. The lack of evident cointegration between $ln(HP_t)$ and $ln(GDP_t)$ is in line with Knoll *et al.*'s (2014) observation that real house price growth has significantly outpaced income growth during the period under study. More importantly for our purpose, this finding shows that the significance of the absolute inequality measures is not due to overall income growth but instead due to an increasingly unequal distribution of income.

[17] Given our use of a 5% significance level we might expect one or two of these tests to incorrectly reject the null hypothesis and, therefore, the small number of violations of weak exogeneity may be due to Type I errors. This may be especially the case for the borderline rejections found for Canada and Spain whereas the rejections for New Zealand are quite strong.

Table 7: robust p-values for Westerlund's (2007) panel cointegration tests of $\boldsymbol{ln(HP_t)}$ on $\boldsymbol{COV_t}$

	$ln(rgdp_t)$	
	Int	Trend
G_τ	0.663	1.000
G_α	0.890	0.983
P_τ	0.293	0.970
P_α	0.123	0.932
Leads	1.44	1.38
Lags	1.13	1.13

Table 7 notes. See notes to Table 1 except the row labelled COV_t denotes the non-inequality covariate involved in the potential cointegrating equation with $ln(HP_t)$ as the dependent variable.

4.5 Does the inclusion of monetary policy change the results?

So far the results showed that the two absolute inequality measures $ln(Var_t)$ and $ln(Top5\$_t)$ cointegrated with $ln(HP_t)$ on their own and that the two relative inequality measures $(Gini_t)$ and $(Top5\%_t)$, and $ln(GDP_t)$ do not cointegrate with $ln(HP_t)$ on their own. We next consider whether these results stay robust when the real short-term interest rate (r_t) is considered as covariate.

First, we find that the interest rate series is unlikely to be cointegrated on its own with $ln(HP_t)$ because in many cases they have a different order of integration. While $ln(HP_t)$ is at least I(1) for the majority of countries, the Cerrato et al. (2011) and Pesaran (2007) based tests suggests that (r_t) is I(0) for 9 countries (BEL, CAN, FIN, GER, ITA, NET, NOR, SPA and SWE) and I(1) for the remaining 7 countries. That the real interest is I(0) for many countries is consistent with the Fisher hypothesis, even when nominal interest rates and the rate of inflation are I(1) on their own (see, for examples, Malliaropulos (2000), Costantini and Lupi (2007), Omay and Yuksel (2015), Panopoulou and Pantelidis (2016)). However, having said this, potentially (r_t) can still form part of the cointegrating relationship with $ln(HP_t)$ when it is considered a covariate with another I(1) explanatory variable.

Table 8 reports Westerlund's (2007) cointegration tests for trivariate regressions of $ln(HP_t)$ on r_t and $INEQ_t$ and $ln(HP_t)$ on r_t and $ln(GDP_t)$. The results show that all four tests unambiguously indicate no evident cointegration for the models involving the two relative inequality variables. The same is true for all four tests where the trivariate regressions consider $ln(Top\$_t)$ and r_t as covariates. This is a surprising result given that $ln(HP_t)$ cointegrates with $ln(Top\$_t)$ in bivariate regressions. Potential explanations could include, first, reduced efficiency due to increased covariates that raise (lower) the coefficient standard error (t-ratio) of the adjustment coefficient upon which the cointegration tests are based. Second, the removal of two countries from the panel when using trivariate models relative to bivariate models.

The trivariate model containing the explanatory variables $ln(GDP_t)$ and r_t also does not suggest cointegration at the 5% level (one tests indicates cointegration at the 10% level). Hence, the only trivariate regression that suggests evidence of cointegration at the 5% level contains $ln(Var_t)$ and r_t. While there is some ambiguity over the support for cointegration (five out of eight tests indicate cointegration at the 5% level)[18], these specifications exhibit the most convincing evidence favouring cointegration of the trivaraite models. Hence, the results of Table 8 broadly confirm our main finding of Section 4.1 that absolute inequality seemingly is cointegrated with real house prices, whereas relative inequality and income are not.

[18] This ambiguity may be due to some loss of efficiency because of the number of variables included in the estimated models.

Table 8: robust p-values for Westerlund's (2007) test of $\boldsymbol{ln(HP_t)}$ considering $\boldsymbol{r_t}$

		$Gini_t$		$Top5\%_t$		$ln(Var_t)$		$ln(Top5\$_t)$		$ln(GDP_t)$	
COV_t	Det	Int	Trend	Int	Trend	Int	Trend	Int	Trend	Int	Trend
r_t	G_τ	0.943	0.995	0.997	0.988	0.277	0.625	0.617	0.923	0.830	0.908
	G_α	0.848	0.572	0.888	0.503	**0.043****	**0.022****	0.788	0.948	0.918	0.675
	P_τ	0.123	0.480	0.287	0.528	**0.000*****	**0.002*****	0.232	0.687	0.090*	0.245
	P_α	0.210	0.500	0.473	0.612	0.092*	**0.042****	0.247	0.392	0.280	0.210
	Leads	1.88	2.00	1.81	2.13	1.75	2.00	1.56	1.88	2.19	2.13
	Lags	2.19	2.06	1.94	2.25	2.06	2.25	1.88	2.13	2.06	1.88

We therefore proceed in estimating the long-run relationship for the regression of $ln(HP_t)$ on $ln(Var_t)$ and (r_t). Given our relatively small time-series dimension panel DOLS equilibrium estimates are arguably more efficient than those obtained from Westerlund's ADL model and are reported in Table 9. The coefficients on both $ln(Var_t)$ and ri_t are significant at the 5% level and have the expected sign. The regression also has plausible coefficients, suggesting that a 1% rise in inequality induces an increase in house prices of around 0.4%, and that a 1% rise in real interest rates causes house prices to fall by about 1.7%. This model is therefore regarded as both theoretically and econometrically supported as a valid cointegrating equation.

Table 9: Trivariate DOLS panel long-run relationships for $\boldsymbol{ln(HP_t)}$

	$ln(VAR_t)$
Determ	Int
ri_t	**-1.735**** (-2.088)
$INEQ_t$	**0.409***** (9.910)

The coefficient of $ln(Var_t)$ from this trivariate regression is lower than that obtained with the bivariate cointegration results (reported in Table 3). This suggests that the removal of two countries from the panel may have some impact on the estimated. This trivariate regression supports cointegration between house prices and absolute inequality is consistent and confirming of our bivariate cointegration analysis. However, we prefer the trivariate estimates because there is support for plausible cointegration between all three variables and they provide partial correlation coefficients rather than the simple correlation coefficients obtained from bivariate equations.

Finally, Table 10 presents individual country long-run relationships for $ln(HP_t)$ on $ln(Var_t)$ and (r_t). With the exception of Japan and Germany, all sample countries exhibit a significant and positive relationship between absolute inequality and real house prices. Again, these findings are in line with the bivariate results (presented in Table 4). The real interest rate, on the other hand, is only significant and has the expected negative sign in nine out of the 16 countries.

Table 10: Individual country DOLS trivariate long-run relationships

	$ln(VAR_t)$	ri_t
AUS	0.559***	-3.351***
	(13.217)	(-4.761)
BEL	0.642***	-4.170*
	(5.344)	(-1.753)
CAN	0.436***	1.897**
	(15.634)	(2.703)
DEN	0.134**	-11.041***
	(2.762)	(-10.299)
FIN	0.597***	9.739***
	(12.464)	(14.591)
FRA	1.018***	-1.648
	(5.975)	(-1.156)
GER	-0.104***	1.666***
	(-4.087)	(3.006)
IRE	0.545***	-4.495***
	(36.878)	(-16.221)
ITA	0.549***	4.492***
	(7.332)	(3.073)
JAP	-0.114*	-3.537
	(-1.907)	(-1.675)
NET	0.811***	-10.259***
	(14.195)	(-13.082)

NOR	0.531***	-1.636
	(6.220)	(-0.461)
SPA	1.030***	5.098
	(6.739)	(1.635)
SWE	0.361***	-4.697***
	(5.853)	(-5.901)
UKD	0.587***	-1.451**
	(9.046)	(-2.425)
USA	0.249***	5.620
	(3.301)	(1.696)

5. Conclusions

The presented results provide two novel insights. First, increasing income inequality contributed to the rise in real house prices in 15 out of 18 countries OECD countries during the period 1975-2010. Second, the results are sensitive to the usage of relative and absolute inequality measures.

To be more precise, the bivariate cointegration analysis suggests that the natural logarithm of the variance ($ln(Var_t)$) and the natural logarithm of the market income of the top 5% ($ln(Top5\$_t)$) individually form irreducible cointegrating equations with $ln(HP_t)$ with theoretically plausible coefficients in 15 out of the 18 countries. There is little ambiguity in these cointegration results, the causation is from inequality to house prices, and the significance of the absolute inequality measures cannot be attributed to an overall growth in incomes but to an increasingly unequal distribution of income. Together with absolute inequality, the short-term real interest rate (r_t) also shows evidence of cointegration with $ln(HP_t)$ in nine countries. The two relative inequality measures used, on the other hand, do not show any signs of cointegration.

The finding that the recent surge in house prices partly was driven by rising absolute income inequality contributes to a growing literature that finds that the recent inequality increase has important negative socio-economic effects (see e.g. OECD, 2015). Moreover, it suggests that the current focus on relative inequality measures is unduly restrictive and that more attention should be given to alternative inequality measures like the ones presented in this article.

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