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Impact of House Price Changes on Durable and Non-Durable Consumption in the United States

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This paper examines the symmetric and asymmetric effects of house price changes and a few other macroeconomic variables on durable and non-durable consumption separately. The study considers the nonlinear panel Autoregressive Distributed Lag (ARDL) approach (Pooled Mean Group (PMG) estimation (Pesaran, 1997; Pesaran et al., 1999)) for cointegration and error-correction modeling, and uses annual data from fifty states of the U.S. The results show that changes in house prices have asymmetric effects on both durable and non-durable consumption in the long run. To dig deeper into the relationship between house price and consumption, I divide the fifty U.S. states into three categories: high-, middle- and low-income states. This helps to examine how the responsiveness of durable and non-durable consumption varies across these three categories. The findings show that the low-income states are affected more by changes in house prices than that of the high- and middle-income states.

Keywords

Nonlinear ARDL, Asymmetry, House Prices, Consumption

JEL Classification

E21, E30, R3

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1. Introduction

Fluctuations in house prices affect the wealth level of an individual. Over the last decade, there has been a significant focus in the literature, especially after the Global Financial Crisis of 2008 on understanding the impact of house prices on consumption via the wealth channel in the U.S. Before the crisis, house prices increased phenomenally and thus increased economic activity and personal wealth. An individual's house is a major component of one's wealth. Therefore, the sharp drop in house prices affected the wealth of individuals drastically.

One of the driving factors of consumption decisions is personal wealth and houses are part of wealth. However, house prices fluctuate over time; therefore, it is important to understand how changes in house prices can affect the consumption decisions of individuals. Increase in house prices might affect consumption through two channels. First, increase in house prices increases the consumption of goods and services because more households perceive that they have an increase in wealth. With more perceived wealth, households tend to increase consumption. Second, an increase in house prices relaxes borrowing constraints as houses can be used as collateral for loans which helps to increase household consumption.

Consumption can be classified into two categories: (1) durable consumption (DC) which involves goods that do not wear out quickly and can be used for longer periods of time; for example, cars, home appliances, furniture, etc., and (2) non-durable consumption (NDC) which involves goods that wear out quickly and must be consumed within a shorter period, for example, food, textile, etc. In this paper, I explore the impact of house prices on both DC and NDC. It is argued that DC would be more affected by changes in wealth due to changes in house prices.

One of the earliest studies to explore the role of wealth in consumption theory is Ball and Drake (1964). They use annual data from the U.K. and U.S. and conclude that utilizing the permanent income concept could yield more robust results if the dynamic aspects of the asset adjustment process are considered. On the other hand, Disney et al. (2010) use annual data from the U.K. and the life cycle consumption model. The authors note that the life cycle impacts of unexpected changes in housing wealth are not strong enough and that there exist an asymmetric behavior between house price increases and decreases. Considering data at the household level from Hong Kong, Gan (2010) reports that households with multiple homes have stronger responses in consumption to housing wealth. Along the same line, Mian et al. (2013) find that for every US$1 of housing net worth lost, there is an associated reduction in household consumption (Marginal Propensity to Consume (MPC)) by 5 to 7 cents. However, the MPC varies based on the type of expenditure. To add to this, Mian and Sufi (2016) also conclude that during the Great Recession, the decline in consumption was more severe in zip codes that experienced a steep decline in housing wealth. By considering state level data from the U.S., Coskun et al. (2019) find that financial wealth has no significant effect on consumption while housing wealth has a statistically significant impact on consumption. Khorunzhina (2021) examines household preferences over DC and NDC and finds evidence of non-separability between total non-DC and housing.

However, none of the above works focus on the long run asymmetric relationship between consumption and house prices by decomposing house price indices into increases and decreases separately and using a nonlinear panel Autoregressive Distributed Lag (ARDL) approach (Pooled Mean Group (PMG) estimation (Pesaran (1997) and Pesaran et al. (1999)) for cointegration. The contribution of this paper is two-fold. First, the work studies the asymmetric effect of house price changes on consumption by focusing on the long run asymmetric relationship for both DC and NDC by considering data from fifty states of the U.S. The existing literature has focused mostly on the assumption of symmetric effects of house price changes on household consumption. However, in considering a few of the non-asymmetric studies in the literature, none of them consider the partial decomposition of changes in house price indices. Assuming a positive relationship, a symmetric effect means that if an increase in house price increases consumption, then a decrease in house price will negatively affect consumption (with the magnitude of change remaining the same in both cases). However, this might not always be true because the degree of increase in consumption due to an increase in house prices might not match the degree of decrease in consumption due to a decrease in house prices. Hence, the effect of the changes in house prices on consumption can be asymmetric. For example, an increase in house prices would provide an increased perception of wealth and the borrowing constraints of the household would be relaxed. This helps to increase consumption of the households. However, when house prices fall, households might not be able to reduce consumption right away due to an already established lifestyle. This paper specifically employs the panel ARDL methodology to assess both the symmetric and asymmetric effects by considering DC and NDC separately. One of the major advantages of the panel ARDL methodology is that it generates valid long run results while at the same time accounting for any short run deviations which is crucial to consider and account for short term fluctuations in house price changes. The data are sourced from the Federal Reserve Economic Database (FRED), St. Louis, which is an open-source database. This increases the scope of the paper by opening avenues to carry out data analysis of this sort with publicly available databases. As expected, the wealth elasticity of demand for durable goods is greater than that for non-durable goods. This is because non-durable goods and thus, consumption of non-durable goods, are a necessity. Therefore, the fluctuations in consumption will be less when house prices change. However, DC might experience a larger increase followed by an increase in income or wealth. So, this paper draws a conclusion based on the type of expenditure as well. Second, this paper groups fifty U.S. states into three categories: high-, middle- and low-income states. This helps to disaggregate the panel data set to examine how the responsiveness of both DC and NDC varies due to changes in house prices based on the average income level of the states. Calomiris et al. (2013) examine cross-state variation in housing wealth effects on consumer spending and find that it depends on age composition, poverty rate, and housing wealth share through interaction terms. However, this paper groups states into high-, middle- and low-income and uses panel ARDL methodology.

The other variables that are considered are personal income (PI), mortgage rates (MRs), delinquency rate (DR), unemployment rate (UR), federal funds rate (FFR), and Consumer Price Index (CPI). Annual state-level data over the period of 1997 to 2019 are used for the U.S. The rest of the paper is organized as follows: Section II provides a review of the literature, Section III describes the model and methodology, Section IV discusses the empirical results and Section V concludes the paper.

2. Literature Review

Some of the early studies, for example, Ball and Drake (1964), consider data from the U.K. and the U.S., and examine the role of wealth with the consumption theory. They show that the aggregate consumption function that they derived from their model is consistent with the time-series data by using the least squares (LS) and two-stage least squares (2SLS) methodologies. Ball and Drake (1964) indicate that utilizing the permanent income concept could yield more robust results if the dynamic aspects of the asset adjustment process are considered. On the other hand, Sundaresan (1989) uses data from the U.S. only and a partial equilibrium model, and shows that the ratio of volatility in consumption changes to the volatility in wealth changes is more applicable to comparable models with separate utility functions.

By focusing on annual data at the ZIP-code level for the U.S. and supply-based hypothesis, Mian and Sufi (2009) find evidence of a sharp incline in mortgage credit followed by a similar increase in defaults with high subprime share ZIP codes. Evidence is found for almost every city in the U.S. They allow for the isolation of factors that affect credit and house prices. However, Mian and Sufi (2011) use an OLS regression with instrumental variables (IVs) and establish a strong link between asset prices and household borrowing. Specifically, they find that this effect is asymmetric and more focused on homeowners with low credit scores and the tendency to borrow on credit cards. Mian et al. (2013) use data from the U.S. They apply OLS and IV regressions and find that for every US$1 of housing net worth lost, there is an associated reduction in consumption by 5 to 7 cents. They also find that MPC differs significantly across ZIP codes by income and leverage (which are independent of each other) and suggest that the aggregate impact of wealth shocks depends on total wealth lost as well as how these losses are distributed across the population.

Kaplan et al. (2020) replicate the work of Mian et al. (2013) and use more easily accessible data on a subset of non-durable goods and house prices. By employing OLS and IV regressions, they find that the elasticity of expenditures to the shock of housing net worth in their study is the same as that in Mian et al. (2013). However, they also find that the housing collapse caused a decline in real consumption of approximately 20% less than nominal expenditures. By focusing on how various consumption measures declined during the Great Recession, Mian and Sufi (2016) find that the decline in consumption measures during the Great Recession was more severe in ZIP codes that experienced a steep decline in housing net worth.

Lin et al. (2014) are among the few works who use socioeconomic factors that might affect consumption. They use demographic variables along with financial variables for the U.S. and hierarchical linear models. The authors find that housing prices in metropolitan statistical areas (MSAs) increase with high populations, high percentages of elderly and Asians, high median household incomes, and rent-income ratio regardless of the effects of various regions.

Gan (2010) considers data from Hong Kong and by using a 2SLS and an IV estimator, finds that households with multiple homes have much stronger responses in consumption to housing wealth. Additionally, mortgage refinancing is also found to increase household consumption sensitivity. Funke and Paetz (2013) also use data from Hong Kong and OLS regressions. Evidence from this paper shows that the Hong Kong housing market is open to foreign investment and that the share of housing in the welfare-relevant aggregate consumption index is between 31% and 52%. The latter carries implications of the effect of the housing bubble on consumption. Among the recent studies, both He et al. (2019) and Cheng (2021) use data from China to study the relationship between house prices and consumption. Using a 2SLS regression and annual data, He et al. (2019) find that the housing boom in China causes higher consumption and that consumption rises by roughly 3% when housing wealth increases by 10%. Additionally, the authors find the average MPC from housing wealth to be roughly 5 cents. On the other hand, Cheng (2021) finds that the college enrollment expansion shock is greatly associated with shocks to housing net worth and housing prices. Cheng (2021) also finds that an increase in consumption from the increase in house prices from 2002 to 2009 is approximately 14-17% of current consumption. Waxman et al. (2020) use different variables related to government revenue and monthly data from China. They observe a 9% reduction in non-housing spending when housing prices increase by 10%. The negative elasticity is said to be driven by the heavy borrowing constraints faced by households and the strong investment incentive in China for housing. However, Disney et al. (2010) focus on yearly data from the U. K. and conclude that the life cycle impacts of unexpected changes in housing wealth are not as strong as previously established in the literature through a regression analysis. They find that the MPC is 0.01 out of unexpected shocks to housing wealth. The authors also note asymmetric behavior between house price increases and declines.

Moving back to data from the U.S., Aladangady (2017) transforms a standard model of consumer behavior from Friedman (1957) and Hall (1978), and uses an OLS regression with an IV estimator. Using quarterly data from the U.S., Aladangady (2017) finds that a US$1 increase in home values lead to a $0.047 increase in spending of homeowners (but the impact is negligible for renters). The observed results include more response from credit constrained households which points to looser borrowing constraints as one of the primary drivers of MPC from housing wealth. However, Berger et al. (2017) find that workhorse models of consumption with incomplete markets calibrated to wealthy cross-sectional micro-data are helpful for predicting large consumption responses.

In summary, the relationship between house prices and consumption has been explored at the country-level and/or state-level in the literature. However, the work cited so far does not consider the asymmetric effects of house price changes on both DC and NDC separately by decomposing house prices into increases and decreases using the panel ARDL approach (Pooled Mean Group (PMG)) to account for short run deviations. In addition, this paper uses data from an open-source database. To further investigate, this paper categorizes the U.S. states into three income-based categories: high-, middle- and low-income, to examine how the responsiveness of consumption varies due to changes in house prices across different income levels.

3. Model and Methodology

In this paper, the primary contribution is the use of a panel ARDL approach (PMG estimation (Pesaran, 1997; Pesaran et al., 1999)) for cointegration and error-correction modeling to capture both symmetric and asymmetric effects. Annual state-level data over the period of 1997 to 2019 for the U.S. have been considered. All data are sourced from the Federal Reserve Economic Database (FRED), St. Louis.

The panel ARDL methodology has several advantages over other estimation methods. The approach can yield valid long run results while simultaneously accounting for any short run deviations. Thus, the panel ARDL methodology has been employed such that long-run relationships can be considered as a steady-state equilibrium, whereas short-run deviations are considered as temporary deviations from the long-run equilibrium. For this research work, it is important to allow any short run fluctuations due to temporary economic shocks (for example, the 2008 Global Financial Crisis) and to account for any long run patterns which are driven by the underlying economic and financial conditions. Thus, using the panel ARDL methodology for this analysis is useful. A few other advantages of this approach are that it generates valid coefficients regardless of the endogeneity of the independent variables. This methodology also yields valid results to test for long run relationships irrespective of whether the variables are purely I(0) or purely I(1) or a combination of both[1], and incorporates the effect of the past values of a variable on its present value.

In the recent literature, there has been an increase in large number of observations (N) for large panels (T). Therefore, the concern over non-stationarity in the data set has increased. In the fixed effects estimation methodology, the data are pooled and only the intercepts differ across the panels. Therefore, a fixed effects estimation will produce inconsistent results if the slope coefficients are not the same. Blackburne and Frank (2007) suggest that one of the primary findings from the studies in the literature with a large N and T has been the assumption of homogeneity of the slope parameters which is often inappropriate. Pesaran (1997) and Pesaran et al. (1999) offer two new techniques to estimate models that consist of nonstationary dynamic panels which allow the estimated parameters to be heterogeneous across groups: the Mean Group (MG) estimator and the Pooled Mean Group (PMG) estimator (Blackburne and Frank, 2007). For each panel, the model is fitted separately for the MG estimator model and N time series regressions are estimated. Thus, both the intercepts and the slope coefficients are allowed to differ across the panels in the MG estimation process. However, the PMG estimation (Pesaran, 1997; Pesaran et al., 1999) involves both pooling and averaging. This restricts the long-run coefficients to be equal across panels but allows the intercept and the short-run coefficients to vary across the panels (Blackburne and Frank, 2007). Therefore, PMG estimation is optimal for examining the objective of this paper such that the short-run coefficients can vary across the panels and allow for flexibility between estimating separate regressions (MG estimation) which consider all coefficients to vary and fixed-effect estimations, which consider that all of the slope coefficients are the same (Pesaran et al., 1999).

Several macroeconomic variables are said to affect consumption. To estimate the effect of house price changes on consumption, two models are estimated by using the panel ARDL methodology: (1) a linear or symmetric model that assesses the effect of house prices (HPs), PI , MRs, DR, UR, FFR and CPI on both DC and NDC respectively, and (2) a non-linear or asymmetric model, which includes a variable that represents increases in house prices and a variable that represents decreases in house prices, with every other variable remaining the same.

[1] Since most macroeconomic data is either I(0) or I(1), therefore, prior unit-root testing is not necessary in panel ARDL methodology.

Symmetric panel ARDL (linear ARDL):

Following Salisu and Isah, (2017), the symmetric panel ARDL model for this paper is represented as:

$$\begin{aligned}\Delta lnDC_{i,t} = \alpha_{0i} &+ \sum_{j=1}^{N1} \alpha_{1ij}\, \Delta lnDC_{i,t-j} + \sum_{j=0}^{N2} \alpha_{2ij}\, \Delta lnHP_{i,t-j} \\ &+ \sum_{j=0}^{N3} \alpha_{3ij}\, \Delta lnPI_{i,t-j} + \sum_{j=0}^{N4} \alpha_{4ij}\, \Delta MR_{t-j} \\ &+ \sum_{j=0}^{N5} \alpha_{5ij}\, \Delta DR_{t-j} + \sum_{j=0}^{N6} \alpha_{6ij}\, \Delta UR_{i,t-j} \\ &+ \sum_{j=0}^{N7} \alpha_{7ij}\, \Delta FFR_{t-j} + \sum_{j=0}^{N8} \alpha_{8ij}\, \Delta lnCPI_{t-j} \\ &+ \beta_{1i} lnDC_{i,t-1} + \beta_{2i} lnHP_{i,t-1} \\ &+ \beta_{3i} lnPI_{i,t-1} + \beta_{4i} MR_{t-1} + \beta_{5i} DR_{t-1} \\ &+ \beta_{6i} UR_{i,t-1} + \beta_{7i} FFR_{t-1} + \beta_{8i} lnCPI_{t-1} + \mu_i \\ &+ U_{it}\end{aligned} \tag{1}$$

where subscript i = 1, ..., N represents each panel, that is, the fifty U.S. states, and t = 1, ..., where T represents the time periods. $DC_{i,t}$ represents the durable consumption at the state-level, $HP_{i,t}$ represents house prices at the state-level, $PI_{i,t}$ denotes PI at the state-level, MR_t is the national level 15-year fixed MR, DR_t denotes the DR at the national level on all loans, $UR_{i,t}$ denotes the UR at the state-level, and FFR_t and CPI_t denote the national level FFR and CPI, respectively. Data on consumption, HPs, PI and CPI are in logarithmic scale, whereas MRs, DR, UR and FFRs are in the percentage form.

Similarly, a model to capture the symmetric effect of HPs on *NDC* can be constructed by replacing *DC* with *NDC* in Equation (1).

For each state, the long run effects are captured by the estimates of β_{2i} to β_{8i}, normalized on β_{1i}. For example, $\frac{\widehat{\beta}_{2i}}{-\widehat{\beta}_{1i}}$ measures the long-run effects of changes in HPs on DC. However, the short-run effects are reflected in the estimates of the coefficients attached to the first-differenced variables. An error-correction model (ECM) of Equation (1) can be written as:

$$\begin{aligned}\Delta lnDC_{i,t} = \gamma_i w_{i,t-1} &+ \sum_{j=1}^{N1} \alpha_{1ij}\, \Delta lnDC_{i,t-j} + \sum_{j=0}^{N2} \alpha_{2ij}\, \Delta lnHP_{i,t-j} \\ &+ \sum_{j=0}^{N3} \alpha_{3ij}\, \Delta lnPI_{i,t-j} + \sum_{j=0}^{N4} \alpha_{4ij}\, \Delta MR_{t-j} \\ &+ \sum_{j=0}^{N5} \alpha_{5ij}\, \Delta DR_{t-j} + \sum_{j=0}^{N6} \alpha_{6ij}\, \Delta UR_{i,t-j} \\ &+ \sum_{j=0}^{N7} \alpha_{7ij}\, \Delta FFR_{t-j} + \sum_{j=0}^{N8} \alpha_{8ij}\, \Delta lnCPI_{t-j} + \mu_i \\ &+ U_{it}\end{aligned} \tag{2}$$

where
$w_{i,t-1} = DC_{i,t-1} - \in_{0i} - \in_{1i} HP_{i,t-1} + \in_{2i} PI_{i,t-1} + \in_{3i} MR_{t-1} + \in_{4i} DR_{t-1} + \in_{5i} UR_{i,t-1} + \in_{6i} FFR_{t-1} + \in_{7i} CPI_{t-1}$ is the error-correction term for each U.S. state. The speed of adjustment is measured by γ_i which captures how long it would take to converge to the long run equilibrium followed by a shock. A negative and significant value of γ_i would imply a long-run equilibrium.

Asymmetric panel ARDL (non-linear ARDL)

The most important assumption of Equation (1) is that all of the exogenous variables have symmetric effects on *DC*. However, the cointegration approach by Shin et al. (2014) allows for asymmetric cointegration. This results in a non-linear ARDL model by calculating new variables to denote the positive and negative changes of an explanatory variable (HPs in this paper) with the use of partial sum decompositions. Equation (1) assumes that HP changes have a symmetric effect on household consumption, which means that, assuming a positive relationship, if an increase in HPs increases consumption, then a decrease in HPs will negatively affect consumption (with the magnitude of change remaining the same in both cases). However, this might not be always true because the degree of increase in consumption due to an increase in HPs might not match the degree of decrease in consumption due to a decrease in HPs; hence, the effect of changes in HPs on consumption can be asymmetric. For example, an increase in HPs would usually provide a perception of increased wealth and also the borrowing constraints of the households would be relaxed. This helps to increase consumption. However, when HPs fall, households might not be able to reduce consumption right away by the same amount due to an already established lifestyle.

To introduce asymmetry in the model, $lnHP_{i,,t}$ (natural logarithm of HP) is decomposed into the partial sum of positive and negative changes as: $\Delta lnHP_{i,t} = lnHP_{i,0} + lnHP_{i,t}^{+} + lnHP_{i,t}^{-}$; where $lnHP_{i,0}$ means no change in

$lnHP_{i,,t}$, $lnHP^{+}_{i,t}$ denotes the positive changes in $lnHP_{i,t}$ and $lnHP^{-}_{i,t}$ denotes the negative changes in $lnHP_{i,t.}$. From this, positive changes that reflect increases in HP (*POS*) and negative changes that reflect decreases in HP (*NEG*) are constructed as follows[2]:

$$POS = lnHP^{+}_{i,t} = \sum_{j=1}^{t} \Delta lnHP^{+}_{i,j} = \sum_{j=1}^{t} max\ (\Delta lnHP_{i,j}\, , 0) \tag{3a}$$

$$NEG = lnHP^{-}_{i,t} = \sum_{j=1}^{t} \Delta lnHP^{-}_{i,j} = \sum_{j=1}^{t} min\ (\Delta lnHP_{i,j}\, , 0) \tag{3b}$$

The following non-linear ARDL model (asymmetric model) allows for the asymmetric effects of HPs on DC, depending on the direction of the change[3]:

$$\begin{aligned} \Delta lnDC_{i,t} = \alpha_{0i} &+ \sum_{j=1}^{N1} \alpha_{1ij}\, \Delta lnDC_{i,t-j} + \sum_{j=0}^{N2} \alpha_{2ij}\, \Delta POS_{i,t-j} \\ &+ \sum_{j=0}^{N3} \alpha_{3ij}\, \Delta NEG_{i,t-j} + \sum_{j=0}^{N4} \alpha_{4ij}\, \Delta lnPI_{i,t-j} \\ &+ \sum_{j=0}^{N5} \alpha_{5ij}\, \Delta MR_{t-j} + \sum_{j=0}^{N6} \alpha_{6ij}\, \Delta DR_{t-j} \\ &+ \sum_{j=0}^{N7} \alpha_{7ij}\, \Delta UR_{i,t-j} \\ &+ \sum_{j=0}^{N8} \alpha_{8ij}\, \Delta FFR_{t-j} + \sum_{j=0}^{N9} \alpha_{9ij}\, \Delta lnCPI_{t-j} \\ &+ \beta_{1i} lnDC_{i,t-1} + \beta_{2i} POS_{i,t-1} \\ &+ \beta_{3i} NEG_{i,t-1} + \beta_{4i} lnPI_{i,t-1} + \beta_{5i} MR_{t-1} \\ &+ \beta_{6i} DR_{t-1} + \beta_{7i} UR_{i,t-1} + \beta_{8i} FFR_{t-1} \\ &+ \beta_{9i} lnCPI_{t-1} + \mu_i + U_{it} \end{aligned} \tag{4}$$

[2] For more on the application of this concept, see Bahmani-Oskooee and Saha (2016), Keefe and Saha (2022), Saha (2022), Shin et al. (2014), and Verheyen (2013).
[3] A model to capture the asymmetric effect of house prices on NDC can be constructed by replacing DC with NDC in Equation (4).

The ECM of the asymmetric model can be represented as:

$$
\begin{aligned}
\Delta lnDC_{i,t} = \theta_i v_{i,t-1} &+ \sum_{j=1}^{N1} \alpha_{1ij}\, \Delta lnDC_{i,t-j} + \sum_{j=0}^{N2} \alpha_{2ij}\, \Delta POS_{i,t-j} \\
&+ \sum_{j=0}^{N3} \alpha_{3ij}\, \Delta NEG_{i,t-j} + \sum_{j=0}^{N4} \alpha_{4ij}\, \Delta lnPI_{i,t-j} \\
&+ \sum_{j=0}^{N5} \alpha_{5ij}\, \Delta MR_{t-j} + \sum_{j=0}^{N6} \alpha_{6ij}\, \Delta DR_{t-j} \\
&+ \sum_{j=0}^{N7} \alpha_{7ij}\, \Delta UR_{i,t-j} + \sum_{j=0}^{N8} \alpha_{8ij}\, \Delta FFR_{t-j} \\
&+ \sum_{j=0}^{N9} \alpha_{9ij}\, \Delta lnCPI_{t-j} + \mu_i + U_{it}
\end{aligned} \tag{5}
$$

where $v_{i,t-1}$ is the error-correction term for each state in the U.S. which captures the long run equilibrium and θ_i measures the speed of adjustment. Also, the bounds testing approach to cointegration with the F test criteria in Pesaran et al. (2001) is applied to the non-linear models to test for a long run relationship. To check for the significance of the asymmetry, the coefficients associated with POS and NEG are tested to determine if they are statistically different and the test statistic follows a chi-square (χ^2) distribution with one degree of freedom. The critical value is 3.84 at the 5% significance level.

The consumption of all the U.S. states would not all be affected by changes in HPs in the same way. To dig deeper into the relationship between HP and consumption, I divide the fifty U.S. states into three categories based on their income level: high-, middle- and low-income. This helps to examine how the responsiveness of DC and NDC varies across the income distribution of the states. It is likely that the consumption in the low-income states would be affected the most by changes in HPs than the high- and middle-income states. Considering the ranking of states by the Chamber of Commerce (as of summer 2021)[4] as a ballpark and then the classification based on the data of each state on median income, all fifty states are categorized into one of the three categories[5]. The data on median household income are collected from FRED, St. Louis database.

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[4] How Rich is Each U.S. State, *Chamber of Commerce,* Retrieved July 2021, from https://www.chamberofcommerce.org/how-rich-is-each-us-state

[5] Table 1A in the Appendix provides a detailed list of the states.

4. Empirical Results

Table 1 presents the descriptive summary statistics for each variable. DC, NDC, HPs and PI are expressed in the logarithmic form to use the panel ARDL methodology, but for the summary statistics, these variables are considered in the units as they are collected from the FRED. It can be noted from Table 1 that there is a significant degree of variation in the change in both DC and NDC with a standard deviation of 26,135.77 USD and 49,113.90 USD respectively. The changes in DC ranges from a minimum of 1308.60 USD to 19,1189.70 USD, and for NDC, between 2495 USD and 355,630.60 USD for the data period. The main variable to measure the asymmetric effects - the HP index, has a standard deviation of 112.91 and ranges between 135.39 and 816.76. The average value of the HP index is 322.44 for the data period 1997 to 2019. Personal income has a high standard deviation value of 313,559.80 USD. The average values of the MRs, DR, UR, FFR and CPI are 4.81%, 2.98%, 5.36% and 2.08% and 210.76, respectively.

Table 1 Summary of Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum	No. of Observations
DC (USD)	22641.60	26135.77	1308.60	191189.70	1100
NDC (USD)	43321.92	49113.90	2495	355630.60	1100
HP	322.44	112.91	135.39	816.76	1100
PI (in USD)	248861.80	313559.80	12633.20	2632280	1100
MR (%)	4.81	1.47	2.93	7.72	1100
DR (%)	2.98	1.62	1.48	6.97	1100
UR (%)	5.36	1.96	2.10	13.70	1100
FFR (%)	2.08	2.02	0.10	6.33	1100
CPI	210.76	28.23	163.01	255.65	1100

Entire sample of fifty U.S. states

Table 2 presents the panel ARDL long run results[6] with one lag for both the symmetric and asymmetric analyses for DC. For the symmetric panel ARDL model, the changes in HPs have a significant and positive effect on DC. With a 1 percent increase in HPs, DC increases by 0.225 percent. This is consistent with the theory that as households perceive an increase in wealth with an increase in HPs, they increase their consumption of durable goods. Households obtain utility from durable goods over a longer period so, DC is sensitive to business cycle fluctuations. As expected, PI has a significantly positive effect on DC, that is, with a 1 percent increase in PI, DC increases by 0.557 percent.

[6] In this paper, only the long run results have been reported for the purpose of the objective. The results of the short run analysis are available from the author upon request.

The relationship between consumption and other variables, such as UR and CPI, are the same as established by the theory. That is, with an increase in UR and CPI, DC decreases. As these two variables increase in value (one at a time), households find it difficult to support the purchase of durable goods.

Upon analyzing the asymmetric response of HPs on DC, it is observed that both "increase in HPs, *POS*" and "decrease in HPs, *NEG*" have positive effects on DC. However, decreases in HPs have less impact on DC. Specifically, with a 1 percent increase in HPs, DC increases by 0.288 percent. However, when HPs decline, the impact is positive but less in value. The statistic following a chi-square distribution is also significant at the 1% level of significance which supports that the coefficients associated with *POS* and *NEG* are significantly different. This provides more evidence that changes in HPs (increases and decreases respectively) have asymmetric effects on DC. This could be because it takes time to adjust to the changes due to already established habits or lifestyle. Thus, HP changes have asymmetric effects on DC since increases and decreases in HPs have different impacts on the DC.

By focusing on the results reported in Table 3 for the symmetric NDC model, it is found that the changes in HPs have a significant and positive effect on NDC. With a 1 percent increase in HPs, NDC increases by 0.204 percent. For the asymmetric model, NDC is also affected by an increase and a decrease in HPs. However, in the asymmetric model, the positive effect is greater (0.216 percent) than the symmetric model (0.204 percent). Nevertheless, the test statistic to support if the values are significantly different is not significant. When the symmetric model is considered, both positive and negative changes are used in an aggregated way. However, switching to the asymmetric model helps to disaggregate the negative changes from positive changes. By comparing the symmetric models for DC and NDC, it is found that the effect of HPs (which affects wealth) is more profound on DC (0.225 percent) than NDC (0.204 percent). This aligns with the theory. It is expected that the wealth elasticity of demand for durable goods (through HP fluctuations) would be larger than that for non-durable goods. This is because non-durable goods and thus, the consumption of non-durable goods are a necessity. Therefore, there are fewer fluctuations in its consumption when HPs change.

The estimated coefficients associated with the ECM terms are negative and significant for both the symmetric and asymmetric models for DC and NDC. This implies that the model converges to the long-run equilibrium and that the estimated model is stable. For example, a value of -0.437 for the estimated coefficient of the ECM term for the asymmetric DC model means that 43.7% of the adjustment process happens in one year (since the data are yearly) towards the long-run equilibrium following an external shock. Also, the F statistic for the bounds test to cointegration is significant for both the symmetric and asymmetric models for DC and NDC, thus implying a long run relationship among the variables.

Table 2 Symmetric and Asymmetric Panel ARDL Results for Durable Consumption Model

DC	Symmetric Model	Asymmetric Model
HP	0.225 ***	
POS		0.288 ***
NEG		0.150 ***
PI	0.557 ***	0.543 ***
MR	0.033 ***	0.036 ***
DR	-0.003	-0.003
UR	-0.016 ***	-0.013 ***
FFR	-0.013 ***	-0.016 ***
CPI	-0.214 ***	-0.313 ***
ECM	-0.431 ***	-0.437 ***
F test statistic for cointegration	54.706 ***	48.246***
Chi-square statistic for testing significance of POS and NEG coefficients		39.11***

Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels respectively.

Table 3 Symmetric and Asymmetric Panel ARDL Results for Non-Durable Consumption Model

NDC	Symmetric Model	Asymmetric Model
HP	0.204 ***	
POS		0.216 ***
NEG		0.248 ***
PI	0.091 ***	0.067 **
MR	-0.016 ***	-0.015 ***
DR	0.012 ***	0.011 ***
UR	-0.003 *	-0.005 ***
FFR	0.004 **	0.002
CPI	0.909 ***	0.933 ***
ECM	-0.332 ***	-0.328 ***
F test statistic for cointegration	125.237***	107.637***
Chi-square statistic for testing significance of POS and NEG coefficients		1.35

Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels respectively.

Results based on three income categories

Tables 4 and 5 report the results from the DC and NDC models respectively. The fifty U.S. states are divided in three categories: low-, middle- and high-income based on the data on the median income of each state. It is observed that the low-income states are more affected by changes in HPs than the middle-and high-income states for the symmetric model. As expected, low-income states react to wealth changes (through changes in HPs) more. As wealth increases, households have more money to spend on goods and services, especially those with low income who can use the extra money to spend on different goods and services. Across the three categories, the effect of HP changes has been found to be asymmetric. The impacts of *POS* and *NEG* on both DC and NDC have different values of estimated coefficients to support this finding. It can also be noted that the coefficients associated with *POS* and *NEG* are statistically different for all models as supported by the test statistic which follows a chi-square distribution except for the low-income states for the DC model.

Table 4 Symmetric and Asymmetric Panel ARDL Results for Durable Consumption Model

	Symmetric Model		
	DC		
	HIGH	***MEDIUM***	***LOW***
HP	0.203 ***	0.232 ***	0.467 ***
POS			
NEG			
PI	0.477 ***	0.682 ***	0.446 ***
MR	0.051 ***	0.037 ***	0.006
DR	0.007	-0.016 ***	0.002
UR	-0.020 ***	-0.008 ***	-0.020 ***
FFR	-0.014 ***	-0.015 ***	-0.007 ***
CPI	0.022	-0.445 ***	-0.308 ***
ECM	-0.363 ***	-0.456 ***	-0.668 ***
	Asymmetric Model		
	DC		
	HIGH	***MEDIUM***	***LOW***
HP			
POS	0.208 ***	0.305 ***	0.611 ***
NEG	0.373 ***	0.003	0.738 ***
PI	0.592 ***	0.596 ***	0.404 ***
MR	0.056 ***	0.039 ***	-0.002
DR	0.005	-0.017 ***	0.006 **
UR	-0.014 ***	-0.005 **	-0.021 ***
FFR	-0.027 ***	-0.015 ***	-0.004 *
CPI	-0.130	-0.442 ***	-0.440 ***
ECM	-0.401 ***	-0.524 ***	-0.570 ***
Chi-square statistic for testing significance of POS and NEG coefficients	13.99***	339.24***	1.76

Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels respectively.

Table 5 Symmetric and Asymmetric Panel ARDL Results for Durable Consumption Model

	Symmetric Model		
	DC		
	HIGH	*MEDIUM*	*LOW*
HP	0.161 ***	0.217 ***	0.555 ***
POS			
NEG			
PI	0.377 ***	0.068 **	0.057
MR	-0.005	-0.012 **	-0.055 ***
DR	0.042 ***	0.011 ***	0.021 ***
UR	-0.031 ***	-0.003	-0.004
FFR	-0.006	0.001	0.012 ***
CPI	0.298	0.958 ***	0.390 ***
ECM	-0.234 ***	-0.357 ***	-0.309 ***
	Asymmetric Model		
	DC		
	HIGH	*MEDIUM*	*LOW*
HP			
POS	-0.011	0.265 ***	0.549 ***
NEG	0.912 ***	0.174 ***	0.419 ***
PI	-0.081 **	-0.004	-0.072
MR	-0.020 ***	-0.002	-0.069 ***
DR	0.016 ***	0.008 ***	0.015 ***
UR	-0.006 ***	-0.010 ***	-0.007
FFR	0.006 ***	-0.006 ***	0.014 ***
CPI	2.035 ***	0.976 ***	0.484 ***
ECM	-0.363 ***	-0.336 ***	-0.286 ***
Chi-square statistic for testing significance of POS and NEG coefficients	112.33***	5.74**	7.72***

Notes: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels respectively.

5. Conclusion

The relationship between consumption and its determinants has been studied widely in the past. However, previous studies assume that the effects of changes in HPs on consumption are symmetric. This study contributes to the literature by employing a nonlinear panel ARDL approach (PMG estimation (Pesaran, 1997; Pesaran et al., 1999) for cointegration and examining whether the effect of HP changes on both DC and NDC is asymmetric by decomposing increases and decreases in changes in the HP index. One of the major advantages of the panel ARDL methodology is the generation of valid long run results while at the same time accounting for any short run deviations which is crucial to account for short term fluctuations in HP changes. It is expected that the wealth elasticity of demand for durable goods would be larger than that for non-durable goods because the consumption of non-durable goods is a necessity. To dig deeper into the analysis, this paper categorizes the fifty U.S. states into high-, middle- and low-income which helps to examine the responsiveness of DC and NDC based on the median income level of the states.

By employing a nonlinear panel ARDL and using annual data from fifty states of the U.S. from 1997 to 2019, it is found that HP changes have an asymmetric effect on both DC and NDC. The data are sourced from an open-source database - FRED, St. Louis. Upon further investigation, it is also found that low-income states are affected more by changes in HPs than high- and middle-income states. The asymmetric effect stems from the fact that an increase in HPs would usually provide a perception of increased wealth and the borrowing constraints of households would be relaxed. This helps to increase consumption. However, when HPs fall, households might not be able to reduce consumption right away due to an already established lifestyle. Also, the impact would be different for DC and NDC. This is mostly because NDC is expected to be less sensitive than DC to changes in wealth.

There are a few important policy implications from this work. For policymakers, it is important to target increases versus decreases in HPs depending on the economic scenario. The results from this paper show that for DC, increases in HP have a different effect in terms of magnitude than decreases in HPs. This would be helpful in targeting policies to boost DC during times of increase in HPs. The results will help to understand the effect of HPs (driven by housing policies) via the wealth channel through which monetary policy and interest rates affect household spending. If an economy is planning to boost consumption, then policymakers can target ways to increase DC specifically. For example, the results have shown that DC is affected more by an increase in wealth through an increase in HPs. Therefore, policies can be targeted to help with better access to home financing and thus, provide opportunities to home buyers to finance homes. Strong fiscal policy responses can also boost consumption and thus help the economy grow.

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Appendix

Table 1A Classification of states based on Chamber of Commerce Ranking and Median Household Income

High-Income States	Alaska, California, Connecticut, Hawaii, Maryland, Massachusetts, Minnesota, New Hampshire, New Jersey, New York, North Dakota, Wyoming.
Middle-Income States	Colorado, Delaware, Florida, Illinois, Indiana, Iowa, Kansas, Maine, Michigan, Missouri, Montana, Nebraska, Nevada, New Mexico, Ohio, Oregon, Pennsylvania, Rhode Island, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, Wisconsin.
Low-Income States	Alabama, Arizona, Arkansas, Georgia, Idaho, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, West Virginia.

Median Household Income (in USD)	
High Income Level	
Low	High
65,134	95,572
Middle Income Level	
Low	High
53,113	84,523
Low Income Level	
Low	High
44,787	70,674