Essays on consumption, wealth and uncertainty

Dimitra Kontana

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To my father Stergios Kontanas

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Chapter 1

Introduction

Wealth is a key determining factor in explaining consumption. Kurz (1968) first examined the impact of wealth effects and presented the form of wealth effects in a model. He proved that in addition to the consumption stream the utility function is also sensitive to the per capita capital stock of the society. Early literature suggests that the size of the wealth effect (i.e., the change in consumption induced by a \$1 increase in wealth) should be approximately 5 cents. Since then, major economic and political shocks (e.g., the OPEC I oil-price shock, the stock market crash of the October 1987, the rise and fall of stock prices associated with the "New Economy" of the 1990s, Gulf war I and II, the 9/11 terrorist attacks, the crisis of 2008 and the covid-19) caused turmoil in the economy and changed the size of wealth effects. An important factor for economic growth has been the spread of computers and the introduction of information technology in businesses and industries. This period characterized as "The new Economy of 1990s" changed the production frontier (Temple 2000). Telecommunication, Media and Information Technology (TMT) stock valuations became much more volatile than non-TMT stock valuations. Households had a smaller propensity to consume out of new economy wealth increases, since households believed that gains and losses are less permanent as there a greater risk involved in investing in new economy stocks. Moreover, the use of stock options as part of compensation had been more widespread in the TMT sectors worldwide and more households had been dependent on developments in valuations of new economy stocks. Changes in stock prices had a significantly bigger impact on consumption than before. (Sloek and Edison 2001)

Researchers have adopted different or similar econometric methods, not necessarily finding the same story. Poterba (2000) shows that the wealth effect of a household in all remaining years of life, in a favorable wealth shock, depends on its life expectancy and the after-lax real interest rate. In the last decades institutional innovations (i.e., second mortgages in the form of secured lines of credit) made the housing wealth effect especially important, as it is as simple to extract cash from housing equity as it was to sell shares or to borrow on margin. Case, Quigley, and Shiller (2005, 2011) examined separately housing and financial wealth effects on aggregate household consumption from a panel of U.S. states observed quarterly from 1978 to 2009. They found a statistically significant and larger effect of housing wealth than the effect of stock market upon household consumption. The impact of these two effects is unclear and hence it becomes an empirical issue if the housing and financial effect has become stronger or weaker over the years. This uncertainty over the magnitude of the wealth effect has stimulated a large amount of recent research.

Recent literature (Carroll et al. 2017; Case et al. 2011; Iacoviello 2011; Sierminska and Takhtamanova 2012) supports that wealth effects depend on the institutional characteristics of each country and the type of data, and are much larger in developed financial markets and in the presence of liquidity constraints. In fact, an emerging literature in economics has been using the assumption of wealth in the utility function to revisit various topics: long-run growth (Kurz 1968), borough constraint (Slacalek 2009; Iacoviello 2011), inequalities, demographics (Calomiris, Longhofer, and Miles 2013; Bampinas, Konstantinou, and Panagiotidis 2017; Vinson 2018), life-cycle saving (Carroll 2000), and capital taxation (Saez and Stantcheva 2018). Researchers model wealth effects functions by using alternative types of wealth. Michaillat and Saez (2018) use the government bonds in the place of wealth in the utility function, capturing in reduced form the special features of bonds relative to other assets, such as safety and liquidity. Jansen (2013) investigates wealth effects on consumption in financial crises for Norway and concludes that real interest rates and wealth need to be included in the long-run relationship. Macroeconomic models with bonds in the utility function examine short-run fluctuations of consumption and responses to income shocks. (Auclert, Rognlie and Straub 2018).

Moreover, Case et al. (2005) based on data from 1978-1999 and provided evidence that the wealth effects are increasing or decreasing equally in a rise or a drop of housing wealth, respectively. Case et al. (2011) based on data which include the volatility of 2008 crisis in asset markets and found that the effects of declines in housing wealth in reducing consumption are larger than the effects of increases in housing wealth in increasing the course of household consumption, implying the existence of uncertainty in bad times. One of the basic phenomena of choice under both risk and uncertainty is that losses loom larger than gains (Kahneman and Tversky, 1984; Tversky and Kahneman, 1991).

Inspiring by those macroeconomics trends in investigating household behavior, we examine the household consumption, wealth and uncertainty in US. Our main objective in this study is to investigate the consumption behavior and the role of the two types of wealth (housing and financial wealth) through the years. Further, our second objective is to measure uncertainty that affects households. We construct two types of uncertainty. The first uncertainty measure is constructed by the volatility of a multivariate GARCH model and the second uncertainty measure is constructed by a FAVAR model under the Bayesian method. Our third objective is to investigate consumption through seasonal fluctuations. This is another aspect that many economists follow. We investigate fluctuations of consumption under the functional data analysis to explore how innovations and uncertainty shift the consumption pattern. The world has experience different types of innovations (the development of stock market worldwide and the dependence of households' wealth on them, the rise of well-equipped firms by Information Technology, and the internet expansion). Prospect theory suggests that people prefer a bet on an event in their area of experience even though the probability to win is vague over unknown events even though are guaranteed (Tversky and Kahnerman 1991). Innovations definitely involve much risk and uncertainty, while the New Economy, the crisis of 2008 and the pandemic of COVID-19 made households live under uncertainty and cope with economic shocks. Hence, we couldn't investigate consumption alone without considering housing wealth, financial wealth and uncertainty as important determinants of households behavior.

This dissertation consists of six chapters. The second chapter deals with wealth effects by adding the ten year treasury constant maturity rate in the Keynesian function, by using cointegration methods. This option raises a number of key questions. Is the long-term interest rate a determinant of spending in unconventional monetary policy? Does this tool of monetary policy affect consumption behavior? The third chapter measures the long run uncertainty of consumption, housing wealth and financial wealth, by estimating a GARCH-DCC model. The fourth chapter measures the macroeconomic uncertainty by adding household data to provide an index that represents household uncertainty, adopting the Bayesian method of FAVAR. Further we provide evidence for impulse responses of consumption, personal income, housing wealth and financial wealth to a 20% rise in uncertainty in the 50 US states and DC. In the fifth chapter we focus on the consumption index and provide evidence that seasonality might be an important factor in explaining household consumption. Here we use the functional analysis approach. In the sixth chapter we conclude. For the empirical analysis of the second and third chapter we use the software of STATA and for the fourth and fifth chapter, the programming and numeric computing platform of MATLAB.

1.1 References

Auclert, A., Rognlie, M., and L. Straub. 2018. "The Intertemporal Keynesian Cross." NBER Working paper 25020.

Bampinas, G., Konstantinou, P., and T. Panagiotidis. 2017. "Inequality, Demographics, and the Housing Wealth Effect: Panel Quantile Regression Evidence for the US." *Finance Research Letters* 23, 19-22.

Calomiris, C., S.D. Longhofer, and W. Miles. 2013. "The Housing Wealth Effect: The Crucial Roles of Demographics, Wealth Distribution and Wealth Shares." *Critical Finance Review* 2 (1): 49-99.

Case, K.E., Quigley, J.M. and J.R. Shiller. 2005. "Comparing Wealth Effects: The Stock Market versus the Housing Market." *Advances in Macroeconomics* 5 (1): 1-34.

Case, K., Quigley, J. and R. Shiller 2011. "Wealth Effects Revisited 1978-2009." In Cowles Foundation Discussion Paper No. 1784. Connecticut: Yale University.

Case, K. E. 2011. "Wealth Effects Revisited 1975-2012." *Critical Finance review* 2: 101-28.

Iacoviello, M. M. 2011, "Housing Wealth and Consumption." In FRB International Finance Discussion Paper No. 1027.

Jansen, E. S. 2013. "Wealth Effects on Consumption in Financial Crises: The Case of Norway."*Empirical Economics* 45:873.

Kahneman, D. and A. Tversky. 1984. "Choices, Values and Frames," *American Psychologist* 39: 341-350.

Koop, G., Potter, S.M., and R.W. Strachan. 2008. "Re-Examining the Consumption–Wealth Relationship: The Role of Model Uncertainty." Journal of Money, Credit and Banking 40 (2–3).

Kurz, M. (1968): "Optimal Economic Growth and Wealth Effects." *International Economic Review* 9: 348-357.

Michaillat, P. & E. Saez, 2018. "A New Keynesian Model with Wealth in the Utility Function." NBER Working Paper 24971.

Poterba, J.M. 2000. "Stock Market Wealth and Consumption." *Journal of Economic Perspectives* 14(2): 99–118.

Saez, E. & S. Stantcheva. 2018. "A simpler theory of optimal capital taxation." *Journal of Public Economics* 162(C): 120-142.

Sierminska, E., and Y. Takhtamanova. 2012. "Financial and Housing Wealth and Consumption Spending: Cross-Country and Age Group Comparisons." *Housing Studies* 27 (5): 685-719.

Slacalek, J. 2009. "What Drives Personal Consumption? The Role of Housing and Financial Wealth." *The B.E. Journal of Macroeconomics* 9 (1): 1-37.

Sloek, T. and H. Edison. 2001. "Wealth Effects and the New Economy." IMF Working Papers, 2001(77).

Temple, J. 2002. The assessment: The New Economy. *Oxford Review of Economic Policy*, 18(3), 241-264.

Tversky, A. and D. Kahneman. 1991. "Loss Aversion in Riskless Choice: A Reference Dependent Model." *Quarterly Journal of Economics* 107(4): 1039-1061.

Vinson, P. 2018. "House Prices and Consumption in the United States." *Real Estate Economics* 49 (2): 635-662.

Chapter 2

Consumption, personal income, financial wealth, housing wealth, and long-term interest rates: a panel cointegration approach for 50 US states

Abstract

This chapter investigates the long-run and short-run relationship between consumption, financial and housing wealth by considering the 10-year treasury rate for the 51 US states. Using an updated set of quarterly data from 1975 to 2018, we perform panel cointegration analysis allowing for cross-sectional dependence. We obtain the following results. First, there is strong evidence for cointegration among consumption and its determinants. Second, estimates of the housing wealth and financial wealth elasticity of consumption range from 0.072 to 0.115 and 0.044 to 0.080, respectively. Finally, Granger causality tests show that there is a bidirectional short-term causal-

ity between per capita consumption, income and financial wealth in the short run and between all the variables in the long run.

JEL codes: E21; E44; R31.

Keywords: Consumption; Financial Wealth; Housing Wealth; Wealth effects; 10-year Treasury Constant Maturity Rate; Panel Cointegration; Granger Causality

2.1 Introduction

During recent years, the consumption response to personal income, housing and financial wealth changes has received substantial attention by policy-makers and economists. Increases in house prices associated with financial innovations from 2002 to 2009 led the US economy to the most severe crisis since the post-World War II era. This crisis spread a deep global recession from which some countries have only recently recovered. Some observers suggest that monetary policy played a central role in the crisis, while others support the position that policy was appropriate under the macroeconomic circumstances at that time and the information that was available to policymakers. In response to the US crisis, on December 16, 2008, the U.S. Federal Reserve's Federal Open Market Committee (FOMC) lowered its traditional monetary policy instrument (federal funds rate) to zero but the recovery remained weak. New unconventional monetary policy tools, such as quantitative easing (QE) and forward guidance, were introduced by the FOMC in response to the inability of the traditional low interest rate policy to stimulate the economy arising from the zero-bound problem.

At the same time, given the deficiency of the federal funds rate as an effective monetary policy instrument, economists proposed new methods to identify unconventional monetary policy and estimate its effects on the real economy. According to the most recent literature (Greenlaw, Hamilton, Harris, and West 2018; Swanson 2015; Williams 2013; Wright 2012; Balduzzi, Elton, and Green 1996), the 10-year treasury constant-maturity rate is strongly associated with QE and is a factor in the market's response to the announcements of the FOMC. Therefore, we conjecture that this interest rate plays an important role in controlling consumption. In the macroeconomics literature, the subject of the determinants of consumption remains a vital open issue for discussion among policymakers, researchers and observers. Therefore, the objective of this paper is to estimate a Keynesian consumption equation that incorporates both wealth and interest rate effects.

In this study we investigate the consumption behaviour in the 51 US states. The theoretical literature reveals that the primary determinants of consumption are income, financial wealth, housing wealth and interest rates. Keynes (1936) suggests that consumption mainly depends on income for a given level of employment and additional factors that should influence spending. Recent literature uses different methodologies and data and concentrates on wealth types that should influence spending (Case Quigley, and Shiller 2005, 2011; Carroll, Otsuka, and Slacalek 2011; Slacalek 2009 etc.).

The main motivation of this work is understanding wealth effects from another view. This is done by adding the 10-year treasury constant maturity rate in the consumption equation and using a new data set based mostly on housing behaviour. We can then shed light on the effect of the interest rate on consumption which from a theoretical point of view is ambiguous, as it depends on the interplay of substitution and income effects (Romer, 2012). The second piece of motivation arises from the importance of the long-term interest rate as a determinant of spending in unconventional monetary policy. This factor has been suggested by the literature as a tool for monetary policy (Balduzzi et al. 1996; Swanson 2015). In this way, we can examine whether the model can explain the effects of unconventional monetary policy on consumption. This is done in two ways. First, we use the methodology of panel cointegration and error-correction proposed by Pedroni (2004) and Westerlund (2007) to test for the long-run relationship between consumption and its four determinants: income, financial wealth, housing wealth, and the interest rate. Second, we employ two Granger causality techniques to address the short-run causal relationships among the variables. This study contributes to the related literature along the following lines. First, we use a newly calculated and updated data set from 1975 to 2018. Second, we test for a long-run relationship among consumption and its determinants using a panel data analysis for the 50 US states over 43 years. Third, we include in the analysis the long-term interest rate as an important variable that relates monetary policy with the real economy, following the unconventional types of monetary policy applied in the US since the onset of the financial crisis. Fourth, we use econometric techniques that allow us to address the endogeneity across variables, heterogeneity, and cross-sectional dependence in the panel. Fifth, we investigate the short run and long-run causal relationships among the variables of interest.

The main results of the study are as follows: First, we find strong evidence for a long-run equilibrium relationship among consumption, income, financial and housing wealth, and a long-term interest rate. Second, in the long run, we find strong evidence for positive income and housing wealth effects on consumption. The estimated income elasticity varies between 0.62 and 1.08, depending on the model specification and the estimated housing wealth elasticity varies between 0.07 and 0.12. Financial wealth and the long-term interest rate do not seem to affect consumption significantly in the long run. Second, in contrast to the long-run effects, in the short run, both forms of wealth and the interest rate are also significant and have a positive and negative effect on consumption, respectively. However, the effect of housing wealth seems to be larger than that of financial wealth. Finally, short-run and long-run causality tests show evidence for the linkage of housing wealth with the 10-year treasury rate in most specifications, confirming that developments in the housing market have a major and predictable effect on real economic activity.

The rest of this study is organized as follows. Section 2 reviews the literature on the determinants of consumption. Section 3 describes the data and our model. Section 4 presents our empirical methodology and findings. Section 5 discusses the main results and Section 6 concludes.

2.2 Literature review

There is an extensive literature investigating the wealth effects on consumption for different countries and sample periods and employing various methodologies. The literature concludes that the long run marginal propensity to consume (MPC) out of housing wealth is about 5–10 cents per dollar. However, MPC depends crucially on the institutional characteristics of each country and the type of data, suggesting that MPC is much larger in developed financial markets and in the presence of liquidity constraints (Carroll et al. 2017; Case et al. 2011; Iacoviello 2011; Sierminska and Takhtamanova 2012). In contrast to countries with no market-based economy, the effect of housing wealth is larger than that of financial wealth for the U.S and UK (Slacalek 2009). Equally, the housing wealth effect has risen substantially after 1988 as it has become easier to borrow against housing wealth, especially in countries with more developed mortgage markets (Case et al. 2013; Slacalek 2009; etc.).

Sierminska, and Takhtamanova (2012) in a sample that includes Canada, Finland, Italy, Germany, and US estimate consumption elasticity with respect to financial wealth to range from 0.01 to 0.03, while the elasticity for housing wealth is 0.04. Campbell and Cocco (2007) suggest that in the UK, elasticity of consumption with respect to housing wealth is 1.22. Correspondingly, Atalay, Whelan, and Yates (2016) using aggregate data suggest that MPC out of housing wealth is around 0.02–0.03 for Australia and Canada by. Hori and Niizeki (2019) investigate the housing wealth effects in Japan over the period 1983–2012. The results report that the consumption response to an increase in housing wealth ranges from 0.0059 to 0.0082 and appears to be larger for older households than that of younger households. While in China the estimated elasticity of consumption for housing wealth is as high as 0.19, much larger in magnitude (almost 10 times) than that of financial wealth (Chen, Hardin, and Hu 2018).

Case et al. (2012) investigate the effects of wealth on consumption by using quarterly state level data from 1975 to 2012 and apply multiple specifications. They introduce the error correction model and find a co-integrated relation between consumption and income. Under the assumption that income includes that derived from the stock market and housing, they don't apply the cointegration method on housing and financial wealth. It is assumed that log levels of consumption and income are cointegrated with the known cointegrating vector (1, -1), suggested by previous research Park (1992) and King, Plosser, Stock, and Watson (1991).

Han and Ogaki (1997) examine the post war consumption and income in US by employing two different methodologies to test cointegration. The canonical cointegration regression suggested by Park (1992) imposing restriction only in the stochastic trend and the cointegration methodology based on stationarity of the difference of log consumption and log income. The results indicate that there is no cointegration between the variables.

More recent studies extend the model of PIH by considering the different types of wealth. Carroll et al. (2011) estimate the eventual MPC out of financial and housing wealth to be in the ranges 0.041-0.064 and 0.087-0.159, respectively. Finally, in US, housing wealth is 7.04 cents against financial which is about 5 cents. After 1988, although financial wealth remains unchanged around 3-4 cents, the housing wealth effect grew from almost zero to 3 cents due to mortgage markets development and their link to housing wealth in most countries. The results are in line with Iacoviello (2011) that the co-movement between housing wealth and consumption is larger in developed financial markets and in the presence of liquidity constraints. Especially in US, the passage of Tax Reform Act loosened borrowing constraints and facilitated borrowers to use the housing equity for consumption (Case et al. 2011; Slacalek 2009). Higher house prices can have substantial effects on consumption as they raise borrowing capacity (Case et al. 2011; Slacalek 2009; Aladangady 2017). Rapach and Strauss (2006) suggest that the housing wealth effect is not uniform across the Eighth District states. Based on cointegration methods, they support the existence of a stable long-run relationship between personal consumption, personal income, housing and financial wealth.

Angrisani, Hurd, and Rohwedder (2019) focus on a sample of American adults over the age of 50 because they are more likely to be home owners and respond distinctly to home values. They provide micro evidence for MPC out of an unexpected change in housing wealth to be 6 cents per dollar for middle-aged consumers.

Generally, households with different levels of wealth have different estimated elasticities of consumption (Calomiris, Longhofer, and Miles 2013; Bampinas et al. 2017). Bampinas, Konstantinou, and Panagiotidis (2017) provide evidence for the long-run coefficient of wealth in the range of 0.053-0.088 by considering the role of inequality and demographics for the 48 US states. Christou, Gupta, Nyakabawo, and Wohar (2018) investigate the long run relation of housing wealth and non-housing consumption during the period 1953-2016 by using various quantile cointegration methods. They conclude that the variables are at most cointegrated at lower quantiles. Additionally, low house prices act as an inflation hedge when inflation is relatively large.

In the same line, Vinson (2018) used panel data for US states during the period 1999-2013 by considering also inequalities and demographics. He found that the elasticity of consumption out of housing wealth is 0.05 for the whole sample and 0.075 for poor households. For the high loan-to-value mortgages households' elasticity of consumption is 0.19. Moreover, the estimated elasticity of consumption tends to be negative or statistically insignificant for younger households.

The literature to date has ignored the impact of the interest rate on consumption decisions. However, this choice is unwarranted from a theoretical point of view given the importance of the interest rate in affecting savings, and hence, consumption decisions (Romer 2012). In particular, interest rate changes cause both a substitution and an income effect which run in opposite directions, thus creating an uncertain effect on consumption. Jansen (2013) investigates wealth effects on consumption in financial crises for Norway and concludes that real interest rates and wealth need to be included in the long-run relationship. This need is associated with their linking with monetary policy. He provides evidence that changes of the correlations between wealth and the real interest rate comove with changes in the monetary policy system.

The U.S. Treasury rate is the sum of two components, the average of expected future short-term rates, and a term premium (Greenlaw et al. 2018). It is also an important economic indicator. Economic announcements affect prices, trading volume and bid-ask spreads. The bid-ask spreads immediately return to normal levels within 5 to 15 minutes. In an experiment Balduzzi et al. (1996) found that only three out of seventeen announcements affect the bill price. Interestingly, for announcements that have a significant impact on prices, the impact occurs within one minute after the announcement. Economic announcements have less effect on trading volume for the three-month bill, although a change in monetary policy leads to an average trading volume up to nine times higher than at non-announcement times. For the 10-year rate, previous research (Balduzzi et al. 1996) found a strong association between announcements and trading volume. Since then, and by the introduction of the unconventional monetary policy, the 10-year treasury rate became an important determinant of consumer decisions (Swanson 2015; Williams 2013; Wright 2012).

Hence, in this study we use the 10-year treasury constant maturity rate as our fourth variable associated with consumption. Since the bond yields represent interest for borrowing money, the yield curve is of tremendous importance, both from a conceptual and a practical point of view. “From a conceptual perspective, the yield curve determines the value that investors place today on nominal payments at all future dates – a fundamental determinant of almost all asset prices and economic decisions. From a practical perspective, the U.S. Treasury market is one of the largest and most liquid markets in the global financial system. In part because of this liquidity, U.S. Treasuries are extensively used to manage interest rate risk, to hedge other interest rate exposures and to provide a benchmark for the pricing of other assets" (Gürkaynak et al. 2006).

2.3 Model and data

We use panel data for the 50 US states to obtain a US consumption function for several reasons. First, obviously by combining cross-sectional and time series data, we increase the size of information and the number of degrees of freedom, and thus the accuracy of estimation. We introduce information on the dynamic behaviour of many entities at the same time. Moreover, panel data allow us to use Westerlund cointegration, which considers the cross-sectional dependence and the heterogeneity of the states. Finally, we can remove the impact of omitted variables bias in the regression results and hence obtain more reliable results. Note that the results of the cointegration test stand for the US and not for the US states separately.

Based on the discussion above, consumption is described as a function of income, financial wealth, housing wealth and the 10-year treasury rate. The empirical model takes the following log-linear form where all variables, except for the interest rate, are expressed in logs:

$$\mathbf{lnC_{it}} = \beta_1 \mathbf{lnY_{it}} + \beta_2 \mathbf{lnFW_{it}} + \beta_3 \mathbf{lnHW_{it}} + \beta_4 \mathbf{MRIN_{it}} + \mathbf{FEffects} + \mathbf{e_{it}} \quad (2.1)$$

where,

lnCit: (log) real per capita consumption in state i at time t,

lnYit: (log) real per capita personal income in state i at time t,

lnFWit : (log) real per capita financial wealth in state i at time t,

lnHWit: (log) real per capita housing wealth in state i at time t,

MRINit: 10-year treasury constant maturity rate in US, and

eit: a disturbance term.

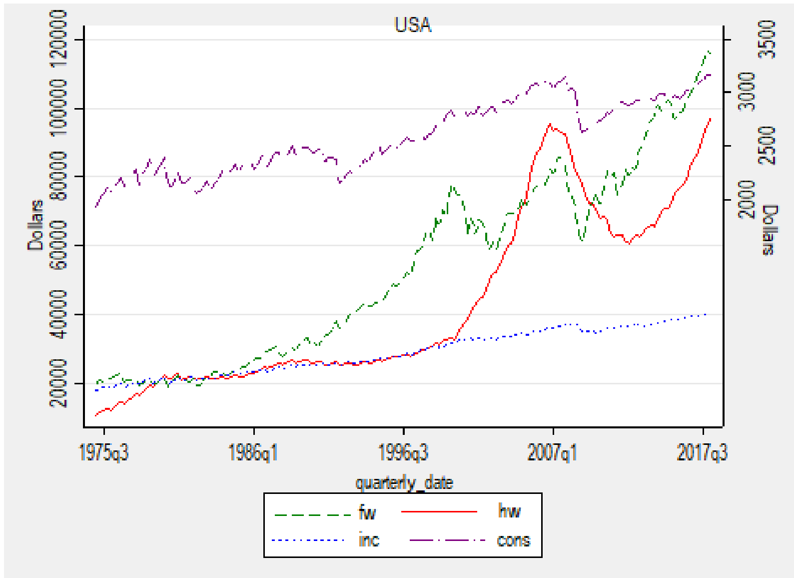
The data used in this study consists of quarterly, state-level panel observations spanning from the 1st quarter of 1975 to 1st quarter of 2018 for consumption, personal income, housing wealth, financial wealth and 10-year treasury for the 51 U.S. states. The data is constructed in the spirit of Case et al. (2005, 2011, 2012).

Figure 2.1 plots the US series of consumption, income, financial and housing wealth. Housing wealth follows an upward trend until the decline instigated by the 2008 crisis, while consumption follows mostly the housing wealth trend up to that period and after the huge decline of 2008 it almost remains stable up to now. Housing wealth also exceeded financial wealth during the three recessions experienced in 1980, 1981-1982, and 2007-2009.

All variables are in chained 2005 dollars and measured per capita. Figure 2.2 presents the 10-year treasury constant maturity rate in daily frequency obtained from the Federal Reserve Bank of St. Louis (FRED).

On June 1, 2012, the 10-year treasury rate dropped to 1.46 percent which was its lowest level in 200 years. This low treasury interest rate level was attributed

Figure 2.1: Personal income, wealth and consumption in U.S.

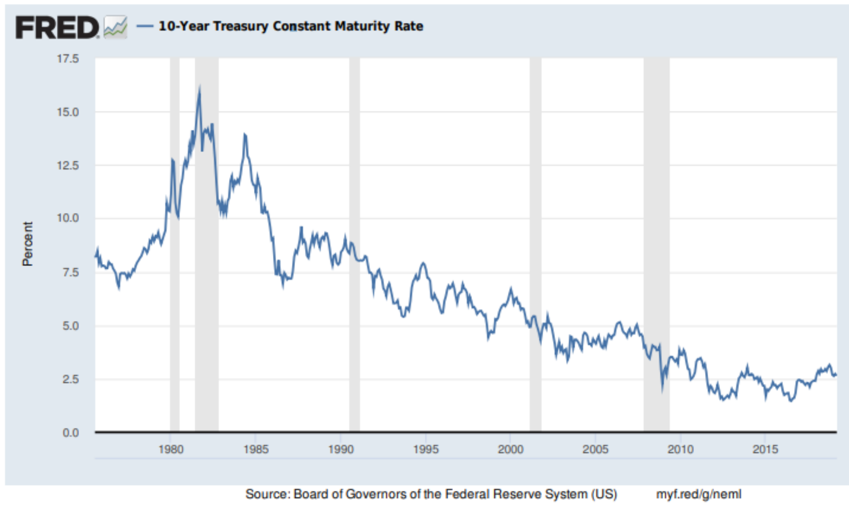


Note: Consumption, financial and housing wealth in USA, during the period 1975-2018, (per capita of US dollars). The right-hand scale measures consumption and the left-hand scale measures income, financial and housing wealth.

to investors' high demand for treasuries associated with the Eurozone debt crisis. Furthermore, on July 5, 2016, the 10-year treasury reached another low record in its history of 1.375 percent arising from the low inflation rate and the UK's referendum vote for Brexit (The CNBC Journal, 2016).

We proceed by presenting our data for consumption. We use retail sales as proxy for consumption. In the spirit of Case, Quigley and Shiller (2011) who stated that there are no measures of consumption spending by households recorded at the state level, we have chosen retail sales as a proxy of household spending. Retail sales account for roughly half of the total consumer expenditures" (Case et al., 2005, p. 14). We source monthly, seasonally adjusted national advance retail sales (excluding food services) from FRED, as state-level retail sales data is not available. We exclude

Figure 2.2: 10-Year Treasury Constant Maturity rate



Note: 10-Year Treasury Constant Maturity Rate USA, during the period 7/3/1975-7/3/2019, in daily frequency.

food services from our data because the change in income or wealth may not adjust the consumption of food services in the same direction. Since retail sales data are not available for US states, we use the allocation of retail trade data for each state to obtain the state-level retail sales. Hence, we follow two steps: First, we calculate the proportion of retail trade of each state in the US total. We then apply these proportions to US retail sales to determine the state retail sales data. Personal income data and state retail trade data are obtained from the Bureau of Economic Analysis (BEA), published on June 21st, 2018.

The series were seasonalized using the CensusX-12 method where necessary. The housing wealth variable is constructed through the following equation:

$$V_{it} = R_{it} N_{it} I_{it} V_{io} \tag{2.2}$$

where,

V_{it}: is the aggregate housing wealth of ownen-occupied housing in state i in quarter t,

R_{it}: is the homeownership rate in state i in quarter t,

N_{it}: is the number of households in state i in quarter t,

I_{it}: is the weighted repeat sales price index, for state i in quarter t, and finally V_{io}: is the mean home price for state i in the base year, 2000.

The mean home price historical data from 1975 to 2005 every decade is obtained from Census and it is transformed to quarterly data through a linear interpolation method based on the previous and next non-missing values. Annual data from 2005 to 2017 are obtained from Factfinder of Census, while for the first quarter of 2018 we use the rises given by Zillow real estate (https://www.zillow.com/wy/home-values/).

The homeownership rate and the data on the number of households are obtained from the Census Bureau and Factfinder of Census Bureau, respectively. We obtain the data of the number of households from 2016 to 2018 through forecasting techniques. For the weighted repeat sales price index, we use the all-transactions house price index for each state obtained by FRED. We convert the base year from 1980 to 2000 to match better our data. Finally, total financial wealth consists of the sum of corporate equity, mutual fund shares and pension funds held by households and is obtained from FRED. The allocation of the financial market (obtained by BEA) is used to allocate data to each state due to data unavailability at state level.

2.4 Methods and findings

This study utilizes panel unit root, cointegration and causality analyses in order to examine the relationship between consumption, income, housing wealth, financial wealth and 10-year treasury constant maturity rate for the U.S. states.

2.4.1 Panel unit root analysis

The first and crucial step in our analysis is to determine the order of integration of the variables. Typically, the linear combination of I(1) variables will itself be I(1), unless the variables are cointegrated. There is a variety of tests for unit roots or stationarity in panel datasets which are classified into two groups. The first-generation tests assume cross-sectional independence while the second-generation tests take into account the dependence across the different units in the panel (cross-sectional dependence). The cointegration analysis becomes more problematic when the unit roots in the different cross section units are due to common random walk components (Breitung and Pesaran 2005). Ignoring cross-sectional dependence of errors can have serious consequences, and the presence of some form of cross-sectional correlation of errors in panel data applications in economics is likely to be the rule rather than the exception (Baltagi, 2015).

Therefore, we first test for the presence of panel cross-sectional dependence using the tests proposed by Frees (1995), Friedman (1937) and Pesaran (2006). Table 2.1 presents the results of the three tests for cross-sectional independence. All tests strongly reject the null hypothesis of cross-sectional independence in our panel.

Having established evidence for cross-sectional dependence, we apply Pesaran's (2007) CIPS unit root test under cross-sectional dependence. Table 2.2 reports strong evidence that all variables are integrated of order one in two specifications: (a) a model that includes a constant term and (b) a model that includes both a constant and a trend. Hence, the next step is to investigate the possibility of a long-run or cointegrating relation among consumption, personal income, financial wealth, housing wealth, and the 10-year treasury rate.

2.4.2 Panel cointegration analysis

We conduct two types of cointegration tests to test for the presence of a long-run relationship among our integrated variables. First, we use Pedroni's (1999, 2004) approach which proposes a residual-based cointegration test for cross-sectionally independent panel and, second, we employ Westerlund's (2007) panel cointegration test which allows for cross-sectional dependence.

Pedroni (1999) developed seven cointegration statistics which allow for considerable heterogeneity among individual members of the panel, in both the long-run cointegrating vectors and the dynamics associated with short-run deviations from these cointegrating vectors. Dynamic OLS involves adding lags and leads of the regressors to eliminate feedback effects and endogeneity. Additionally, these tests are appropriate both for the case with common autoregressive roots and for heterogeneity of the autoregressive root under the alternative hypothesis in the spirit of Im, Pesaran, and Shin (2003). The most significant reason cited in empirical literature for using Pedroni test is the increased power arising from accounting both the time series and cross-sectional dimensions. Despite this, many researchers, such as Ho (2002), failed to reject the null hypothesis of no cointegration and supported that the international capital mobility is high although theory suggested the opposite. The explanation of this failure lies on the common factor restriction, which requires that the long-run cointegrating vector for the variables in their levels must be equal to the short run adjustment process for the variables in their differences.

Results for the panel cointegration tests are presented in Table 2.3. All seven test statistics are distributed as N(0,1), under the null of no cointegration. The tests were performed for two models: a model including a constant and a model including both a constant and a trend. Almost all test statistics reject the null of no cointegration hypothesis at one percent significance level. This implies that consumption, financial wealth, housing wealth and the 10-year treasury rate are linked by a long-run equilibrium relationship.

In the next step, we present the results of the long-run equilibrium relationships using the estimation method of Dynamic OLS (DOLS) for heterogeneous panels (Pedroni, 2004). Results of the group mean average regression are shown in Table 2.4. Two lags and leads are selected by the Akaike information criterion. The estimated long-run coefficients are all statistically significant except for the long-run interest rate. As expected, income and the two wealth proxies have a positive effect on consumption. The estimated income elasticity is 0.87 and it is much larger than the wealth elasticities. According to our results, financial and housing wealth have a similar impact on consumption.

Given our evidence for cross-sectional dependence, the results of the Pedroni cointegration tests are not highly informative. Westerlund (2007) proposed four new panel tests based on structural dynamics, to test the null of no cointegration in the presence of cross-sectional dependence. These tests do not impose any common factor restriction. They are designed to test whether the error correction term in a conditional error-correction model is equal to zero. If this term is statistically different from zero, then the null hypothesis of no cointegration is rejected. Each test involves individual specific short-run dynamics with serially correlated error terms, non-strictly exogenous regressors, individual-specific intercept and trend terms, individual specific slope parameters and cross-sectional dependence. Bootstrap tests are also proposed to handle applications with cross-sectional dependence. The error-correction tests assume the following data-generating process:

The error-correction tests assume the following data-generating process:

$$\Delta y_{it} = \delta' d_t + a_i \left(y_{i,t-1} - \beta_i' x_{i,t-1}\right) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + e_{it} \qquad (2.3)$$

where t=1,...,T and i=1,...,N are the index and the sectional units, respectively, pi and qi are the lags and leads[1]orders and are permitted to vary across individuals, allowing for a heterogeneous serial correlation structure. The parameter λ_i determines the speed at which the system returns to the equilibrium after a sudden shock. If λ_i <0 and statistically significant, then the variables are cointegrated. If λ_i=0, there is no cointegration. We assume that errors are independent across both i and t. We

[1] 'By adding leads and not just lags of δxit, we can allow for regressors that are weakly but not necessarily strictly exogenous' (Westerlund, 2007:234).

handle any dependence across i by means of bootstrap methods (Westerlund 2007).

Based on the general form of Equation (2.3), we specify the estimated error-correction equation for consumption as follows:

$$\Delta C_{it} = a_i^C + \lambda_i^C C_{i,t-1} + \left(-\lambda_i^C\right)\beta_{1i}^c Y_{i,t-1} + \left(-\lambda_i^C\right)\beta_{2i}^c FW_{i,t-1} + \left(-\lambda_i^C\right)\beta_{3i}^c HW_{i,t-1} + \left(-\lambda_i^C\right)\beta_{4i}^c MR_{i,t-1} + \sum_{j=1}^{p_i}\theta_{i,j}^c \Delta Y_{i,t-j} + \sum_{j=0}^{p_i}\varphi_{i,j}^c \Delta C_{i,t-j} + \sum_{j=0}^{p_i}\delta_{i,j}^c \Delta \mathrm{FW}_{i,t-j} + \sum_{j=0}^{p_i}\zeta_{i,j}^c \Delta \mathrm{HW}_{i,t-j} + \sum_{j=0}^{p_i}\eta_{i,j}^c \Delta MR_{i,t-j} + e_{it} \tag{2.4}$$

Here, the parameters $\lambda^{\nu}, \nu \in (C,\ Y,\ FW,\ HW,\ R)$

are the parameters of error correction term and provide estimates of the speed of error correction towards of the long run equilibrium for each state (i).

Table 2.5 presents the results of the four Westerlund test statistics and the coefficient cointegration. The tests are carried out with 100 bootstrap replications. The number of lags is chosen according to the information criteria of Akaike, which depends on the data and T rule [2] as a function of T. Additionally, all tests are constructed with bandwidth chosen according to the rule recommended by Newey and West (1994). Several interesting conclusions are obtained from the results reported in Table 2.5. First, there is strong evidence for cointegration under most test

[2] It holds under the function: $2 * (T/100)^{2/9}$

statistics and in most cases of the lag specification. Second, the coefficient of the error-correction term is negative and significant at 1% in all four estimated models and ranges from 0.190 to 0.281 in absolute value. The results depend on the number of the imposed lags, leads and bandwidth. Third, the estimated income elasticity is positive and significant and varies between 0.62 and 1.08, depending on the model specification. Fourth, the estimated housing wealth elasticity is positive and significant at 1% in all specifications with size varying between 0.07 and 0.12. Fifth, the estimated financial wealth elasticity is in general insignificant except for one case where the sign is negative and significant at 5%. Finally, the effect of the long-term interest rate on consumption is negative and insignificant except for one case where significance obtains. The interpretation of the interest rate coefficient suggests that an increase of one percentage unit in the treasury rate decreases consumption by 0.32%.

It would be interesting to compare the estimated income and wealth elasticities across the different estimation methodologies. Estimates of the income elasticity of consumption are 0.87, under both the Pedroni DOLS estimation and Westerlund cointegration test, when lags are chosen according to the AIC. According to the Westerlund cointegration test, the elasticity of consumption with respect to income is on average 0.92. In Pedroni's DOLS, the estimates of the elasticity of consumption for housing wealth and financial wealth are relatively similar (0.059 vs. 0.044). Under the Westerlund methodology, the estimated elasticity of consumption for housing wealth is 0.07 in most specifications, with the three lags specification giving the highest elasticity of 0.115. In contrast, financial wealth seems to have an insignificant impact on consumption. Finally, the long-term interest rate has a statistically insignificant effect on consumption under most cases in the Westerlund estimations. Similarly, the effect is insignificant under the Pedroni estimation.

In Table 2.5 we also report the short-run effects of each determinant on consumption. Short-run effects are captured by the coefficients of the variables in lagged first differences. In all the estimated models, the short-run effects of income, financial and housing wealth on consumption are positive and statistically significant at 1%. As in the case of the long-run effects, income in the short run has a larger impact on consumption than both measures of wealth, financial and housing wealth. Both financial and housing wealth have a similar positive effect on consumption. However, for financial wealth there is an important difference between short and long run. In the short run, as opposed to the long run, financial wealth generates a strong positive effect on consumption. As in the case of the long-run effects, the evidence suggests that housing wealth has a bigger effect on consumption than that of financial wealth. Across all estimated specifications, a change of 1% in financial wealth causes a change of 0.059% in consumption in the same direction. This result is slightly below that of housing wealth. In the short run, a one percentage unit change of housing wealth generates increases in consumption between 0.062% and 0.092% with an average of 0.072%. In marked contrast, the short-term financial wealth effect appears stronger than that of the long run and eventually fades out.

2.4.3 Panel causality analysis

Given the evidence for cointegration, we perform causality analysis in order to investigate causal interactions among the variables. We perform two causality tests. First, we test for causality by performing the Westerlund cointegration test, thus regressing each variable against the other four to obtain the causal linkages in our panel data. The panel VECM can be written as follows:

$$\Delta Y_{it} = a_i^Y + \lambda_i^Y Y_{i,t-1} + \left(-\lambda_i^Y\right) \beta_{1i}^Y C_{i,t-1} + \left(-\lambda_i^Y\right) \beta_{2i}^Y FW_{i,t-1} + \left(-\lambda_i^Y\right) \beta_{3i}^Y HW_{i,t-1} + \left(-\lambda_i^Y\right) \beta_{4i}^Y MR_{i,t-1}$$
$$+ \sum_{j=1}^{p_i} \theta_{i,j}^Y \Delta Y_{i,t-j} + \sum_{j=0}^{p_i} \varphi_{i,j}^Y \Delta C_{i,t-j} + \sum_{j=0}^{p_i} \delta_{i,j}^Y \Delta \mathrm{FW}_{i,t-j} + \sum_{j=0}^{p_i} \zeta_{i,j}^Y \Delta \mathrm{HW}_{i,t-j} + \sum_{j=0}^{p_i} \eta_{i,j}^Y \Delta MR_{i,t-j} + e_{it} \tag{2.5}$$

$$\Delta FW_{it} = a_i^{FW} + \lambda_i^{FW} FW_{i,t-1} + \left(-\lambda_i^{FW}\right) \beta_{1i}^c Y_{i,t-1} + \left(-\lambda_i^{FW}\right) \beta_{2i}^{FW} C_{i,t-1} + \left(-\lambda_i^{FW}\right) \beta_{3i}^{FW} HW_{i,t-1}$$
$$+ \left(-\lambda_i^{FW}\right) \beta_{4i}^{FW} R_{i,t-1} + \sum_{j=1}^{p_i} \theta_{i,j}^{FW} \Delta \mathrm{FW}_{i,t-j} + \sum_{j=0}^{p_i} \varphi_{i,j}^{FW} \Delta Y_{i,t-j} + \sum_{j=0}^{p_i} \delta_{i,j}^{FW} \Delta C_{i,t-j}$$
$$+ \sum_{j=0}^{p_i} \zeta_{i,j}^{FW} \Delta \mathrm{HW}_{i,t-j} + \sum_{j=0}^{p_i} \eta_{i,j}^{FW} \Delta R_{i,t-j} + u_{it} \tag{2.6}$$

$$\Delta HW_{it} = a_i^{HW} + \lambda_i^{HW} HW_{i,t-1} + \left(-\lambda_i^{HW}\right) \beta_{1i}^{c} C_{i,t-1} + \left(-\lambda_i^{HW}\right) \beta_{2i}^{c} Y_{i,t-1} + \left(-\lambda_i^{HW}\right) \beta_{3i}^{HW} FW_{i,t-1} + \left(-\lambda_i^{HW}\right) \beta_{4i}^{HW} R_{i,t-1} + \sum_{j=1}^{p_i} \theta_{i,j}^{HW} \Delta \mathrm{HW}_{i,t-j} + \sum_{j=0}^{p_i} \varphi_{i,j}^{HW} \Delta C_{i,t-j} + \sum_{j=0}^{p_i} \delta_{i,j}^{HW} \Delta Y_{i,t-j} + \sum_{j=0}^{p_i} \zeta_{i,j}^{HW} \Delta \mathrm{FW}_{i,t-j} + \sum_{j=0}^{p_i} \eta_{i,j}^{HW} \Delta R_{i,t-j} + \varepsilon_{it} \quad (2.7)$$

$$\Delta R_{it} = a_i^{R} + \lambda_i^{R} R_{i,t-1} + \left(-\lambda_i^{R}\right) \beta_{1i}^{R} C_{i,t-1} + \left(-\lambda_i^{R}\right) \beta_{2i}^{c} Y_{i,t-1} + \left(-\lambda_i^{R}\right) \beta_{3i}^{R} FW_{i,t-1} + \left(-\lambda_i^{R}\right) \beta_{4i}^{R} HW_{i,t-1} + \sum_{j=1}^{p_i} \theta_{i,j}^{R} R_{i,t-j} + \sum_{j=0}^{p_i} \varphi_{i,j}^{R} \Delta C_{i,t-j} + \sum_{j=0}^{p_i} \delta_{i,j}^{R} \Delta Y_{i,t-j} + \sum_{j=0}^{p_i} \zeta_{i,j}^{R} \Delta \mathrm{FW}_{i,t-j} + \sum_{j=0}^{p_i} \eta_{i,j}^{R} \Delta \mathrm{HW}_{i,t-j} + z_{it} \quad (2.8)$$

Based on the above specifications, we can test for both short-run and long-run causality. We examine the evidence for short-run causality by testing through the Wald restriction test the joint significance of the parameters for the variables in their lagged differences. We examine the evidence for long run causality as implied by the statistical significance of the t-statistics on the error-correction parameter.

Additionally, we also employ the panel causality methodology suggested by Dumitrescu & Hurlin (2012), thereafter DH. Individual Wald statistics of Granger noncausality converge sequentially to a standard normal distribution characterized for a fixed T sample. Monte Carlo experiments show also that these standardized panel statistics have very good small sample properties, even in the presence of cross-sectional dependence (DH 2012). DH, based on the seminal paper of Granger (1969), provide an extended test designed to detect causality in panel data.

Table 2.6 presents the results of the Granger causality based on the Westerlund cointegration model under the four alternative lag specifications reported in Table 2.5. Table 2.7 summarizes the corresponding directions among the variables. In the first estimated model where the variables are estimated with 3 lags, personal income exhibits bidirectional causality with consumption at 1% significance level, and financial wealth Granger causes consumption at the 5% level, whereas housing wealth and the 10-year treasury rate are insignificant. According to equation (2.5), the 10-year treasury rate Granger causes personal income at 10% significance level. In two equations personal income and financial wealth exhibit bidirectional causality at 5% significance level. Further, in equation (2.7) consumption and income Granger cause housing wealth at 10 and 5 %, respectively.

Moreover, the error correction term is statistically significant at the 1% level in all regressions with a fast speed of adjustment to long-run equilibrium in the first three regressions, where consumption, income and financial wealth are the dependent variables (equations 2.4-2.6). The speed of adjustment toward long-run equilibrium appears much faster in equation (2.5) than in equations (2.4) and (2.6). Equally, the estimated coefficients in the specifications with 4, 5 and 6 lags indicate similar results.

Table 2.8 reports the results of Granger causality tests under the DH (2012) methodology. These results are summarized in Table 9. When the optimal number of lags are chosen by Bayesian Information Criterion (BIC), two bidirectional causal relationships exist: between income and consumption, and income and housing wealth. Moreover, financial wealth Granger causes income and housing wealth. Each of the Treasury rate and consumption also Granger causes housing wealth.

The optimal number of lags chosen according to BIC is different for each equation, while in the first equation it is even different for each variable. Consequently, we specify an additional model with four lags for all equations and variables. Table 2.9 also includes the results by imposing four lags in all variables (4). The results indicate more bidirectional linkages among the variables.

2.5 Discussion of the results

Our findings appear to be in line with the results of most empirical studies in the literature, using alternative econometric methods and data, such as those by Carrol (2003) and Carrol et al., (2011, 2017), Rapach and Strauss, (2006), Mian (2013), Case et al. (2012) and Bampinas et al. (2017). We provide evidence for positive long-run effects of income and housing wealth on consumption and short-run effects of financial wealth that stand stronger than those in the long run. The volatility in financial wealth may cause an immediate large effect on consumption which eventually fades out. Consumption exhibits larger response to housing wealth changes compared to those of financial wealth. The elasticity of consumption with respect to housing wealth is getting stronger over time compared to that of financial wealth which seems to be negligible. Our findings confirm that housing wealth effects on consumption in the short run are significant and large and the coefficient ranges from 0.062 to 0.092. In the long run, the estimated elasticity is between 0.072 and 0.154 indicating the persistence of housing wealth over time and its high significance in consumption growth.

According to Slacalek (2009), the US, among other countries, such as Belgium and the Netherlands, possess more financial wealth than housing wealth. Consequently, the aggregate effect of financial wealth on consumption appears larger in the short run simply because these countries have more financial wealth. In line with this background, our data shows that the periods in which housing wealth surpassed financial wealth were 1980-1985 and the recent Great Recession. Gabriel et al. (2008) suggest that short-term deviations in the consumption-wealth ratio will forecast either asset returns or consumption growth; the first when changes in wealth are transitory, the second when changes in wealth are permanent.

As a result, consumption responses to financial wealth shocks appear stronger in the short run than the elasticity of consumption for housing wealth and gradually fade out. Figure 1 documents the finding of most literature (Helbling and Terrones 2003; Slacalek 2009) that housing wealth follows a smoother path than financial wealth. "In contrast to stock prices, when housing prices fall, they typically do so gradually over several quarters or even years rather than days" (Slacalek 2009, p. 15).

Equally, our findings report the elasticity of consumption with respect to housing wealth to be greater than that of the stock market wealth in accordance with most of the literature. It may be worth mentioning that the short-run coefficient of income starts from 0.640 and rises over time getting to an average of 0.865 for all times according to the Pedroni test and to 0.870 according to the Westerlund test, a finding in line with Kuznets (1946). In his seminal work, he found that the proportion of consumption to income was equal to about 0.87 in three sub-samples during the period 1869-1933.

With respect to the 10-year treasury rate, the estimated coefficient appears positive and relatively large in the short run, whereas it is getting negative or/and insignificant in the long run. We find that for a one-unit increase in the 10-year treasury rate, consumption rises by about 40 cents in the short run. Our evidence for a positive short-run association between the interest rate and consumption is in line with standard textbook analysis that emphasises the interplay of the substitution and income effect of an interest rate change (Romer 2012). Moreover, this result supports consumer behavior influenced by expectations of future economic policies that affect consumer decisions only in the short run. This second explanation is more in line with our evidence that the interest rate is insignificant in the long run[3]. In addition, this result squares with the literature (Swanson 2015; Williams 2013; Wright 2012). Note the strong association between the 10-year treasury rate and trading volatility which is an indicator for information flow (Balduzzi et al. 1996).

In recent years, the 10-year treasury rate is associated with large scale asset purchase announcements and provides information about interest rate expectations

[3]To test whether this interpretation is consistent with our empirical analysis, we use trade volume data which reflect policy news and test for a short-run and a long-run relationship with the 10-year Treasury rate. We find that the interest rate Granger-causes trade volume but there is no long-run relationship between the two variables.

and risk premia over long horizons of 10 years (Swanson 2015). Besides, long-term interest rates are – among other macro-indicators, such as, long-run inflation and unemployment rates – crucial in explaining the Federal Funds Rate (Wölfel & Weber 2017). Under the unconventional policy, the monetary authority compresses the spread (e.g. the difference between the long-term bond and short-term bill rate) via large-scale asset purchases to support economic activity and promote higher inflation. However, large-scale asset purchases by the central bank seem to signal further purchases in the future. Asset prices do not significantly impact unconventional monetary policy measures (Agnello, Castro, Dufrénot, Jawadi, and Sousa 2019).

Regarding the Granger causality tests, the strongest bidirectional causality exists among consumption and income. Generally, our findings support the short-run adjustments of cointegration tests. Moreover, the short-run causality analysis implies that housing wealth has a predictive power in forecasting the 10-year treasury rate, or equivalently, the dynamics of housing wealth provide information on the future movements of interest rates.

Consequently, there is considerable evidence of the importance of the housing wealth channel in consumption movements. Wealth may reflect a new view of future profits in an increase in the treasury rate. Hence, this study confirms previous studies (Mishkin 2007) that interest rates directly influence expectations of future house price movements, and housing supply; and indirectly influence the real economy.

2.6 Conclusion

This chapter examines the empirical relationship among consumption and its determinants in a panel set up. Using an original data set for the 50 US states and the cointegration methodology of Pedroni (1999) and Westerlund (2007), we investigate the short run and long-run relationship among consumption, income, financial, and housing wealth, and a long-term interest rate. Using both cointegration and error-correction analysis we obtain the following results. First, in the long run, we find strong evidence for positive income and housing wealth effects on consumption. The estimated income elasticity varies between 0.62 and 1.08, depending on the model specification and the estimated housing wealth elasticity varies between 0.07 and 0.12. Financial wealth and the long-term interest rate do not seem to affect consumption significantly in the long run. Second, in contrast to the long-run effects, in the short run, both forms of wealth and the interest rate are also significant and have a positive and negative effect on consumption, respectively. However, the effect of housing wealth seems to be larger than that of financial wealth.

We also test for short-run and long-run causality between consumption and its determinants. The causality tests indicate a strong bidirectional short-term causality between per capita consumption, income and financial wealth and a long-term causality between all the variables. The long-run causality analysis also shows that sudden shocks arising from variables other than income, i.e., financial wealth, consumption and the 10-year treasury, have an immediate effect on housing but the speed at which will eventually be offset is slower compared to the other systems where the dependent variable is consumption, financial wealth, income or 10-year treasury. Finally, the high significance of housing wealth and its linkage with the 10-year treasury rate in most specifications, confirms that developments in the housing market have a major and predictable effect on real economic activity.

2.7 References

Agnello, L., V. Castro, G. Dufrénot, F. Jawadi, and R. M. Sousa. 2019. "Unconventional Monetary Policy Reaction Functions: Evidence from the US."*Studies in Nonlinear Dynamics & Econometrics* 0 (0):1-18.

Aladangady, A. 2017. "Housing Wealth and Consumption: Evidence from Geographically Linked Microdata." *American Economic Review*, 107(11): 3415–3446.

Angrisani, M., M. Hurd, and S. Rohwedder. 2019. "The Effect of Housing Wealth Losses on Spending in the Great Recession." *Economic Inquiry* 57 (2):972-96.

Atalay, K., S. Whelan, and J. Yates. 2016 "House Prices, Wealth and Consumption: New Evidence from Australia and Canada." *Review of Income and Wealth* 62(1): 69–91.

Balduzzi, P., Elton J. E., Green T. C. 1996. "Economic News and the Yield Curve: Evidence from the US Treasury Market." In Working paper Series Fin-96-13 Stern School of Business. New York University.

Baltagi, H. B. 2015. *The Oxford Handbook of PANEL DATA.* NY: Oxford University Press.

Bampinas, G., Konstantinou, P., Panagiotidis, T. 2017. "Inequality, Demographics, and the Housing Wealth Effect: Panel Quantile Regression Evidence for the US." *Finance Research Letters* 23, 19-22.

Breitung, J., and M. H. Pesaran. 2005. "Unit roots and Cointegration in Panels." In Cambridge Working Papers in Economics. University of Cambridge.

Calomiris, C., S. D. Longhofer, and W. Miles. 2013. "The Housing Wealth Effect: The Crucial Roles of Demographics, Wealth Distribution and Wealth Shares." *Critical Finance Review* 2 (1): 49-99.

Campbell, J. Y., and J. F. Cocco. 2007. "How Do House Prices Affect Consumption? Evidence from Micro Data." *Journal of Monetary Economics* 54 (3): 591-621.

Carroll, D. C. 2003. "Macroeconomic Expectations of Households and Professional Forecasters." *Quarterly Journal of Economics* 118 (1): 269-98.

Carroll, D. C., M. Otsuka, and J. Slacalek. 2011. "How Large Are Housing and Financial Wealth Effects? A New Approach." *Journal of Money, Credit, and Banking* 43 (1): 55-79.

Carroll, C., J. Slacalek, K. Tokuoka, and N. M. White. 2017. "The Distribution of Wealth and the Marginal Propensity to Consume." *Quantitative Economics* 8 (3): 977-1020 (forthcoming).

Case, K. E. 2011. "Wealth Effects Revisited 1975-2012." *Critical Finance review* 2: 101-28.

Case, K. E., J. M. Quigley, and J. R. Shiller. 2005. "Comparing Wealth Effects: The Stock Market versus the Housing Market." *Advances in Macroeconomics* 5 (1): 1-34.

Case, K., J. Quigley, and R. Shiller 2011. "Wealth Effects Revisited 1978-2009." In Cowles Foundation Discussion Paper No. 1784. Connecticut: Yale University.

Chen, J., W. Hardin III, and M. Hu. 2018. "Housing, Wealth, Income and Consumption: China and Homeownership Heterogeneity." *Real Estate Economics* (00): 1-33 (forthcoming).

Christou, C., R. Gupta, W. Nyakabawo, and M. E. Wohar. 2018. "Do House Prices Hedge Inflation in the US? A Quantile Cointegration Approach." *International Review of Economics & Finance* 54: 15-26.

Dumitrescu, E. I., and C. Hurlin. 2012. "Testing for Granger Non-causality in Heterogeneous Panels." Economic Modelling 29 (4): 1450-60.

Engle, R. F., and C. W. J. Granger. 1987. "Co-integration and Error Correction: Representation, Estimation, and Testing." *Econometrica* 55: 251-276.

Frees, W. E. 1995. "Assessing Cross-Sectional Correlation in Panel Data." *Journal of Econometrics* 69 (2): 393-414.

Friedman, M. 1937. "The Use of Ranks to Avoid the Assumption of Normality Implicit in the Analysis of Variance." *Journal of the American Statistical Association* 32 (200): 675-701.

Friedman, T. 1957. "The Permanent Income Hypothesis." In A Theory of the Consumption Function, 20-37. National Bureau of Q5 Economic Research. Princeton, NJ: Princeton University Press.

Gabriel, V. J., F. Alexandre, and P. Bação. 2008. "The Consumption-Wealth Ratio under Asymmetric Adjustment." *Studies in Nonlinear Dynamics & Econometrics*12 (4): 1-33.

Granger, C. W. J. 1969. "Investigating Causal Relations by Econometric Models and Cross Spectral Methods." *Econometrica* 37 (3): 424-38.

Greenlaw, D., Hamilton, D. J., Harris, E., and West, D. K. (2018), "A Skeptical View of the Impact of the FED's Balance Sheet." In NBER Working Paper No. 24687.

Guo, S., and G. W. Hardin. 2014. "Wealth, Composition, Housing, Income and Consumption." *The Journal of Real Estate Finance and Economics* 48: 221.

Gurkaynak, S. R., B. Sack, and H. J. Wright. 2006. "The U.S. Treasury Yield Curve: 1961 to the Present." In Finance and Economics Discussion Series 2006-28. U.S.: Board of Governors of the Federal Reserve System.

Han, H. L., and M. Ogaki. 1997. "Consumption, Income and Cointegration." *International Review of Economics & Finance* 6 (2): 107-17.

Helbling, T., and M. Terrones. 2003. "When Bubbles Burst." In World Economy Outlook, Chapter II, 61-94. Washington, DC: International Monetary Fund.

Ho, T. 2002. "A Panel Cointegration Approach to the Saving-Investment Correlation." *Empirical Economics* 27: 91-100.

Hori, M., and T. Niizeki. 2019. "Housing Wealth Effects in Japan: Evidence Based on

Household Micro Data." *The B.E. Journal of Economic Analysis & Policy*, 19 (2): 1-28.

Iacoviello, M. M. 2011, "Housing Wealth and Consumption." In FRB International Finance Discussion Paper No. 1027.

Im, K. S., M. Pesaran, and Y. Shin. 2003. "Testing for Unit Roots in Heterogeneous Panels." *Journal of Econometrics* 115: 53-74.

Jansen, E. S. 2013. "Wealth Effects on Consumption in Financial Crises: The Case of Norway."*Empirical Economics* 45:873.

Keynes, J. M. 1936. The General Theory of Employment, Interest and Money. NY: Harcourt, Brace.

King, R. G., C. I. Plosser, J. H. Stock, and M. W. Watson. 1991. "Stochastic Trends and Economic Fluctuations." *The American Economic Review* 81: 819-40.

Kuznets, S. 1946. National Income: A Summary of Findings. New York: National Bureau of Economic Research.

Mian, A., R. Kamalesh, and A. Sufi. 2013. "Household Balance Sheets, Consumption and the Economic Slump." *Quarterly Journal of Economics* 128 (4): 1687-726.

Mishkin, S. F. 2007. "Housing and the Monetary Transmission Mechanism." In NBER Working Paper Series No. 13518.

Newey, K. W., and D. K. West. 1994. "Automatic Lag Selection in Covariance Matrix Estimation." In Technical Working Paper No. 144.

Park, J. Y. 1992. "Canonical Cointegrating Regressions." *Econometrica* 60: 119-43.

Park, J. Y., and M. Ogaki. 1991. "Inference in Cointegrated Models Using VAR Prewhitening to Estimate Short-Run Dynamics." In Rochester Center for Economic Research, Working Paper 281. University of Rochester.

Pedroni, P. 1999. "Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors." *Oxford Bulletin of Economics & Statistics* 61: 653-70.

Pedroni, P. 2004. "Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with an Application to PPP Hypothesis: New Results." *Econometric Theory* 20: 597-627.

Persyn, D., and J. Westerlund. 2008. "Error Correction-Based Cointegration Tests for Panel Data." *STATA Journal* 8 (2): 232-41.

Pesaran, M. H. 2004. "General Diagnostic Tests for Cross Section Dependence in Panels. University of Cambridge." In Cambridge Working Papers in Economics 0435. Faculty of Economics.

Pesaran, M. H. 2006. "Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure." Econometrica 74: 967-1012.

Rapach, E. D., and J. Strauss. 2006. "The Long-Run Relationship between Consumption and Housing Wealth in the Eighth District States." *Regional Economic Development* 2:140-7.

Romer, D. 2012. Advanced Macroeconomics. New York: McGraw-Hill.

Sierminska, E., and Y. Takhtamanova. 2012. "Financial and Housing Wealth and Consumption Spending: Cross-Country and Age Group Comparisons." *Housing Studies* 27 (5): 685-719.

Slacalek, J. 2009. "What Drives Personal Consumption? The Role of Housing and Financial Wealth." *The B.E. Journal of Macroeconomics* 9 (1): 1-37.

Swanson, E. 2015. "Measuring the Effects of Unconventional Monetary Policy on Asset Prices." In Working Paper 21816. National Bureau of Economic Research.

The CNBC Journal. 2016. "US 10-year Treasury Yield Closes at Record Low of 1.375 pct. by Clinch, Matt, Markets Bonds." https://www.cnbc.com/2016/07/05/us-10-year-treasury-yield-falls-to-record-low.html (accessed April 4, 2019).

The Zillow Inc. Home Prices and Values. USA. Also available at https://www.zillow.com/wy/home-values/ (accessed November 2, 2018).

Vinson, P. 2018. "House Prices and Consumption in the United States." *Real Estate Economics* 49 (2): 635-662.

Westerlund, J. 2007. "Estimating Cointegrated Panels with Common Factors and the Forward Rate Unbiasedness Hypothesis." *Journal of Financial Econometrics* 5: 191-522.

Williams, J. 2013. "Lessons from the Financial Crisis for Unconventional Monetary Policy," Panel Discussion at the NBER Conference on Lessons from the Financial Crisis for Monetary Policy. http://frbsf.org/ourdistrict/press/presidents/speeches/williamsspeeches/2013/october/research-unconventional-monetarypolicy-financial-crisis (accessed 26 June 1997).

Wölfel, K., and C. S. Weber. 2017. "Searching for the Fed's Reaction Function." Empirical Economics 52: 191. Wright, J. 2012. "What Does Monetary Policy Due to Long-Term Interest Rates at the Zero Lower Bound?" *Economic Journal* 122: F447-66.

2.8 Appendix

Table 2.1: Cross-sectional independence tests

	Cd-test	Frees-test (Q stat.)	Friedman's-test
Statistic	135.609	10.931	2545.962
P-Value	0.000	0.000	0.000
Avg of absolute value	0.414	0.414	0.414

Notes: The tests boil down to verifying whether sum of correlations between panel units is equal to zero.

Table 2.2: Results for panel unit root tests of Pesaran (2007) Panel Unit Root test (CIPS)

	Pesaran's CADF t-bar statistics			
	4 lags		3 lags	
Variables	Constant	Constant trend	Constant	Constant trend
lnConsumption	-1.921	-2.025	-1.553	-1.681
	[0.150]	[0.998]	[0.970]	[1.000]
lnIncome	-2.207	-1.929	-2.233	-1.989
	[0.000]	[1.000]	[0.000]	[0.999]
lnFinancialWealth	-1.872	-2.070	-1.797	-2.020
	[0.259]	[0.994]	[0.478]	[0.998]
lnHousingWealth	-2.124	-1.908	-1.806	-1.551
	[0.004]	[1.000]	[0.449]	[1.000]
ΔlnConsumption	4.814	-4.897	-5.284	-5.378
	[0.000]	[0.000]	[0.000]	[0.000]
ΔlnIncome	-5.277	-5.393	-5.584	-5.707
	[0.000]	[0.000]	[0.000]	[0.000]
ΔlnfinancialWealth	-5.557	-5.699	-5.908	-6.419
	[0.000]	[0.000]	[0.000]	[0.000]
ΔlnHousingWealth	-3.605	-3.679	-4.328	-4.409
	[0.000]	[0.000]	[0.000]	[0.000]

Note: Δ is the first difference operator. Numbers in brackets are p-values. Akaike Criterion was used to determine the optimal lag length. CIPS test assumes cross-section dependence in form of a single unobserved common factor.

Table 2.3: Pedroni statistics

Test	Constant	Constant and Trend
Panel v-statistic	-0.885	0.0872
Panel ρ statistic	0.888	-1.76**
Panel PP-statistic t	0.392	-2.78***
Panel ADF-statistic	4.23***	2.873***
Group-statistic	-0.3261	-2.108***
Group PP-statistic (non-parametric)	-0.591	-3.028***
Group ADF-statistic (non-parametric)	4.173***	2.861***

Table 2.4: The panel cointegration coefficients in Pedroni's.PDOLS (Group mean average)

Variables	**Beta**	**t-stat**
lnIncome	0.8704	32.78***
lnFinancialWealth	0.0439	1.807***
lnHousinglWealth	0.0589	9.92***
10YearTreasuryRate	-0.1868	-0.2832

Notes: Pedroni's PDOLS (Group mean average. Number of Panel units: 51. Lags and leads: 2. Number of obs: 8568. Avg obs. per unit: 168. Data has been time-demeaned.

Table 2.5: Statistics and the panel cointegration coefficients in the Westerlund model

Dependent Variables	Long-run coefficient	Short-run coefficient	ECT	Statistics	P-value	Robust P-Value	Lags/Leads/ lrwindow
Income	0.624 [0.000]***	0.790 [0.000]***	-0.190 [0.000]***	Gt	0.000	0.020	3/2/4
Financial Wealth	0.191 [0.138]	0.081 [0.000]***		Ga	0.004	0.080	
Housing Wealth	0.115 [0.009]***	0.092 [0.000]***		Pt	0.072	0.180	
10-Year Treasury Rate	0.822 [0.332]	0.417 [0.000]***		Pa	0.058	0.170	
Constant	-1.220 [0.226]	-0.413 [0.001]***					
Trend	-0.004 [0.018] **	-0.001 [0.000]***					
Income	0.871 [0.000]***	0.638 [0.000]***	-0.215 [0.000]***	Gt	0.000	0.000	4/3/4 (AIC)
Financial Wealth	-0.025 [0.449]	0.060 [0,000]***		Ga	0.002	0.150	
Housing Wealth	0.072 [0.000]***	0.071 [0.000]		Pt	0.000	0.030	
10-Year Treasury Rate	-0.140 [0.153]	0.492 [0.000]***		Pa	0.004	0.140	
Constant	-1.253 [0.113]	-0.397 [0.003]***					
Trend	-0.002 [0.000]***	-0.001 [0.000]***					
Income	1.096 [0.000]***	0.640 [0.000]***	-0.254 [0.000]***	Gt	0.000	0.000	5/4/10
Financial Wealth	-0.090 [0.044]**	0.051 [0.000]***		Ga	0.656	0.360	
Housing Wealth	0.071 [0.000]***	0.062 [0.000]***		Pt	0.001	0.020	
10-Year Treasury Rate	-0.329 [0.001]***	0.413 [0.000]***		Pa	0.697	0.460	
Constant	-2.823 [0.004]***	-0.898 [0.000]***					
Trend	-0.002 [0.000]***	-0.001 [0.001]***					
Income	1.084 [0.000]***	0.685 [0.000]***	-0.281 [0.000]***	Gt	0.000	0.000	6/5/11
Financial Wealth	-0.137 [0.124]	0.044 [0.000]***		Ga	0.904	0.400	
Housing Wealth	0.076 [0.000]***	0.067 [0.000]***		Pt	0.161	0.060	
10-Year Treasury Rate	-0.226 [0.217]	0.445 [0.000]***		Pa	0.965	0.540	
Constant	-2.298 [0.028]**	-0.923 [0.000]***					
Trend	-0.001 [0.108]	-0.001 [0.000]***					

Notes: P-values are in brackets and ***, ** are estimated value significant at the 1% and 5% level respectively.The tests are carried out with 100 bootstrap replications. The number of lags is chosen according to AIC and the T rule.

Table 2.6: Panel causality test results based on the Westerlund cointegration model

Dependent Variables	Sources of causation (Independent Variables)											
	SHORT RUN										LONG RUN	
	ΔConsumption		ΔIncome		ΔFinancial Wealth		ΔHousing Wealth		Δ10-Year TreasuryRate		ECT	
	3 lags	4 lags	3 lags	4 lags	3 lags	4 lags	3 lags	4 lags	3 lags	4 lags	3 lags	4 lags
ΔConsumption [Eq.(4)]	—	—	21.87(-) [0.0000]***	23.04(+) [0.0000]	3.59(+) [0.0155]	3.95(+) [0.0047]	0.22(+) [0.8814]	0.38(+) [0,8234]	0.74(-) [0.5308]	1.67(-) [0.1613]	-0.190 [0.0000]	-0.215 [0.0000]
ΔIncome [Eq.(5)]	6.77(-) [0.0003]	7.64(-) [0.0000]	—	—	2.67(-) [0.0500]	3.37(+) 0.0117]	3.72(-) [0.0132	2.66(-) [0.0356]	2.44(-) [0.0675]	3.57(-) [0.0087]	-0.235 [0.0000]	-0.218 [0.0000]
ΔFinancial Wealth [Eq.(6)]	2.06(-) [0.1087]	2.65(-) [0.0365]	8.94(-) [0.0001]	8.37(-) [0.0000]	—	—	0.41(+) [0.7452]	0.43(+) [0.7858]	0.34(-) [0.7931]	1.05(-) [0.3837]	-0.143 [0.0000]	-0.166 [0.0000]
ΔHousing Wealth [Eq.(7)]	2.23(-) [0.0872]	0.94(-) [0.4405]	6.60(-) [0.0002]	2.095 (+) [0.210]	0.78(-) [0.5051]	0.82(-) [0.5147]	—	—	1.10(-) [0.3522]	0.86(-) [0.4925]	-0.047 [0.0000]	-0.048 [0.0000]
ΔTreasuryRate [Eq.(8)]	0.26(-) [0.8556]	0.37(-) [0.8296]	0.02(+) [0.9970]	0.07(-) [0.9919]	0.26(+) [0.8523]	0.19(-) [0.9412]	2.92(+) [0.0365]	2.30(+) [0.0622]	—	—	-0.099 [0.0000]	-0.078 [0.0000]
	5 lags	6 lags	5 lags	6 lags	5 lags	6 lags	5 lags	6 lags	5 lags	6 lags	5 lags	6 lags
ΔConsumption [Eq.(4)]	—	—	26.72(+) [0.000]	24.72 (+) [0.0000]	4.99(+) [0.0004]	0.020	0.10(+) [0.9914]	0.32(+) [0.9256]	1.33(-) [0.2555]	0.97(-) [0.4522]	-0.254 [0.0000]	-0.281 [0.0000]
ΔIncome [Eq.(5)]	11.01(-) [0.0000]	12.16(-) [0.0000]	—	—	4.12(+) [0.0018]	0.020	0.82(-) [0.5376]	0.74(-) [0.6150	2.99(-) [0.0142]	2.12(-) [0.0569]	-0.229 [0.0000]	-0.255 [0.0000]
ΔFinancial Wealth [Eq.(6)]	4.03(-) [0.0021]	5.17(-) [0.0001]	8.19(-) [0.0000]	8.31(-) [0.0000]	—	—	0.13(+) [0.9859]	0.36(+) [0.9000]	1.74(-) [0.1316]	2.03(-) [0.0686]	-0.203 [0.0000]	-0.224 [0.0000]
ΔHousing Wealth [Eq.(7)]	0.70(-) [0.6254]	0.63(-) [0.7043	7.51(-) [0.0000]	7.35(-) [0.0000]	1.12(-) [0.3545]	0.020	—	—	1.10(-) [0.3633]	1.33(+) [0.2529]	-0.056 [0.0000]	-0.060 [0.0000]
ΔTreasuryRate [Eq.(8)]	0.06(-) [0.9978]	0.13(-) [0.9915]	0.10(-) [0.9923]	0.22(-) [0.9690]	0.13(+) [0.9852]	0.020	2.60(-) [0.0292]	3.04(+) [0.0090]	—	—	-0.081 [0.0000]	-0.096 [0.0000]

Notes: F-statistics reported with respect to short-run changes in elasticity in the independent variables. Probability values are in brackets and reported underneath the F-statistic. ECT represents the coefficient of the error correction term with the P-values in brackets. For the co-joint test, we used the Wald-test. Positive or negative signs of the causality are reported in the parenthesis.

Table 2.7: Dumitrescu & Hurlin (2012) Granger non-causality test results

Dependent Variables	**Sources of causation (Independent Variables)**				
	Optimal number of lags selected by BIC / lags tested: 1 to 55.				
	ΔConsumption	ΔIncome	ΔFinancial Wealth	ΔHousing Wealth	Δ10-Year TreasuryRate
ΔConsumption	—	77.214{4} (74.684) [0.000]	-3.492{1} (-3.479) [0.160][0.150]	2.1808{1} (2.076) [0.240][0.240]	0.558{1} (0.487) [0.910][0.920]
ΔIncome	30.285{4} (29.217) [0.000]	—	29.141{4} (28.109) [0.000]	16.761{4} (16.115) [0.000]	-2.183{4} (-2.239) [0.600] [0.600]
ΔFinancial Wealth	-2.419{1} (-2.429)[0.420] [0.420]	4.003{1} (43.860)[0.130] [0.140]	—	-2.333{1} (-2.344)[0.150] [0.140]	4.493{1} (4.340)[0.190]
ΔHousing Wealth	34.505{4} (33.306)[0.000]	65.646 4(63477)[0.000]	6.892{4} (6.553) [0.000]	—	6.230{4} (5.917)[0.030]
Δ10-Year TreasuryRate	4.054{1} (3.911) [0.350] [0.390]	-3.535{1} (- 3.521) [0.510]	-3.462{1} (- 3.450)[0.390]	-0.103{1} (-0.160)[1.000] [0.930]	—
	Optimal number of lags: 4				
ΔConsumption	—	77.214 (74.684) [0.000]	7.9759 (7.603) [0.050]	17.822 (17.143) [0.000]	2.231 (2.037) [0.730]
ΔIncome	30.285 (29.216)	—	29.141 (28.109) [0.000]	16.761 (16.115) [0.000]	-2.183 (-2.239) [0.570] [0.560]
ΔFinancial Wealth	49.623 (47.959) [0.000]	64.867 (62.721) [0.000]	—	15.916 (15.295) [0.000]	-5.177 (-5.140) [0.240] [0.230]
ΔHousing Wealth	34.505 (33.306) [0.000]	10.931	65.646 (63.476)[0.000]	—	6.230 (5.912) [0.010]
Δ10-Year TreasuryRate	424 (3.193) [0.470] [0.490]	-1.497 (-1.575) [0.820]	-5.177 (-5.140) [0.350] [0.340]	3.447 (3.215) [0.300] [0.310]	—

Notes: Z-statistics reported with respect to four period changes in the independent variables. Z-tilde-statistics are denoted in parentheses.Probability values are in brackets and reported underneath the corresponding partial z-statistic and z-tilde-statistic respectively.Single bracket means the same value for both statistics. P-values computed using 100 bootstrap replications. P-values computed using 100 bootstrap replications.

Table 2.8: Direction of Causality

Methodology: Westerlund(2007) Cointegration Model / Wald Test

<table>
<tr><th>Number of lags: 3</th><th>Number of lags: 4</th><th>Number of lags: 5</th><th>Number of lags: 6</th></tr>
<tr><td colspan="4">Housing Wealth → 10 Year Treasury Rate
10 Year Treasury Rate → Income
Income ↔ Financial Wealth
Consumption ↔ Income</td></tr>
<tr><td>Income → Housing Wealth</td><td>Housing Wealth → Income</td><td colspan="2">Income → Housing Wealth</td></tr>
<tr><td></td><td colspan="3">Financial Wealth ↔ Consumption</td></tr>
<tr><td></td><td></td><td></td><td>10 Year Treasury Rate → Financial Wealth</td></tr>
</table>

Table 2.9: Direction of Causality Methodology: Dumitrescu & Hurlin (2012)

<table>
<tr><th>Number of lags: Bayesian Information Criteria</th><th>Number of lags: 4</th></tr>
<tr><td colspan="2">Consumption ↔ Income
Income ↔ Housing Wealth
10 Year Treasury Rate → Housing Wealth</td></tr>
<tr><td>Financial Wealth → Income</td><td>Financial Wealth ↔ Income</td></tr>
<tr><td>FinancialWealth → HousingWealth</td><td>Financial Wealth ↔ Income</td></tr>
<tr><td>Consumption → Housing Wealth</td><td>Consumption ↔ Housing Wealth</td></tr>
<tr><td></td><td>FinancialWealth ↔ Consumption</td></tr>
</table>

Chapter 3

Household economic uncertainty in US

Abstract

This chapter examines how various newly proposed aspects of household uncertainty such as consumption uncertainty, financial wealth uncertainty, and housing wealth uncertainty with the normalization of personal income affect US household decisions. These new measures of economic uncertainty display significant differences from the recently released World uncertainty index. In contrast, they show similar behavior in the long run with the well-known economic policy uncertainty index (EPU). The results support the highly significant effect of housing wealth uncertainty upon consumption. The effect is especially large relative to that of financial wealth uncertainty. We conclude that enhancing the predictability of economic policy will play a critical role in depressing uncertainty and its real effects.

JEL codes: D81; E21; E44; R31.
Keywords: Consumption uncertainty; Housing wealth uncertainty; Financial wealth uncertainty; Impulse responses; DCC-GARCH.

3.1 Introduction

The literature on macroeconomic uncertainty has mushroomed in recent years. A number of events has contributed to rising uncertainty, including the Global Financial Crisis (GFC) of 2007-2009 and the eurozone debt crisis. The housing sector has been at the forefront of the US financial crisis. The collapse of US house prices in late 2000s has contributed to a sharp fall in housing wealth. It is expected that falling wealth has a negative effect on private consumption. High volatility in the financial markets and house prices also creates uncertainty about the levels of financial wealth and housing wealth, respectively. Uncertainty about housing wealth as well as financial wealth is also expected to contribute towards falling consumption. However, the recent literature on macroeconomic uncertainty has overlooked the issue of wealth uncertainty and how it affects consumption. The present paper is an attempt to fill this gap in the literature.

The primary aim of this paper is to measure uncertainty about housing and financial wealth and estimate uncertainty effects on consumption and wealth using US data. To this end, we first estimate a Dynamic Conditional Correlation (DCC) GARCH model to obtain proxies for uncertainty regarding housing and financial wealth. We then use VAR and impulse response function (IRF) analysis to estimate the dynamic effects of uncertainty on consumption. We also use two alternative measures of macroeconomic uncertainty, the US Economic Policy Uncertainty (EPU) index and the World Uncertainty Index (WUI) for the US, to investigate the sensitivity of our results. Our major results are as follows: First, housing uncertainty estimated by a GARCH model affects consumption negatively in the long run whereas the short run effect is variable. Second, uncertainty in financial wealth reduces consumption only in the short run with the maximum impact observed at the end of the first year. Third, World Uncertainty in the US affects consumption and stock market wealth only in the first two quarters but has no effect on housing wealth. Fourth, when uncertainty is estimated by the EPU index, the results are similar with the first finding above. Finally, housing wealth DCC uncertainty has the largest effect on consumption than any other uncertainty measure.

The paper makes a number of contributions in the related literature: First, we construct a time-varying measure of uncertainty about housing and financial wealth using a DCC model. Second, we perform IRF analysis to estimate the dynamic effects of uncertainty shocks on consumption. Third, we compare the dynamic effects of our constructed measures of uncertainty on consumption and wealth with the effects of alternative uncertainty measures such as the EPU index and World EPU index.

The rest of the paper is structured as follows. In the next section we summarize the most relevant literature. In section 3 we discuss the methodology, and in sections 4 and 5 we present the data and our results, respectively. Section 6 offers a discussion of the main results and finally section 7 concludes the paper.

3.2 Literature

Case and Shiller (1989) measure housing wealth volatility by computing the ratio of the standard deviation of a variable to the average standard error for that variable. As a result, the ratio for the quarterly difference of the log indexes is 1.64 for Atlanta, 1.61 for Chicago, 1.35 for Dallas, and 1.54 San Francisco-Oakland. These values are close to 15% a year for annual percentage change. Further, individual prices are not influenced by the aggregate market price. Case and Shiller (1989) first showed substantial evidence that increases in prices over any year are followed by increases in the subsequent year.

Moreover, evidence suggests the macroeconomic impact of housing wealth on GDP. Boldrin, et al. (2016) support that the correlations of house prices with employment and GDP is 0.44 and 0.42, respectively. Rios-Rull and Sanchez-Marcos (2008) also suggest the comove of housing wealth volatility with GDP. Moreover, the average correlation of US GDP with housing prices is 0.67. Loutskina and Strahan (2015) support that the financial integration amplified the way that the housing wealth shocks affected real economy during the Great Recession.

Heathcote and Perri (2018) developed a model with fluctuations in unemployment to study the business cycle implications of the household wealth declines. These falls increase macroeconomic volatility and make economy susceptible to confidence shocks. The level of wealth controls the consumer confidence fluctuations. Households are divided into two types related to the risk of their income. The risky-household type faces risky income and the other does not. Risky income is associated to risky household and signals the motive of the precautionary savings. Savings are associated with the risk of unemployment and plays a precautionary role. There is an extensive literature (Alan et al., 2012; Mody et al., 2012; Carroll et al., 2011), that support that the precautionary motive towards the risk of unemployment is the primary reason for increased savings.

Bahadir and Gumus (2019) use the real business cycle (RBC) model to test the connection of housing wealth with household and business credit shocks and how they affect real economy in the emerging markets. They suggest that household and business credit shocks affect the key macroeconomic variables (output, consumption, investment, labor and house prices) differently.

More recent studies measure output uncertainty, by the conditional variance that is estimated from Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models. *'This technique represents a superior approach to measure uncertainty compared to the moving standard deviation or variance of the estimated variable series. This superiority arises from the possibility of allowing a separation between anticipated and unanticipated changes in the same variable. By using the variance or standard deviation early studies have used inflation variability instead of uncertainty'* (Aksoy et al. 2017: 3). Miller and Peng (2006) use GARCH and var model to estimate housing volatility and its linkage to real economy. In the US covering 277 MSAs. Evidence implies the existence of volatility in 17% of the MSAs. Fountas et al. (2006) use GARCH methodology to measure inflation and gdp for G7.

Evidence supports that business cycle variability and the rate of economic growth are related. Further in the US Aksoy et al. (2017) find that inflation is positively related with relative price dispersion using a VARMA GARCH-M model.

Another way to measure uncertainty is by the frequency that the word uncertainty appears in newspapers or reported in media. Baker et al. (2015) by confirming the newspaper reliability in several ways, support that innovations in policy uncertainty is associated with reduction in investment, output and employment in US. In the same line Ahir et al. (2019) provide evidence about the connection of reductions in productivity growth during periods of high uncertainty. As a result, firms that are credit constrained switch the composition of investment. The key of the link between investment and economic growth lies on information and communication technology (ICT) capital—which is more subject to liquidity risks.

3.3 Econometric methodology

3.3.1 GARCH analysis

In this paper we use the DCC model introduced by Engle (2002), a generalization of the constant conditional correlation (CCC) GARCH model (Bollerslev, 1990), where the conditional correlation matrix is designed to vary over time. We employ a trivariate DCC(1,1)–GARCH specification to estimate the conditional volatilities of the personal income shares of consumption, financial wealth, and housing wealth simultaneously.

DCC models provide important time-varying features that might otherwise be difficult to quantify. They are the most accurate among other estimators of multivariate GARCH when the criterion is mean absolute error, diagnostic tests, or tests based on value at risk calculations. Despite the potential of large covariance matrices estimation of large systems, DCC models are also accurate for simpler structures. Moreover, multivariate and univariate volatility forecasts are consistent with each other, unchanged when new variables are added to the system and superior to moving average methods (Engle, 2002).

Two steps are involved to estimate these models from univariate GARCH estimates of each equation. In the first step we estimate a univariate AR(1) Garch(1,1) model for each variable in order to obtain the estimation of $\sqrt{h_{ii,t}}$ as the expressions for $h_{ii,t}$ are typically thought of univariate GARCH models. In the second step, we estimate a conditional correlation estimator by using transformed residuals resulting from the first stage (Engle and Sheppard, 2001). Note that these models could certainly include functions of the other variables in the system as predetermined variables or exogenous variables (Engle 2002).

There is evidence of serial correlation in the raw data (the results are not reported) and we add the AR(1) terms to capture the speed that market information is reflected in our variables.

The general form of the mean equation is defined as:

$$\mathbf{y}_t = \mu + \theta_{\mathbf{1}}\mathbf{y}_{\mathbf{t}\ -\mathbf{1}} + \mathbf{e}_{\mathbf{t}} \tag{3.1}$$

where

$$\mathbf{y}_t = (\mathbf{\Delta CR_t}, \mathbf{\Delta FWR_t}, \mathbf{\Delta FWR_t})' \tag{3.1.a}$$

and

$$\mathbf{e}_t|\mathbf{I}_{t\ -1} = (\mathbf{e_{1,t}}, \mathbf{e_{2,t}}, \mathbf{e_{3,t}})|\mathbf{I}_{t\ -1} \sim \mathbf{N}(\mathbf{0}, \mathbf{H_t}) \tag{3.1.b}$$

and θ_1 is a finite vector of parameters. Furthermore, the conditional mean vector is specified as a VAR (1) representation of yt to deal with the autocorrelation issues. The VAR(1) model takes the following form:

$$\Delta \text{CR}_t = \mu_1 + \theta_{1C}\Delta\text{CR}_{t-1} + \theta_{2C}\Delta\text{FWR}_{t-1} + \theta_{3C}\Delta\text{HWR}_{t-1} + \mathbf{e_{1,t}} \tag{3.1.1}$$

$$\Delta \text{FWR}_t = \mu_2 + \theta_{1FW}\Delta\text{CR}_{t-1} + \theta_{2FW}\Delta\text{FWR}_{t-1} + \theta_{3FW}\Delta\text{HWR}_{t-1} + \mathbf{e_{2,t}} \tag{3.1.2}$$

$$\Delta \text{HWR}_t = \mu_3 + \theta_{1HW}\Delta\text{CR}_{t-1} + \theta_{2HW}\Delta\text{FWR}_{t-1} + \theta_{3HW}\Delta\text{HWR}_{t-1} + \mathbf{e_{3,t}} \tag{3.1.3}$$

where,

ΔCR_t: real per capita consumption rate in log deference at time t,

ΔFWR_t: real per capita financial wealth rate in log deference at time t,

ΔHWR_t: real per capita housing wealth rate in log deference at time t,

e_{it}: a disturbance term.

The Variance-Covariance matrix Representation is defined as follows:

$$\mathbf{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t \tag{3.2}$$

where,

D_t=diag $\sqrt{h_{i,t}}$ is a n X n diagonal matrix, which elements are standard deviations from univariate GARCH models. Therefore, it includes the conditional volatilities modelled by the previous set of univariate GARCH equations (Bollerslev, 1990; Engle, 2002). Consequently $h_{i,t}$ is defined as the conditional variance obtained from the univariate AR(1)–GARCH (1,1) model shown by equation (1).

Thus, in the second step, the standardized residuals are used for the estimations of the conditional covariances. The method is to smooth the series of standardized residuals obtained from the first step. Consequently $h_{ii,t}$ is defined as the conditional variance obtained from the univariate AR (1)–GARCH (1,1) model (eq.3.1).

Additionally, R_t is the conditional correlation matrix of the standardized residuals obtained at the first step. The dynamic correlation model differs from its simplest form (CCC) only in allowing R to be time varying (Engle 2002:4) and decomposed as follows:

$$R_t = \overline{\mathbf{Q}}_t^{-1/2}\mathbf{Q}_t\overline{\mathbf{Q}}_t^{-1/2} \tag{3.2.1}$$

where,

Qt is defined as the unconditional covariance (long run) and has appeared in different specifications in the literature. One specification proposed by Caporin and McAleer (2012) is:

$$\mathbf{Q}_t = S + A(D_t^{-1} e_{t\ -1} e'_{t\ -1} D_{t\ -1}^{-1} - S) + B(Q_{t\ -1} - S) \tag{3.2.1.a}$$

where,

A and B are symmetric parameter matrices and S is referred to as a long-run correlation matrix, that is the unconditional correlation matrix of the epsilons.

Another specification suggested by Enders (2015) is the exponential smoother:

$$\mathbf{Q}_t = q_{ijt} = (1 - \lambda) s_{it} s_{jt} + \lambda q_{ij(t-1)} \tag{3.2.1.b}$$

where λ denotes the sum of A and B under the restriction: $\lambda\ < 1$. The dynamic conditional correlations are defined as: $\rho_{ijt} = q_{ijt}/(q_{iit} q_{ijt})^{0.5}$.

The specifications of long run (unconditional) variances in this paper are created as follows:

$$\mathbf{q}_{ijt} = (1 - \lambda_1 - \lambda_2)\bar{q}_{iit} + \lambda_1 s_{t-1}^2 + \lambda_2 q_{t-1}^2 \tag{3.3}$$

where,

$\bar{q}_{iit}$ is the mean variance of the series of standardized residuals,

s_{t-1}^2 is the lagged squared standardized residuals, and,

q_{t-1}^2 is the lagged variance of standardized residuals.

3.3.2 Var analysis

We estimate three VAR models to perform impulse response analysis. Each model uses a different definition of uncertainty. First, we make use of the estimated DCC model to calculate the long run (or unconditional) variances which we use as endogenous variables in our VAR1 model. Therefore, we estimate a VAR model on our quarterly data to evaluate the impact of uncertainty shocks on consumption and consequently the real economy. Second, to construct VAR2, we replace our calculated uncertainties with the measure of world uncertainty index constructed by Ahir et al. (2019). Third, we measure uncertainty using the EPU index to construct VAR3. In each VAR, the appropriate number of lags is selected based on the Akaike information criterion (AIC).

VAR1 includes the following six variables: personal income shares of consumption, financial wealth, and housing wealth, and the three unconditional variances obtained from the DCC estimation.

This could be written as:

$$\mathbf{y}_t = \alpha + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \varphi_2 y_{t-3} + \varphi_2 y_{t-4} + u_t \tag{3.4}$$

where,

y_t is the vector of the endogenous variables:

$$\mathbf{y'}_t = logCR_t,\ logFWR_t,\ logHWR_t\ ,UCR_t,\ UFWR_t, UHWR_t \tag{3.4.1}$$

where $UCR_t, UFWR_t, UHWR_t$ are the estimated unconditional variances of shocks to the consumption ratio, the financial wealth ratio, and the housing wealth ratio, respectively, obtained from the DCC-GARCH(1,1) model.

Furthermore,

$\varphi_1,\ \varphi_2,\ \varphi_3,\ \varphi_4$: coefficients associated to lags 1, 2, 3 and 4,

a: vectors with coefficients associated to the intercept, and

u_t is a white noise disturbance term with E(u_{1t})=0, (i=1, 2,..., 8), E($u_{1t}, u_{2t}, u_{3t}, u_{4t}$)=0

Following the estimation of VAR1, we repeat the estimations by replacing the GARCH estimated uncertainties by US world uncertainty and US EPU in VAR2 and VAR3, respectively.

An issue that deserves some discussion is the decision to estimate a VAR in levels versus a VAR in first differences. Note that it is assumed to require first differencing to induce stationarity, unless one or more characteristic roots of (4.1) is greater than or equal to unity and therefore are integrated. Table (3) presents the results of Johansen cointegration test[1].

The results confirm previous research (Kontana and Fountas, 2021) that the variables are cointegrated. Therefore, we use these variables in their non-stationary levels. We discuss this issue further in the next session.

[1] We employ trace statistic and information-criteria methods to estimate the number of cointegrating equations.

3.4 Data

The data in this paper are obtained from Federal Reserve Bank of St Louis (FRED), the Bureau Economic Analysis and the US Census Bureau. The sample is quarterly time series encompassing the period from 1975q1 to 2018q1, and includes US data for consumption, personal income, financial wealth, and housing wealth. We choose to use the personal income shares of consumption, financial wealth, and housing wealth instead of levels for several reasons to be discussed below.

The sample for the VAR1 model ranges from 1976q1 to 2018q1, for the VAR2 from 1996q1 to 2018q1, and for VAR3 from 1985q1 to 2018q1. The difference in the starting date arises from the different starting dates of the uncertainty variable datasets.

Although house prices sold in US comove with housing prices (Rios-Rull et al. 2008), they have an even larger volatility. Therefore, we consider the variable of housing wealth as a four-dataset variable to consider not only the housing sales index, which is very common in most empirical literature but also the housing prices, the houseowner rate and the number of households. The concept behind the construction of our data is based on Case et al. (2012). Moreover, financial wealth consists of corporate equities, mutual and pension reserve funds held by households. The variable of consumption represented by retail sales which are used as a proxy and account for half of consumer expenditures (Case et al., 2012). Furthermore, consumption must be measured by the imputed value of service rendered and not the expenditure on durable consumer goods, which can be regarded as capital expenditure. Thus, the difference between the statistical estimates and the theoretical constructs is reduced and is therefore highly desirable (Friedman, 1957).

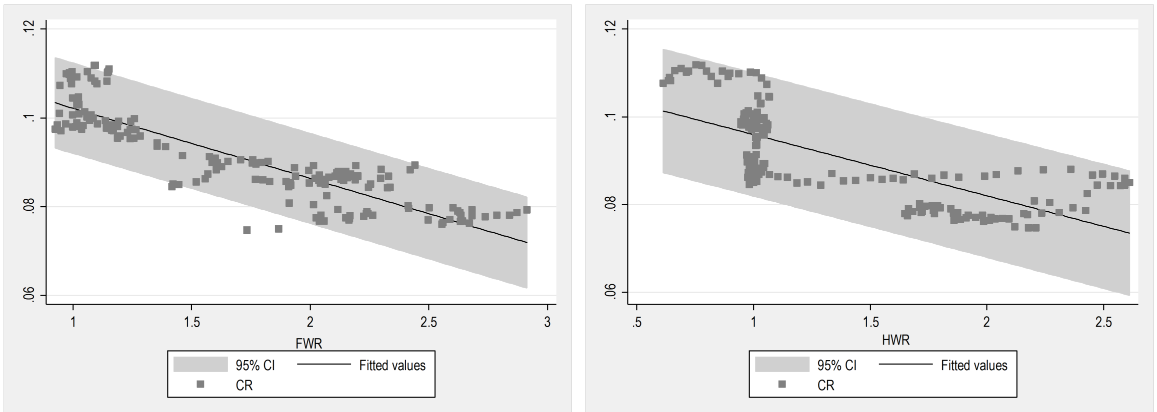
To remove the effect of income on housing wealth or, in other words, the effect of inequalities in our estimations of uncertainty, we estimate the proportion of the variables to income. Therefore, we divide consumption, financial and housing wealth by income to obtain the proportion of the variables. This technique is quite common in the literature (i.e. Gau 1985; and Carroll et al., 2011).

This technique is traditionally used for avoiding multicollinearity in the regressions. In spite of this, several studies attempt to avoid the 'spurious significance' resulted by nonstationary variables even if their stationarity is firmly confirmed. This stationarity can be destroyed *'by the introduction of labor income uncertainty, time-varying after-tax interest rates, demographics, or many other real-world complications'* (Carroll et al., 2011: 58). Thus, they use consumption and wealth normalized by income. Moreover, high regional income growth is mostly associated with temporally isolated local events that decrease volatility (Dolde and Tirtiroglu, 2002). Hence, the estimation of the share of consumption and wealth to income can remove the impact of these occasional events on volatility.

Figure 3.1 shows the trend line of consumption share with respect to financial and housing wealth share.

All three variables are in logarithms, measured on a per capita basis, and denoted CR, FWR and HWR. Both graphs show the existence of a great deal of

Figure 3.1: Trend line of consumption



Note: CR, FWR and HWR denote the consumption, financial and housing wealth share to income, respectively.

variability in consumption when the rate of consumption share to personal income (indicated in the y axis) is equal to one with both types of wealth share (indicated in x axis).

Figure 3.2 plots the recently released World uncertainty index, developed by Ahir et al. (2019) and Figure 3 presents the EPU index, developed by Baker et al. (2015). Both series are taken from FRED. Ahir et al. (2019) expanded the existing world uncertainty indices, offering 286 new uncertainty indicators for different countries. The methodology behind this measurement of uncertainty is based on frequency counts of the word uncertainty and its variants in the quarterly Economist Intelligence Unit country reports. Along similar lines, the EPU Index measures the frequency of articles in 10 leading US newspapers that contain the following triple: “economic” or “economy”; “uncertain” or “uncertainty”; and one or more of “congress”, “deficit”, “Federal Reserve”, “legislation”, “regulation” or

"White House" (Baker, et al., 2015).

Figure 3.2 (Appendix) illustrates the graphs of the share of consumption, financial and housing wealth to personal income in logs and log differences. We notice increased volatility of financial wealth during the recent 2008 recession in contrast to other variables that exhibit low volatility at the same period.

Summary statistics are displayed in Table 3.1. All variables are skewed to the left and exhibit excess kurtosis (fat tails). Therefore, the model parameters are estimated by the maximum likelihood approach under the Student's t error distributions to accommodate the presence of leptokurtosis. The fact that the value of the financial wealth standard deviation is about the double of each of the other variables might reflect the 2007/2008 sub-prime crisis, which strongly affected the financial sector (Righia and Ceretta, 2012).

3.5 Empirical results

3.5.1 Unit Root tests

We perform the augmented Dickey–Fuller (1979) and the Phillips–Perron (1988) tests to test for a unit-root process. The null hypothesis for the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests is that the variable contains a unit root, and the alternative is that the variable was generated by a stationary process with a constant and a constant with trend. The PP test uses Newey–West (1987) standard errors to account for serial correlation, whereas the ADF test uses additional lags of the first-differenced variable. The optimal lag length chosen on the basis of the AIC is four.

Table 2 presents the unit root test results. Evidence indicates that all variables are non-stationary in the log-levels and stationary in their log-differences. HWR is nonstationary in log differences in the ADF test but when we consider the break unit root test, HWR exhibit similar behaviour process with this of CR and wealth rates. Therefore, all three variables CR, FWR and HWR are first-difference stationary.

We decide to use raw data because differencing can cause a significant loss of information and power to the estimated unconditional volatilities. In the VAR 1 model we add the three estimated unconditional variances obtained by the GARCH-DCC model. These variables represent the unconditional variances for CR (UCR), FWR (UFWR) and HWR (UHWR). In the VAR2 model we replace the above uncertainties by the World Uncertainty Index and in VAR3 we use the US EPU index. All used uncertainty datasets included in the VARs are stationary (the results are not reported). Therefore, since the VAR models are estimated in levels, they include stationary and non-stationary variables.

Finally, Figure 3 shows visually that all the eigenvalues of VARs lie inside the unit circle, thereby VAR 1, VAR 2 and VAR 3 satisfy the stability condition. However, for robustness we repeat our impulse response results (fig. 12) by performing the VAR 1 in log-differences also.

There is extensive research (i.e. Phillips and Durlauf, 1986; Fanchon and Wendel, 1992) showing that variable differencing is not necessary if the non-stationary data is also cointegrated because estimation with such data will yield consistent parameter estimates.

Fanchon and Wendel (1992) use raw data of corn and cattle price series, where each price series is integrated of order 1, or I(1). Moreover, microeconomic theory supports the cointegration among such prices because are linked by derived supply and demand relationships. A cointegration regression is also applied to confirm the theory. Finally, they showed that the VAR model estimated in levels outperforms the VEC model.

3.5.2 DCC model results

We proceed by estimating the relationship between the shares of consumption, financial and housing wealth to income using the trivariate AR(1)–GARCH (1,1)–DCC model in USA defined in equation (1). The specification of the model is chosen according to likelihood ratio tests and the minimum value of the information criteria, while the lag order (1,1) is selected by Akaike (AIC) and Schwarz (SIC) information criteria.

Table 3.4 in Appendix 1 describes the estimation sample and reports a Wald test against the null hypothesis that all the coefficients on the independent variables in the mean equations are zero. Here the null hypothesis is rejected at the 5% level.

Moreover, for the consumption rate equation, the lagged consumption rate coefficient is -0.1054 and the lagged financial wealth rate coefficient is 0.0417 and statistically significant at 10 percent significance level. The ARCH and GARCH parameters are significant at the 5 and 1 percent level, respectively. Equations (3) and (4) report estimates of the conditional mean and variance of financial wealth rate. All the lagged coefficients are statistical insignificant. Both the GARCH and ARCH parameters are significant. For the HWR equation the lagged housing wealth rate coefficient is 0.7328 and highly significant, The GARCH parameter is significant at the 1 percent level and the ARCH at the 10 percent level. The sum of the ARCH and GARCH parameters for HWR is 0.989, for FWR 0.515 and for CR 0.976. These results provide a highly persistent existence in the conditional correlations for HWR and CR, with the former showing a slight superiority over the latter.

The conditional quasicorrelation between the standardized residuals for CR, FWR and HWR are statistically insignificant. However, the correlation between CR and FWR is marginally significant at 10 percent level.

The two scalar parameters (lambda 1, lambda 2) are represented in eq. (3) in subsection (4). Lambda 1 describes how much the correlation depends on shocks, while lambda 2 describes how much the correlation depends on its own lag.

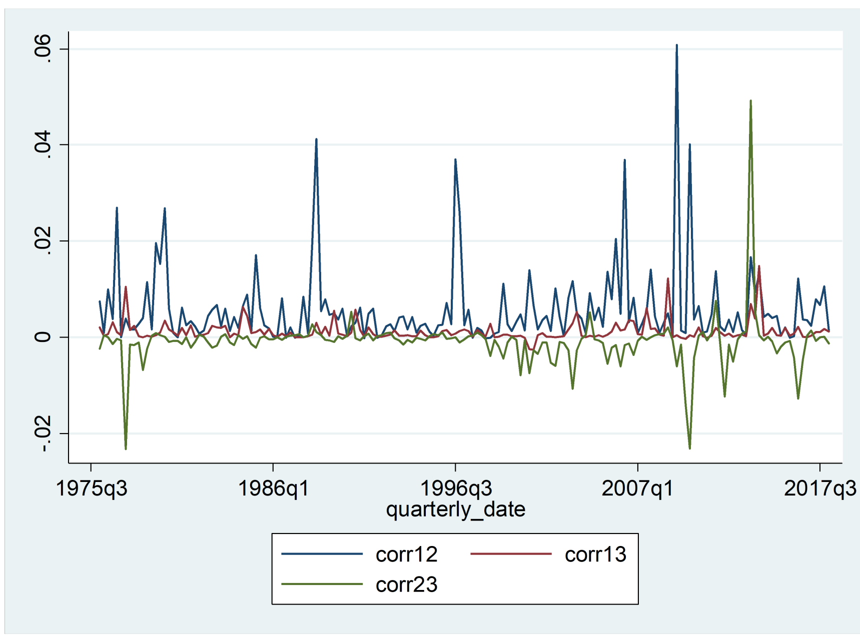
They satisfy a stability constraint of the form lambda 1+ lambda 2 < 1. The estimated lambda 1 and 2 coefficients of 0.1471 (z-statistic=1.87, p=0.061) and 0.4535 (z-statistic=1.68 p=0.092) respectively, are significantly different from zero which indicates a substantial persistence of the unconditional level correlations. Further Wald test rejects the null hypothesis that lambdas = 0 at all conventional levels. Note that the DCC model reduces to the CCC model when lambdas are zero.

Furthermore, the t-student degrees of freedom parameter (df) is highly significant for all variables. This result confirms the choice of the t-student as an appropriate distribution.

Figure 3.4 (Appendix 1) presents the Autocorrelation and the cumulative periodogram white noise test for the standardized residual of the model using 20 lags. We can see in graphs that the values never appear outside the confidence bands. So, we conclude that the process is not different from white noise.

Figure 3.2 presents the graph of the correlations. The variables exhibit negative correlations related to financial wealth.

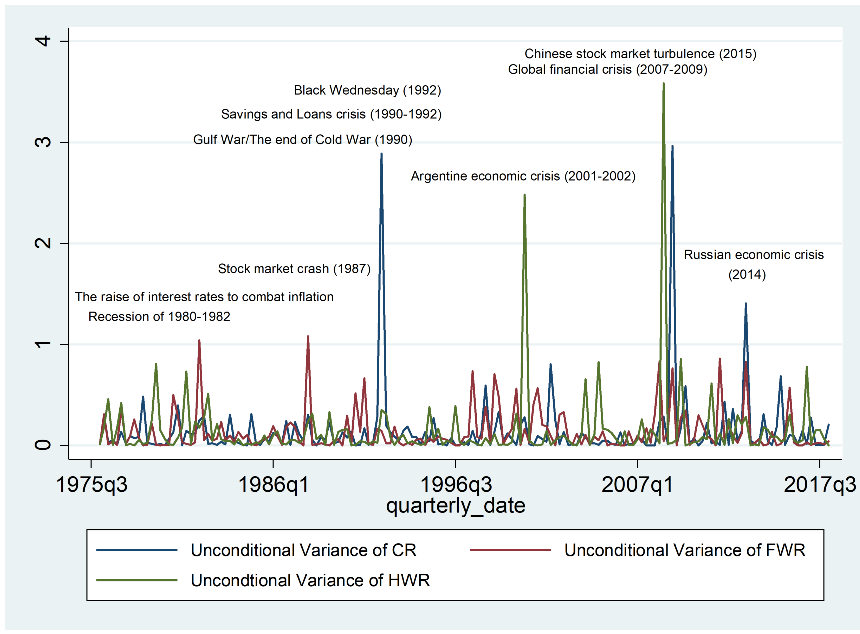
Figure 3.2: Graph of the correlations of shocks



Note: Variables are represented by numbers in the graph. Consumption share to Income (1), Financial Wealth share to Income (2), Housing Wealth share to Income (3).

Figure 3.3 illustrates the unconditional variances of the variables. Uncertainty appears to jump up after major shocks like the OPEC I oil-price shock, Gulf war I, the 9/11 terrorist attack and the Great Recession between 2000-2010. Consumption uncertainty appears to dramatically increase after major economic and political shocks.

Figure 3.3: Unconditional Variances of the variables



Note: CR, FWR and HWR stand for the share of consumption, financial wealth and housing wealth of personal income, respectively.

3.5.3 Generalized impulse response analysis

We employ the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) to determine the appropriate number of lag length of the VAR model. The generalized impulse response functions do not require orthogonalization of shocks in contrast to the traditional ones and are invariant to the ordering of the variables in the VARs.

Figure 3.7 presents the impulse response of CR to a shock in the unconditional variances (uncertainty) of CR, FWR and HWR. The CR response to a shock in HWR uncertainty appears more severe among the others lasting for the full estimated period. After a sharp and immediate decline, it jumps up to almost the 0.01 line and dies out after three quarters while remaining negative for the whole estimated period (thirty quarters). The CR exhibits a negative response to a FWR uncertainty shock lasting for eight periods (two years) and then becomes insignificant. Note it starts to recover in the middle of that period of 8 quarters, that is the first year of its deep decline. The CR increases in response to its own shocks immediately and remains at a higher level for the remaining period, although statistical significance applies mostly for the latter part.

Figure 3.8 illustrates the impulse responses of the FWR and HWR to HWR uncertainty. HWR exhibits a large response to its own uncertainty innovation. FWR drops sharply to recover one year later and decline gradually. Figure 9 illustrates the impulse responses arising from VAR 2, where uncertainty is proxied by the US World uncertainty (WUI) index. The US World uncertainty has an instant effect on

CR of almost 0.03 percent and drops rapidly to zero. Similarly, FWR has a large immediate response to an innovation of US World Uncertainty and rapidly dies out. The third panel of figure 9 presents the response of HWR to US World Uncertainty. HWR remains immune to such innovations indicating the huge difference between monetary policy index (EPU) and US World uncertainty Index. EPU as shown below is strongly associated with HWR.

Figure 3.9 presents the responses of the variables of interest to a shock in EPU. The first panel shows that EPU affects CR negatively in the long run and therefore it really matters to the economy as consumption is a part of GDP (retail sales). Moreover, there is a huge response of HWR to an innovation presented by EPU, that enhance the importance and the link to each other. However, the FWR seems not to be affected statistically significantly by a shock in the EPU index. Figure 11 illustrates the responses of the variables to a shock in the HWR. US World uncertainty responds to such a shock with a more permanent manner. This is shown in the last panel in figure 11. More clearly, its impact response is one percent, declining sharply to an average of -0.5% around the third quarter, showing a cyclical pattern over a relatively protracted period of time. It is rising slightly above to zero in the 11th quarter and it remains positive thereafter.

Generally, the most severe response of CR is caused by HWR and FWR. Figure 3.11 shows that the HWR shocks have larger and more persistent effects on CR, followed by FWR. After a sudden shock of HWR, CR is rising to almost 5% in the 6th quarter, then declining gradually under zero without any significant recovery ever after. Further, CR follows a negative path as a response to a FWR shock, starting in the 3rd quarter after the shock and it remains under zero (fig 3.7). The most important responses of FWR are associated with the shocks of HWR and its long run volatility (fig 3.8). A shock to UHWR causes a significant loss of power to FWR. HWR only responds to its own shocks and uncertainty (fig 3.8). HWR shock has a permanent negative effect on CR and FWR and positive effect on their uncertainties during the observation time of 10 years. Further, the UHWR response is associated with CR shocks in the long run.

3.6 Discussion of the results

Innovations in consumption uncertainty, financial wealth uncertainty and housing wealth uncertainty have a different impact on the real economy. There is much more similarity between DCC housing wealth uncertainty (UHWR) and EPU than that between WUI and EPU, considering that UHWR ranges from 1976-2018 and EPU from 1985-2018. Consumption declines immediately after a sudden shock as households wait for uncertainty to be resolved.

Innovations in UHWR and EPU reveal very similar patterns after one year resulting in identical cyclical pattern over a relatively protracted period. The longest, more serious, and permanent impacts on consumption and financial wealth are associated with housing wealth shocks. Initially, innovations in the housing market cause a decrease in consumption and financial wealth after a succession of short fluctuations decrease while increases their uncertainties. In contrast, WUI jumps up to 10 percent in the first few quarters after the shock and sharply dies out. There are several reasons for this depressive effect of uncertainty including a precautionary spending motive towards the risk of unemployment by households (Alan et al. ,2012; Mody et al., 2012; Carroll et al., 2011), upward pressure on the cost of finance, managerial risk-aversion and interactions between nominal rigidities and search frictions (Baker et al., 2015).

In particular, households appear to behave largely as the theoretical models would suggest. An uncertainty shock produces an immediate drop in spending followed by a rebound. The response of CR to UHWR (fig. 3.7) follows this bust-boom pattern that the theory suggests. It is the same path of manufacturing responses to a large uncertainty shock described by Bloom (2007) and Khan and Knotek (2011). Large uncertainty shocks immediately depress consumption. The theory behind this aspect lies on two facts. The real options framework and its reversibility.

The real option framework is based on financial market. The buyer of a call option acquires the right to purchase a financial asset at a given price by a particular time in the future. The buyer can wait to obtain more information and decide to make the transaction or not. Economists use this notion of the real options framework to suggest that there may be a benefit to waiting and acquiring more information before making a decision to invest. Moreover, this decision cannot be reversed costlessly. These irreversibilities make households to wait before acting. In other words, the value of the real option of waiting is greater after an uncertainty shock than in normal times. Bernanke (1983) suggests the term 'bad news principle' as an explanation for the downward of the economy after a shock. According to this principle, 'given the current return of the most profitable investment i, the willingness to invest in t depends only on the average expected severity of bad news for i that may arrive in the next period. Potential, good news for the investment does not matter at all' (Bernanke 1983:91). If enough firms follow the "bad news principle", then this uncertainty shock can produce an economic downturn. Uncertainty shocks are usually felt throughout the economy, affecting households as well. In fig. 9 the response of CR increases immediately giving an opposite reaction of fig. 7. Households avoid consuming durable goods, as notably cars or houses, which are difficult to reverse. As a result, they raise their consumption of non-durable goods and services. In particular, fig. 9 represents the WUI behavior which draws on ICT capital which is more subject to liquidity risks and households save less and consume more when the tax rate on asset income rises (Romer, 2012).

Therefore, the comparison of the figures of UHWR, WUI and EPU impulse responses illustrate substantial differences that could be attributed to the differences in the way they have been constructed. Moreover, the discrepancies might be attributed to the fact that household and business credit shocks affect the key macroeconomic variables (output, consumption, investment, labour, and house prices) differently (Bahadir and Gumus, 2019).

3.7 Conclusion

The core issue in this paper is uncertainty. We estimate three VAR models by using different types of uncertainty dataset in order to perform impulse response analysis. The impulse response functions test the effect of uncertainty shocks on future values of macroeconomic variables (consumption, financial, and housing wealth shares to personal income). Our study focuses on household's response to a rise in uncertainty. First, we provide three new measures of uncertainty of consumption, financial wealth, and housing wealth by estimating a GARCH-DCC model. Second, we also use two other popular uncertainty indices, EPU and WUI to obtain the impulse responses of consumption, housing wealth and financial wealth to uncertainty shocks.

We find that the different types of uncertainties reveal different impacts on these variables. Initially, a shock in the housing market decreases consumption and financial wealth in the long run and increases their associated uncertainties. Housing wealth uncertainty may increase consumption for a short period whereas depresses consumption in the long run. In contrast WUI and EPU have an immediate effect on household decisions which eventually is being offset. WUI is inefficient to transmit new information in housing wealth but efficient enough to shake consumption and household financial wealth only for a very short period. WUI, EPU and housing wealth uncertainty have different impact on macroeconomic variables as these types of uncertainty indices are constructed in a different way. Probably, our findings are related to the fact that household and business credit shocks affect output, consumption, investment, labour and house prices differently. Finally, our proxy of housing uncertainty seems to have a more persistent impact on personal consumption and financial wealth than that of EPU and WUI, possibly indicating the different ways of constructing uncertainty and its relative accuracy as household uncertainty index.

3.8 References

Ahir, H., N. Bloom and D. Furcerir. 2019. ”The World Uncertainty Index.” Working Paper No. 19-027. Stanford Institute for Economic Policy.

Aksoy, G., D. Bredin, and S. Fountas. 2017. ”Relative Price Dispersion and Inflation: Evidence for the UK and the US.” *Credit and Capital Markets* 50 (1): 3-24.

Alan, S., Crossley, T. and H. Low. 2012. ”Saving on a Rainy Day, Borrowing for a Rainy Day.” Working Paper, No. 1212, Koç University-TÜSİAD Economic Research Forum (ERF), Istanbul.

Badahir, B., and I. Gumus. 2019. ”Transmission of Household and Business Credit Shocks in Emerging Markets: The Role of Real Estate.” *Real Estate Economics.* (0): 1–31.

Baker, S., N. Bloom, and J.S. Davis. 2015. ”Measuring Economic Policy Uncertainty”. Working paper. National Bureau of Economic Research.

Bernanke, S.B. 1983. ”Irreversibility, Uncertainty and Cyclical Investment.” *The Quarterly Journal of Economics* 98 (1): 85-106. Oxford University Press.

Bloom, N. 2007. ”The Impact of uncertainty shocks.” National Bureau of Economic Research. NBER Working Papers.

Boldrin, M., Garriga, C., Peralta-Alva, A. and Sanchez, J.M. 2016. Reconstructing the great recession. Working Papers 2013-006, Federal Reserve Bank of St. Louis.

Bollersev,T. 1990. Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized Arch Model. *The Review of Economics and Statistics*, 72(3) 498-505.

Caporin, M. and M. McAleer. 2012. ”Do we really need both BEKK and DCC? A tale of two multivariate Garch models.” *Journal of Economic Surveys* 26 (4): 736–751.

Carroll, D.C., M. Otsuka, and J. Slacalek. 2011. ”How Large are Housing and Financial Wealth Effects? A New Approach.” *Journal of Money, Credit and Banking* 43 (1): 55-79.

Case, K. E. and J. R. Shiller. 1989. ”The Efficiency of the Market for Single-Family Homes.” *American Economic Review* 79 (1): 125–137.

Case, K. E., J. M.Quigley, and J. R. Shiller. 2012. ”Wealth Effects Revisited 1975-2012.” *Critical Finance review* 2: 101-128.

Gau, W.G. 1985.”Public Information and Abnormal Returns in Real Estate Investment.” *AREIJEA Journal & Finance* 13 (1): 15-31.

Dolde, W. and D. Tirtiroglu. 2002. ”Housing Price Volatility Changes and Their Effects.” *Real Estate Economics* 30 (1):41–66.

Enders, W. 2015. *Applied Econometric Time Series.* University of Alabama, Fourth edition.

Engle R.F. 2002. Dynamic Conditional Correlation. *Journal of Business & Economic Statistics* 20:3, 339-350. DOI: 10.1198/074500102288618487.

Engle R.F. and F.K Kroner. 1995. "Multivariate simultaneous generalized ARCH." *Econometric Theory* 11: 122–150.

Fanchon P. and J. Wendel. 1992. "Estimating VAR models under non-stationarity and cointegration: alternative approaches for forecasting cattle prices." *Applied Economics* 24 (2): 207-217.

Fountas S., M. Karanasos, and J. Kim 2006. "Inflation Uncertainty, Output Growth Uncertainty and macroeconomic Performance." *Oxford Bulletin of Economics and Statistics* 68 (3).

Friedman, T. 1957. "The Permanent Income Hypothesis". *A Theory of the Consumption Function.* National Bureau of Economic Research. p. 20-37.

Heathcote J. and F. Perri. 2018. "Wealth and Volatility". *The Review of Economic Studies* 85 (4): 2173–2213.

Khan, S. and Knotek, E.S. (2011). How do households respond to uncertainty shocks? Economic Review. Federal Reserve Bank of Kansas City, 96(QII).

Kontana, D. and Fountas, S. 2021. "Consumption, personal income, financial wealth, housing wealth, and long-term interest rates: a panel cointegration approach for 50 US states." *Studies in Nonlinear Dynamics & Econometrics*" (), 20200057. https://doi.org/10.1515/snde-2020-0057

Loutskina, E. and Strahan P.E. (2015). Financial Integration, Housing and Economic Volatility. *Journal of Financial Economics* 115(1), 25-41.

Miller, N., and L. Peng. 2006. "Exploring Metropolitan Housing Price Volatility." *The Journal of Real Estate Finan and Econ* . 33 (5): 5-18.

Mody, A., Ohnsorge, F.L., and D. Sandri. 2012. "Precautionary Savings in the Great Recession." IMF Working Papers, vol. 042; 10.5089/9781463936433.001.A001

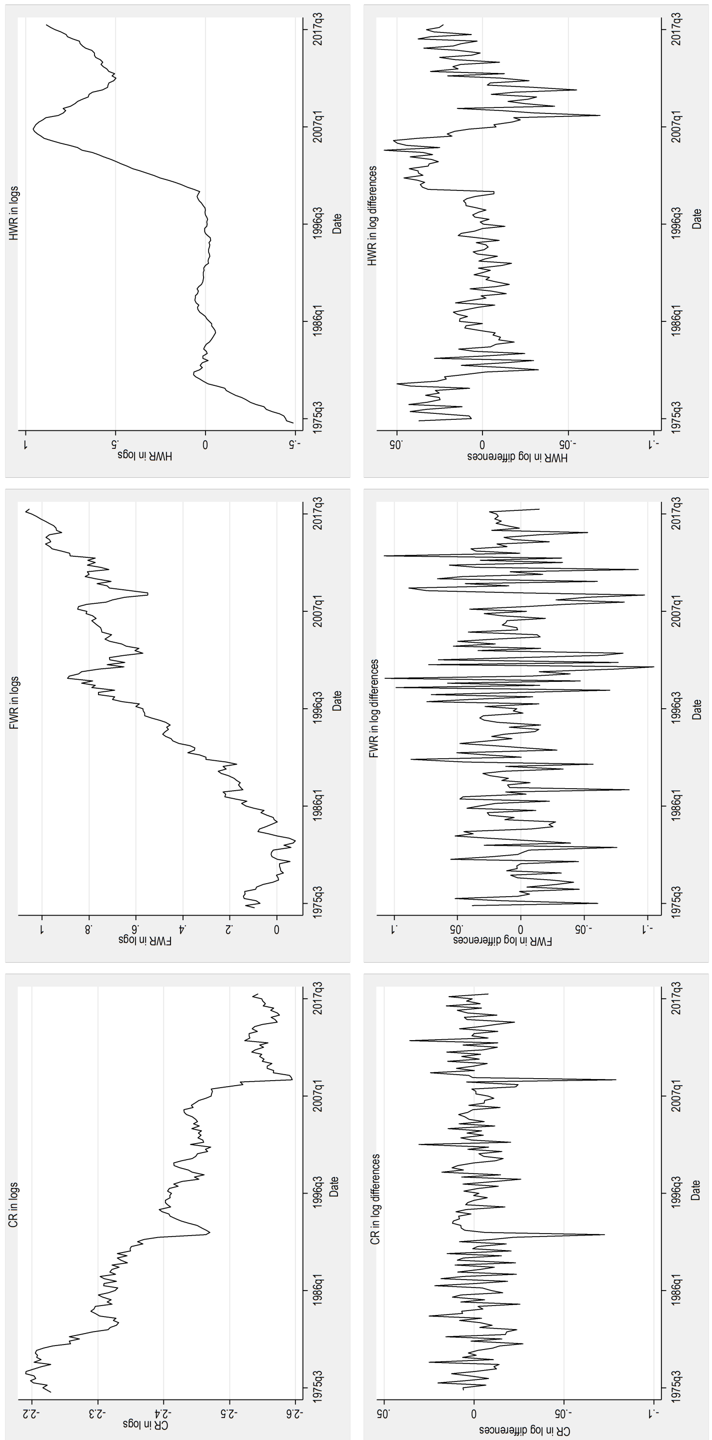
Phillips, P. and S. Durlauf. 1986. "Multiple time series regression with integrated processes." *Review of Economic Studies* 53: 473-495.

Righia B. M. and S. P. Ceretta. 2012. "Multivariate generalized autoregressive conditional heteroscedasticity (GARCH) modelling of sector volatility transmission: A dynamic conditional correlation (DCC) model approach." *African Journal of Business Management* 6 (27): 8157-8162.

Rıos-Rull JV. and Sánchez-Marcos V. (2008). "Aggregate Shocks and the Volatility of House Prices", Working Paper.

3.9 Appendix

Figure 3.4: The graphs of CR, FWR and HWR in logs and log-differences to Personal Income in logs and log differences



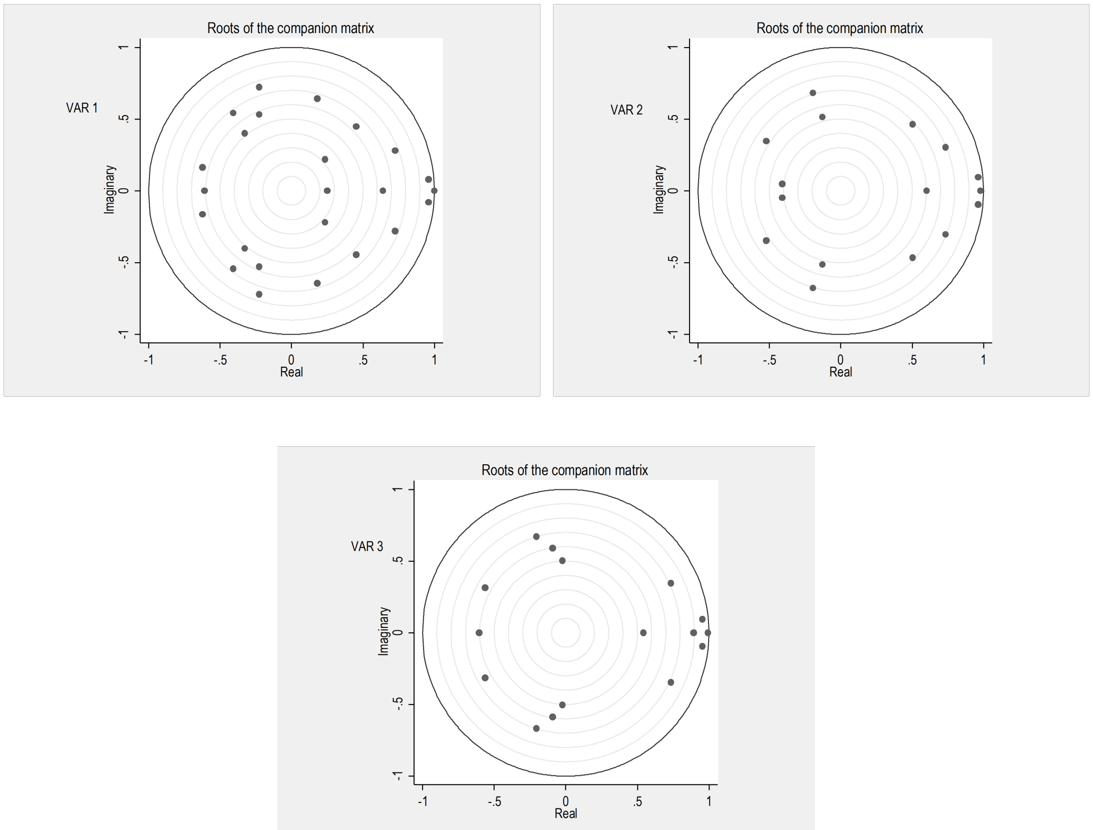
Note: CR, FWR and HWR stand the consumption, financial and housing wealth share of personal income, respectively.

Table 3.1: Summary statistics of Shares of Consumption, Financial Wealth and Housing Wealth to Personal Income in logs and log differences

Coefficient	**Mean**	**Maximum**	**Minimum**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Variance**
lnCR	-2.4052	-2.1908	-2.5949	0.1127	0.2296	2.0424	0.0127
lnFWR	0.4822	1.0693	-0.0792	0.3462	-0.1344	1.5669	0.1199
lnHWR	0.2393	0.9590	-0.4880	0.3742	0.4310	1.9680	0.1400
ΔlnCR	-0.0018	0.0359	-0.0789	0.0142	-1.4791	10.0358	0.0002
ΔlnFWR	0.0056	0.1077	-0.1049	0.0393	-0.2739	3.4958	0.0015
ΔlnHWR	0.0080	0.0573	-0.0686	0.0213	-0.2451	3.3707	0.0005

Notes: Δ is the first difference operator. The variables are in logs and in log-differences. Observations: 173.

Figure 3.5: Eigenvalue stability condition for var1, var2 and var3 models



Note: All the eigenvalues lie inside the unit circle. VAR satisfies stability condition.

Table 3.2: Results for panel unit root tests of Dickey Fuller (1979) and Phillips-Perron (1988)

	Dickey-Fuller Z(t) statistic		**Kwiatkowski-Phillips-Schmidt-Shin test**		**Phillips-Perron test**	
	4 lags		4 lags		Newey-West, lags=4	
Variables	**Constant**	**Constant trend**	**Constant**	**Constant trend**	**Constant**	**Constant trend**
lnCR	1.432 [0.5688]	3.251 [0.0747]*	3.3	0.189	1.135 [0.7011]	3.197 [0.0850]
lnFWR	0.131 [0.9462]	2.743 [0.2188]	3.31	0.294	0.255[0.9316]	2.666[0.2503]
lnHWR	1.395 [0.5848]	3.840 [0.0147]**	2.85	0.274	0.993 [0.7558]	1.532 [0.8181]
ΔlnCR	5.870 [0.0000]***	5.902 [0.0000]***	0.0446***	0.0309***	13.744 [0.0000]***	13.720 [0.0000]***
ΔlnFWR	6.493 [0.0000]***	6.535 [0.0000]***	0.0881***	0.0684***	13.572 [0.0000]***	13.577 [0.0000]***
ΔlnHWR	2.420 [0.1361]	2.370 [0.3956]	0.149**	0.149**	5.455 [0.0000]***	5.424 [0.0000]***

Notes: Δ is the first difference operator. Numbers in brackets are p-values. ADF test is presented with no lags, one lag and 3 lags, chosen by AIC and BIC. PP test is presented with 4 lags to robust the results. Newey-West was used to determine the optimal lag length. **,*** indicates the rejection of the null hypothesis of stationarity at 5% and 1% significant level, respectively. The MacKinnon critical values are 3.45(1%), 2.87(5%), 2.57(10%). The KPSS critical values for H0, that the indicated variable is stationary, are 10%: 0.347 5% : 0.463 2.5%: 0.574 1% : 0.739. —kpss val— > —critical value— = null rejected

Table 3.3: Johansen tests for cointegration

Sample: 1976q1 - 2018q1						Number of obs =169, Lags = 4		
Maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value	SBIC	HQIC	AIC
0	30	1292.9708	—	39.1520	29.68	-14.3908	-14.7209	-14.9464
1	35	1307.4825	0.1578	10.1287*	15.41	-14.4107*	-14.7959	-15.0589
2	38	1312.5148	0.0578	0.0640	3.76	-14.3792	-14.7974*	-15.0830
3	39	1312.5468	0.0004	—	—	-14.3492	-14.7784	-15.0715

Notes: Notes: The * by the trace statistic at rank=1 indicates that this is the value of r selected by Johansen's multiple-trace test procedure. We cannot reject the null hypothesis that there is one cointegrating equation at 5 percent statistically significance. The SBIC and the HQIC estimators suggest that there are one and two cointegrating equations in the data, respectively.

Table 3.4: Trivariate AR (1)-dynamic conditional correlation MGARCH (1,1) Model

Sample: 1975q1 - 2018q1	Log likelihood= 1324.809	Number of obs= 171
Distribution: t	Prob> chi2= 0.00001	Wald chi2(9)= 185.31

Consumption rate equations

$$(1)\quad \Delta CR_t = \underset{(0.69)}{0.0007} - \underset{(1.83)}{0.1054}\Delta CR_{t-1} + \underset{(1.84)}{0.0417}\Delta FWR_{t-1} - \underset{(0.33)}{0.0138}\Delta HWR_{t-1} + \epsilon_{ct}$$

$$(2)\quad h_{ct} = \underset{(1.13)}{5.16\text{e-}06} - \underset{(1.94)}{0.0295}\epsilon^2_{c,t-1} + \underset{(54.98)}{1.0028}h_{c,t-1}$$

Financial wealth rate equations

$$(3)\quad \Delta FWR_t = \underset{(2.44)}{0.0071} - \underset{(0.10)}{0.0199}\Delta CR_{t-1} + \underset{(0.51)}{0.0424}\Delta FWR_{t-1} - \underset{(0.18)}{0.0228}\Delta HWR_{t-1} + \epsilon_{ft}$$

$$(4)\quad h_{ft} = \underset{(1.93)}{0.0002} - \underset{(2.00)}{0.1824}\epsilon^2_{f,t-1} + \underset{(6.55)}{0.6974}h_{f,t-1}$$

Housing wealth rate equations

$$(5)\quad \Delta HWR_t = \underset{(2.21)}{0.0022} - \underset{(0.86)}{0.0559}\Delta CR_{t-1} + \underset{(1.48)}{0.0333}\Delta FWR_{t-1} - \underset{(12.49)}{0.7238}\Delta HWR_{t-1} + \epsilon_{ct}$$

$$(6)\quad h_{ht} = \underset{(0.94)}{9.08\text{e-}06} + \underset{(1.64)}{0.1788}\epsilon^2_{h,t-1} + \underset{(7.75)}{0.8102}h_{h,t-1}$$

Dynamic conditional correlation

$$(7)\quad h_{cf,t} = \underset{(1.58)}{0.1692}\sqrt{h_{c,t}}\sqrt{h_{c,t}}$$

$$(8)\quad h_{ch,t} = \underset{(1.39)}{0.1479}\sqrt{h_{c,t}}\sqrt{h_{h,t}}$$

$$(9)\quad h_{fh,t} = \underset{(1.20)}{0.1692}\sqrt{h_{f,t}}\sqrt{h_{h,t}}$$

Adjustment

Lambda 1: 0.1453
(2.01)

Lambda 2: 0.4642
(2.10)

Wald test for H0 that lambdas= 0

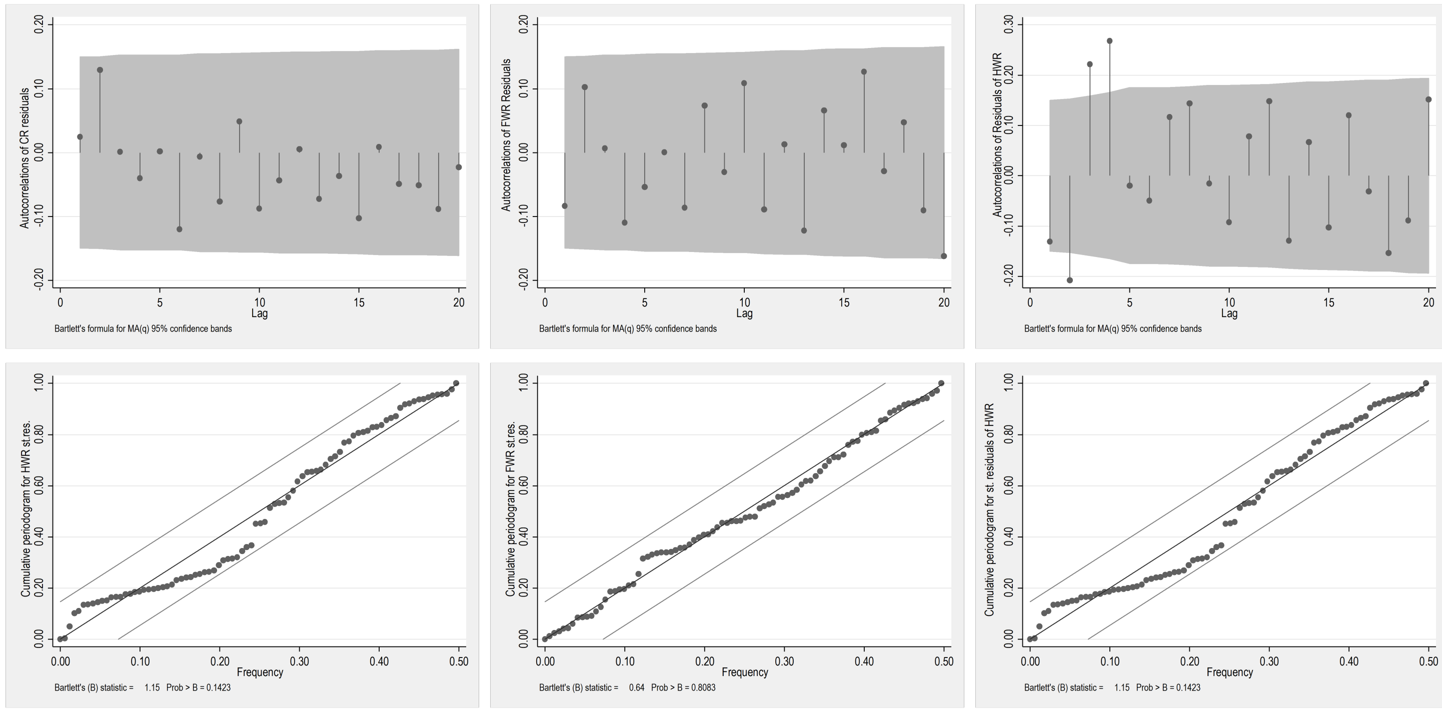
chi2(2) = 18.36

Prob >chi2 = 0.0001

df: 5.6954
(3.97)

Notes: Table 4 reports parameter estimates of the trivariate AR (1)-dcc MGARCH (1,1) model for the US data. The initials df is denoted for the degree of freedom. The numbers in parentheses are absolute z-statistics.

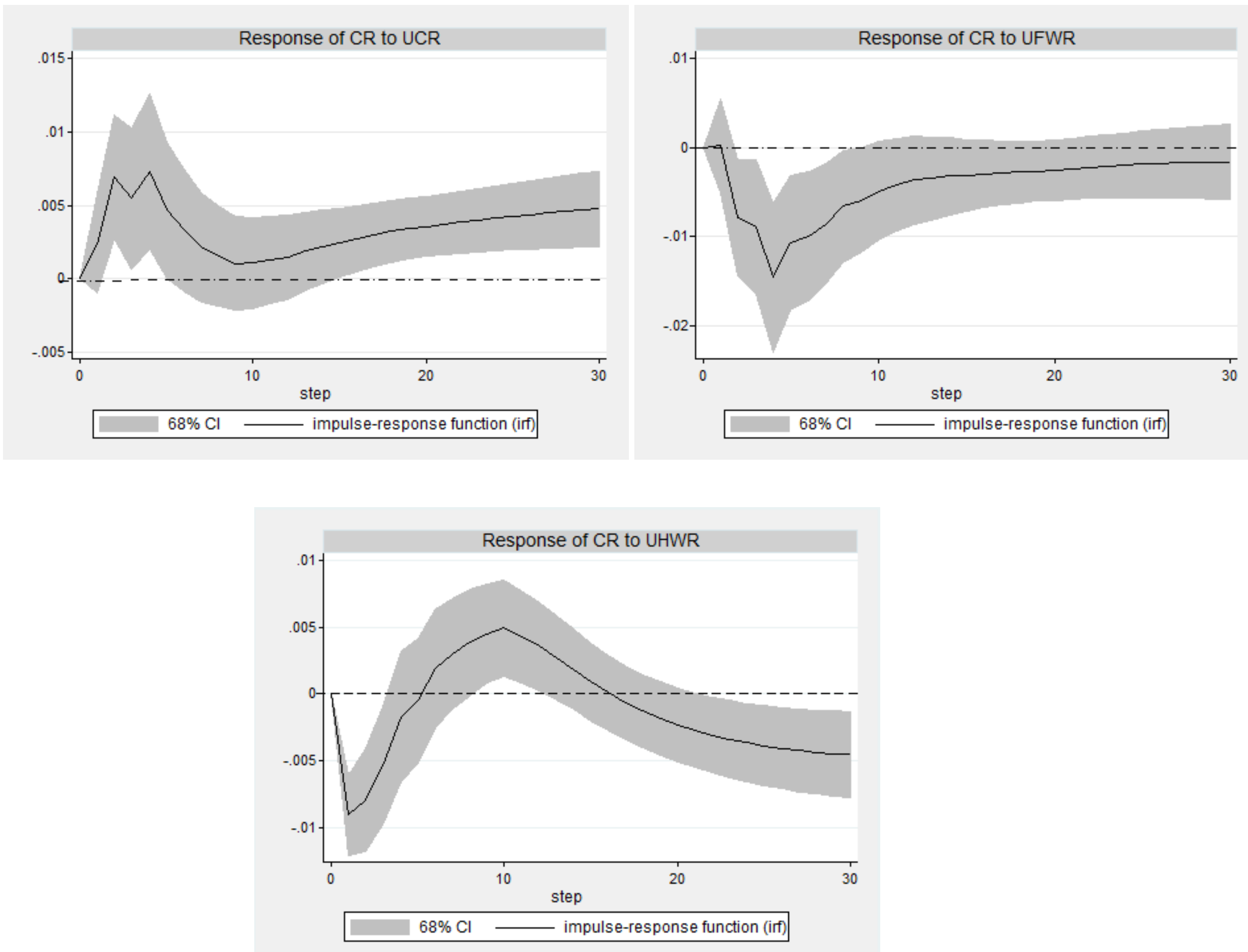
Figure 3.6: Autocorrelation and cumulative periodogram white noise test for standardized residuals of CF, FWR and HWR obtained from the DCC model



CR Standardized Residuals Portmanteau test for white noise	FWR Standardized Residuals Portmanteau test for white noise	HWR Standardized Residuals Portmanteau test for white noise
Portmanteau (Q) statistic = 0.0311 Prob ¿ chi2(1)= 0.8601	Portmanteau (Q) statistic = 0.1883 Prob ¿ chi2(1)= 0.6644	Portmanteau (Q) statistic = 0.5502 Prob ¿ chi2(1)= 0.4582

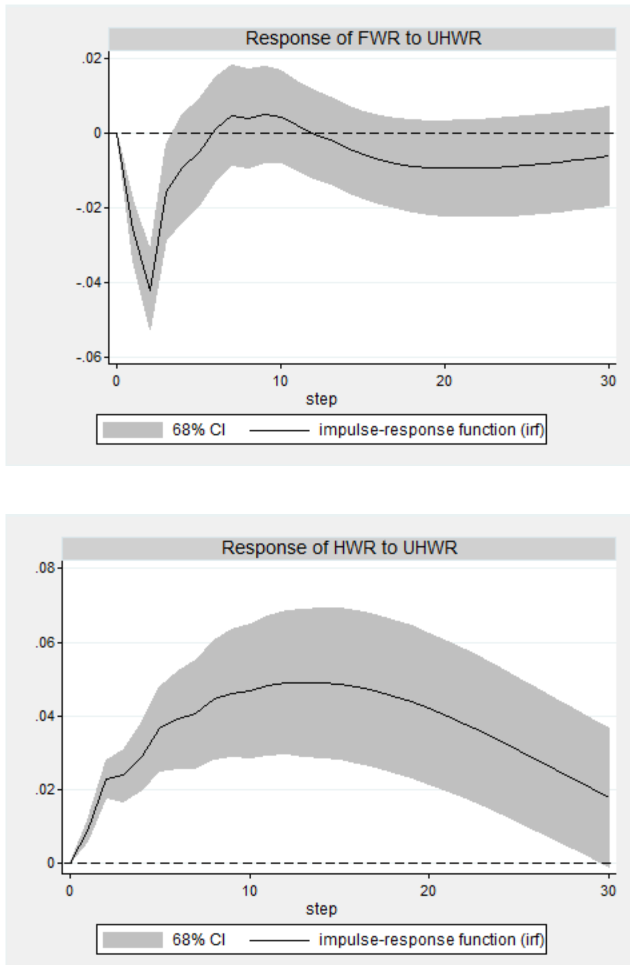
Notes: CR, FWR and HWR stand for consumption, financial and housing wealth share to personal income, respectively. McLeod and Li (1983) multivariate Portmanteau statistics do not reject the null hypothesis of no serial correlation (using 20 lags).

Figure 3.7: Responses of CR to UCR, UFWR and UHWR



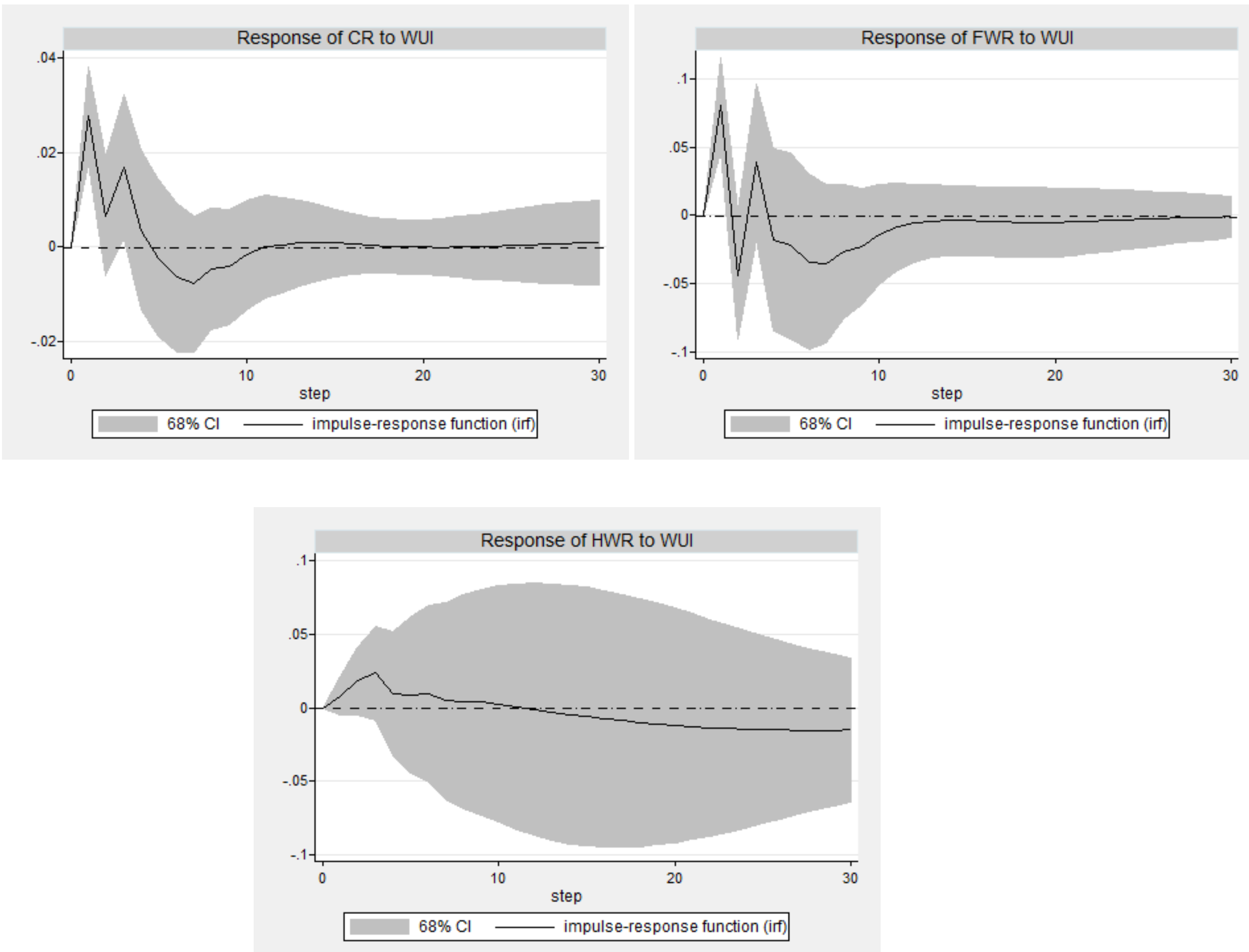
Note: CR, FWR and HWR stand for consumption, financial and housing wealth share to personal income, respectively.

Figure 3.8: Responses of FWR and HWR to UHWR



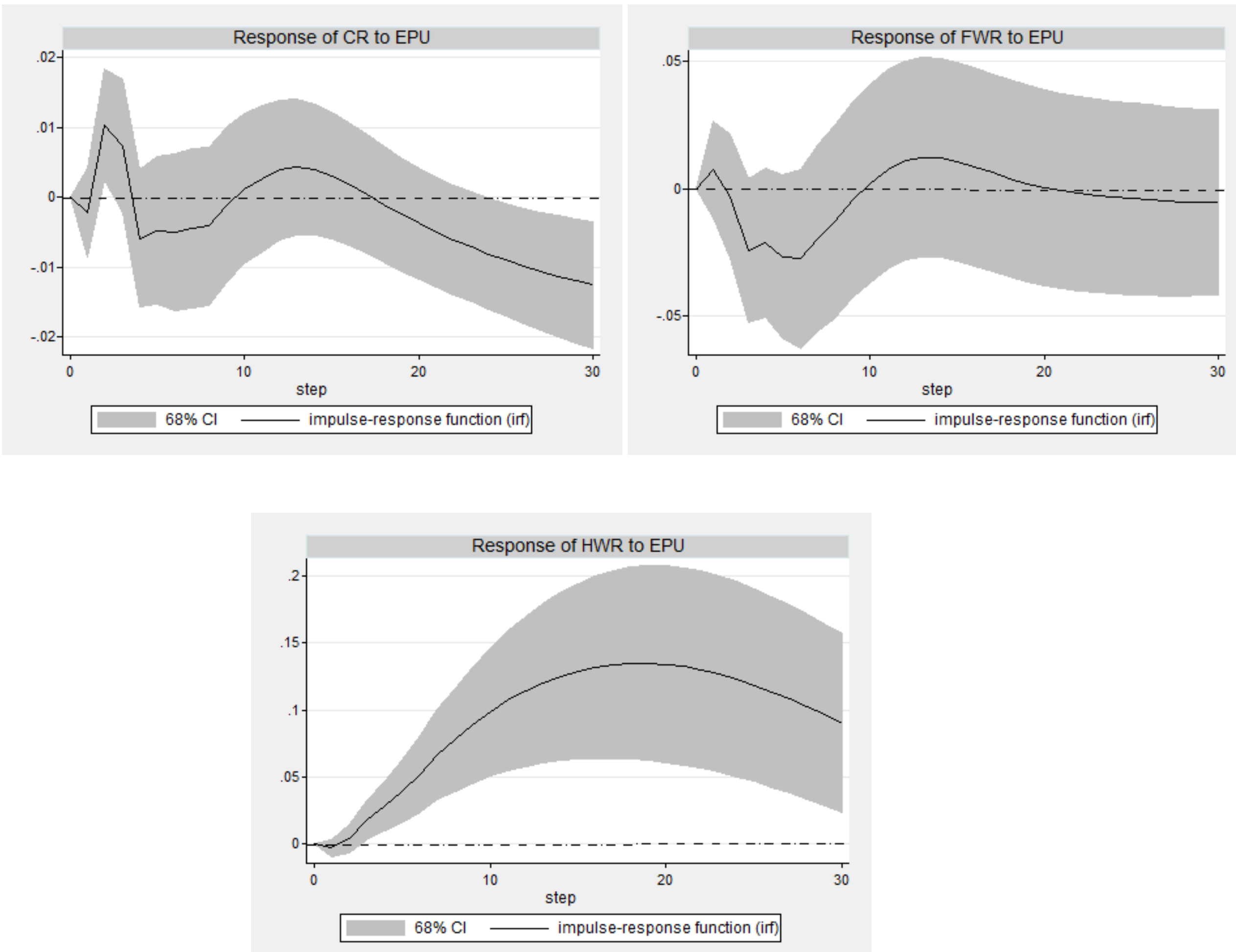
Note: FWR, HWR and UHWR stand for financial wealth share, housing wealth share and uncertainty of housing wealth share to personal income, respectively.

Figure 3.9: Responses of the CR, FWR and HWR to WUI



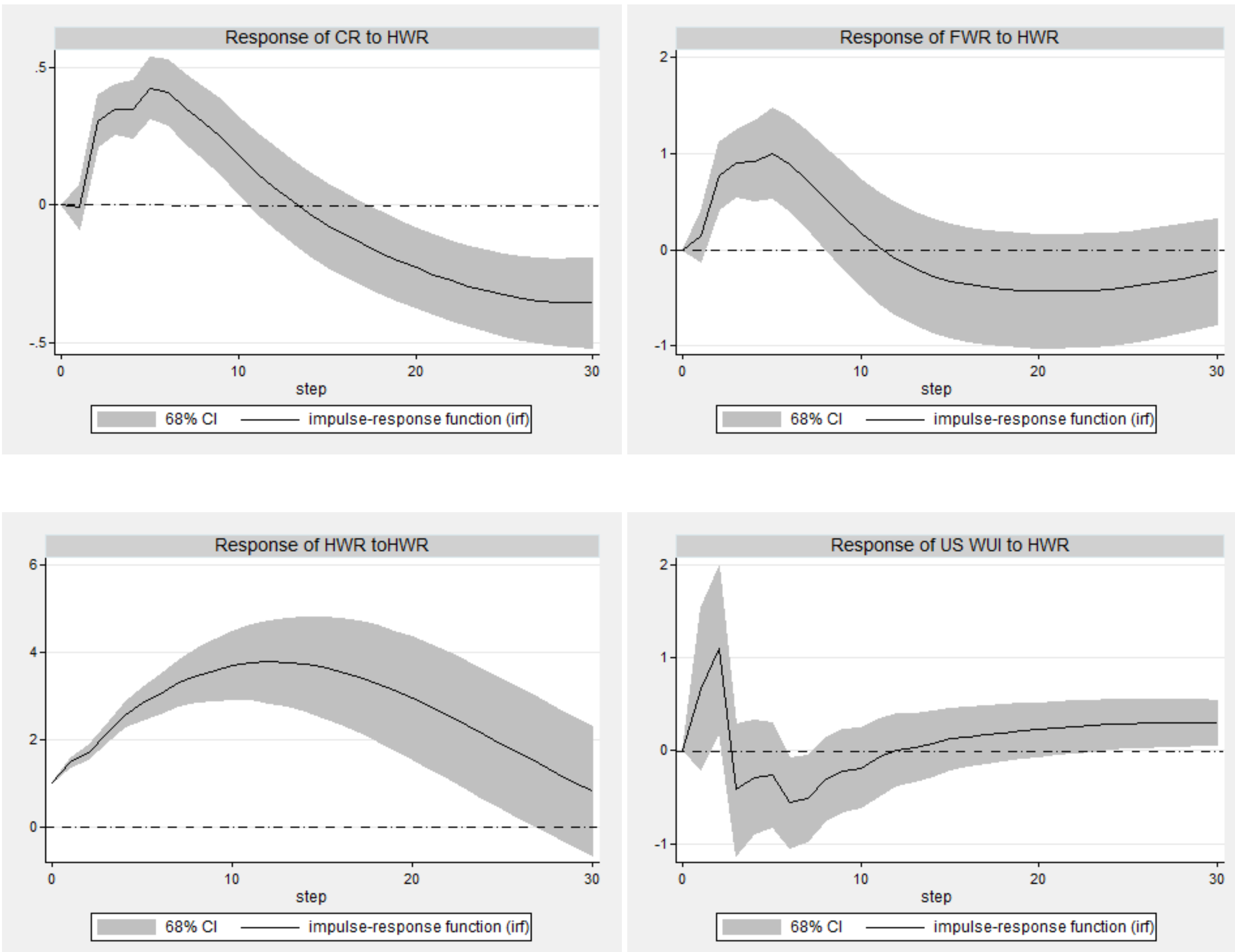
Note: CR, FWR and HWR stand for consumption, financial and housing wealth share to personal income, respectively.

Figure 3.10: Responses of the CR, FWR and HWR to EPU



Note: CR, FWR and HWR stand for consumption, financial and housing wealth share to personal income, respectively. EPU stands for Economic Policy Uncertainty Index.

Figure 3.11: Response of CR, FWR, HWR and WUI to HWR



Note: CR, FWR and HWR stand for consumption, financial and housing wealth share to personal income, respectively.

Chapter 4

Measuring uncertainty: a Bayesian analysis approach

Abstract

In this chapter, we introduce a new US uncertainty index which is more sensitive to consumer spending and therefore reflects households' decisions. We find evidence that macroeconomic uncertainty shocks impose negative, statistically significant, and long-lasting effects on consumption, income and financial wealth held by households. In contrast, housing wealth is not affected by uncertainty. Evidence suggests significant variation in housing wealth response to a rise of uncertainty emphasizing the heterogeneity among states. Possibly housing wealth is a key identifier that incorporates long-term differences in households.

Key words: uncertainty, consumption, housing wealth, financial wealth, US states.

JEL classification numbers: C11, E21

4.1 Introduction

The Global financial crisis of 2007-2008 also called subprime mortgages, originated in the US and was essentially the result of the collapse of housing market. The main causes of this crisis were the decisions of the Fed about interest rates, the extend of consumer credit at a low rate, and the subprime lending. This paper aims to construct an uncertainty index which is more sensitive to consumption decisions than others. Consumers and firms make decisions today based on expectations of an uncertain future. Generally economic uncertainty is a driving force of the business cycle which rises sharply in recessions. Therefore, it is a common sense for researchers and policymakers to construct macroeconomic models that involves uncertainty.

Nowadays more than ever it gained increasing attention. COVID-19 pandemic urges researchers to include uncertainty into their models or measure it to investigate, solve crisis or predict potential and future crisis.

Baker et al. (2020) assess five types of uncertainty measures to investigate the economic impact of the COVID-19 pandemic. Some of these measures are used in the long literature on economic uncertainty while others are newer. Stock Market Volatility increased 500% during the period 15 January 2020 to 31 March 2020 when the COVID-19 pandemic occurred. Economic Policy Uncertainty index (EPU), which is newspaper-based measures of uncertainty, quadrupled from January 2020 to March 2020. The Forecaster Disagreement measure is the standard deviation of point forecasts about macroeconomic outcomes across the 50 odd forecasters that provide regular forecasts. The Statistical Forecast Uncertainty is defined as the conditional volatility implied by a GARCH model. These approaches forecast uncertainty for GDP growth, industrial production, employment, trade, and other standard measures. The stock market volatility is a commonly used as proxy for uncertainty in literature (Bloom, 2009; Bloom, et al., 2007; Baker et al. 2015 etc.) because it is available in real time and is reasonably comparable across countries.

But how these uncertainty proxies affect consumer spending and consequently household decisions? This paper aims to shed light on this aspect. A deeper understanding of how uncertainty shocks have affected personal consumption, housing wealth and financial wealth hold by households is likely to help policymakers assess how future shocks to uncertainty might affect demand and supply prospects. To construct our proxy for uncertainty we update and modify the macro-uncertainty developed by Jurado, Ludvigson and Ng (2015), hereafter JLN, and extended and modified by Mumtaz (2018).

We updated this existing macroeconomic uncertainty from 1976q1 to 2018q1 and added two key variables in the quarterly state-level data, financial wealth held by households and personal consumption to capture household decisions. Two others variables were important for our research, personal income and housing wealth included in Mumtaz (2018) version of the code for macroeconomic uncertainty provided by JLN (2013). This uncertainty measure provides the average time-varying variance in the unpredictable component of a large set of real and financial time series. Then we compare our proxy for uncertainty with other popular uncertainty indexes to verify its connection with personal consumption. And finally, we employ the Gibbs algorithm and take the impulse response functions (IRFs) to describe the response of our key variables to a shock in our uncertainty index. We verify the counter cycle pattern of uncertainty with income, consumption and wealth. Evidence implies that uncertainty shocks have little role to play in housing wealth compared to financial wealth, income and consumption as the impact of a 20% macroeconomic uncertainty shock on housing wealth is close to zero.

The rest of the chapter is organized as follows. The second section of this chapter presents the related literature about uncertainty, how economists quantify uncertainty and how the latter affects economic activity. The third section describes the data and the methodology. The fourth section presents the results. The fifth section discusses the results. The sixth section concludes.

4.2 Literature review

Nowadays measuring uncertainty is very popular in literature. The traditional measure of uncertainty relies on the stock market volatility. The measures of volatility of stock market returns, firm profits, stock returns, or productivity, have the advantage of being directly observable. However, Jurado, Ludvigson and Ng (2015), hereafter JLN, argues that their adequacy as proxies for uncertainty depends on how strongly they are correlated with the stochastic process. VIX, a very popular measure for uncertainty that measures market expectation of near-term volatility conveyed by stock index option prices, it is driven by factors associated with time varying risk aversion rather than economic uncertainty. Indeed, much variability in the stock market is not generated by a movement in genuine uncertainty across the broader economy. Methodology of FAVAR is very common in literature (Bernanke et al. 2005; Carriero et al. 2018) to identify the effects of shocks to economic conditions. JLN use a FAVAR model by employing data from a rich economic environment to measure macroeconomic uncertainty based on economic indicators that are more or less predictable and consequently less or more uncertain. Results support that the common macro uncertainty shocks affect monetary policy shocks and are associated with the variance in production and hours worked than with stock market volatility shocks. JLN macro uncertainty measure is strongly countercyclical, and far more persistent than common uncertainty proxies.

Mumtaz (2018) extended and modified the JLN (2015) uncertainty code to identify the impact of a shock on real activity for each US state. They use both the forecast error variance one year ahead for the estimation of the macroeconomic uncertainty. Mumtaz and Theodoridis (2017) also employ a FAVAR model to decompose the movements in volatility of real activity, inflation and financial series from eleven OECD countries. The volatility of the key series (GDP, CPI inflation and stock market returns) is driven by uncertainty that is common to all eleven OECD countries and uncertainty that is country and series-specific. They use world and country- specific factors to compose two var models, which errors are heteroscedastic and represent the shocks. Shocks that lead to transfer of resources across countries imply comovement in volatility of endogenous variables. Strong trade links among countries affect positively these comovements in volatility.

However, changes in monetary policy rule and/or the Phillips curve that don't affect the common components in volatility. The comovements in volatility interpret the role of common movements in uncertainty among macroeconomic and financial variables and highlight potential consequences of globalization. These volatilities represent measures of uncertainty associated with the states wide economic conditions and state specific economic conditions.

4.3 Empirical model and data

4.3.1 Model

The Bayesian theory is based on a degree of belief in an event, that is a prior knowledge about the event and not on the limit of the relative frequency of an event after many trials. The posterior distribution via Bayes' Theorem is expressed as:

Posterior is proportional to Likelihood X Prior

Our panel model estimates for each US state how uncertainty affects consumption, personal income, financial wealth held by households and housing wealth. Econometrically, it allows for both entity-fixed effects and time-fixed effects and is described in the following equation:

$$\mathbf{Y}_t = \mathbf{a}_i + \mathbf{d}_t + \sum_{\mathbf{i=1}}^{\mathbf{k}} \gamma_{it} \mathbf{Y}_{\mathbf{it}\ \mathbf{-k}} + \sum_{\mathbf{i=1}}^{\mathbf{k}} \beta_{it} \mathbf{U}_{\mathbf{it}\ \mathbf{-k}} + \mathbf{v}_{\mathbf{it}} \tag{4.1}$$

where for a_i and d_t are state and time fixed effects, Y_{it} is a measure of consumption, personal income, financial and housing wealth. U_{it} stands for uncertainty in the current and past periods and it is estimated via a FAVAR which is analyzed in the next session. We use instruments to estimate uncertainty to avoid the correlation with the disturbance error v_{it}. It is described in the following equation:

$$\mathbf{U}_{it} = \mathbf{c}_i + \delta_i \mathbf{Z_{it}} + \mathbf{e_{it}} \tag{4.2}$$

where Z_{it} stands for the instrumental variables and denotes a set of instruments assumed to be uncorrelated with v_{it}.

According to the Bayesian approach we assign priors to all the unknown parameters. As we fully specified the Y_{it} and U_{it} the only unknown parameters in eq (1) is the set of coefficients. The choice of prior distributions represents information available about unknown parameters. Provided it does not overly distort the representation of such functions, it is convenient to choose mathematically convenient forms of prior distributions which result in computationally tractable posterior distributions. In general, this is achieved through the use of conjugate prior distributions. The cross-sectional weighted mean of the coefficients $\bar{\beta}$ is unknown and its posterior distribution is approximated by the estimation of Gibbs algorithm (Mumtaz 2018).

4.3.2 Data and specification

The variable of macroeconomic uncertainty is constructed for each of the 51 US states using the code described by Mumtaz (2018). In this code, there are two types of data constructed with the methods of Jurado et al. (2015). Jurado et al. (2015) employ a factor VAR. We use the factor model to decompose the time varying variance of Macroeconomic and financial variables into common components that contribute to uncertainty common to all states. The common components derived from factors include 226 datasets. In this dataset we use eight variables which are personal income and its components plus consumption and the financial wealth held by households. For the rest datasets we update the same 218 variables and get data from 1977q1 until 2018q1. From these 626 variables we got the forecasting errors. This dataset involves two types of information. The first type refers to macroeconomic and financial indicator in monthly frequency and the second type refers to common firm-level uncertainty and it is based on the quarterly firm level dataset. This measure of uncertainty is not based on the changes of some macroeconomic variables but on the predictability of the economy. Economy is measured through a data rich environment of 626 datasets. For example, GDP, real personal consumption expenditures for durable, non-durable goods and services, real private domestic investments (equipment, etc), fixed private investment, stock prices, numbers of employees in industries etc.

In the first step we select the data for factors from personal income and its components and a panel of 218 dataset from FRED. Then we get the forecast errors and their volatility. The functional form of h period ahead uncertainty$U_{it}^{\mathbf{y}}(h)$ in a vector of variables $y_{it} \in Y_t = (y_{1t}, \ldots, y_{Nyt})'$ is expressed as:

$$\mathbf{U}_{it}^{y}(h) \equiv \sqrt{E\left[\left(y_{jt+h} - E[y_{jt+h}|I_t\right)^2 |I_t\right]} \tag{4.3}$$

where $E[\bullet|I_t]$ is the expectation today of the variance of the variables of interest h period ahead with their expectations at that period with respect of information I_t.

The idea is to measure uncertainty by inferring whether macroeconomic variables in a rich environment dataset in a conditional panel model is predictable or not. If it is predictable there is no uncertainty. Consequently, it is not measured via conditional volatility of the variables but could explain their differences of conditional variances and covariances. Jurado et al. (2015) proceed with the calculation of macro uncertainty index using aggregation weights w_j. Another important feature of uncertainty is to remove the entire forecastable component in order to extract only the uncertain part from variables. Further, they underline that the index based on the common variation of the variables and not on each of them separately. That is, that macroeconomic uncertainty is a measure of the common variation in uncertainty across many series. Therefore, we define the common factors (diffusion indices) of the 216 timeseries plus the eight variables. Then we define the h-step-ahead forecast error as:

$$\mathbf{V}^{y}_{jt+h} \equiv y_{jt+h} - E[y_{jt+h}|I_t] \tag{4.4}$$

As we see, we remove the forecastable component before computing conditional volatility to avoid to take into account forecastable variations as "uncertain". The final ingredient for macroeconomic volatility is constructed from the individual uncertainty measures and it is interpreted as the common factor in the individual measures of uncertainty. This takes the following form:

$$\sum\nolimits_{\mathbf{j=1}}^{\mathbf{Ny}} w_j \mathbf{U}^{\mathbf{y}}_{\mathbf{jt}}\,(h) \tag{4.5}$$

Thus, we obtain 51 uncertainty measures for each US state. State-level uncertainty U_{it} is defined as the average of the one year ahead uncertainty measures for the j = 1, 2, . . . , J series for state i. X_{it} includes the growth rate of real personal income per capita and its components (social insurance, dividends, benefits and other income), employment growth, unemployment change and real house prices growth. The data is obtained from the Federal Reserve Bank of St Louis data base for the period 1976Q1 to 2018Q1 for 50 states and the District of Columbia. The factors in the forecasting regressionF_{it} for state i are extracted using data for the remaining states and a US wide panel of macroeconomic and financial data (FRED-QD database). We use the log differences of the variables. Jurado et al. (2015) code is used to calculate macroeconomic uncertainty for each state. We use the forecast error variance one year ahead to estimate uncertainty. In our final model (eq. 1) all variables are in logs.

4.4 Results

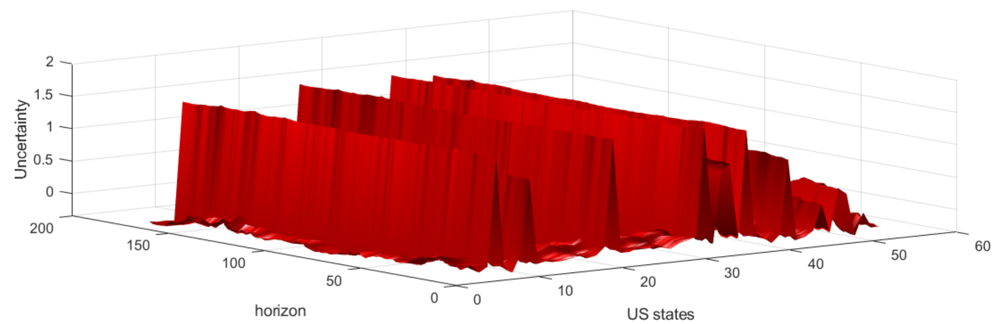
This section consists of five subsections. The first subsection provides the results of our measure of US uncertainty. How does our proxy of uncertainty affect consumption, personal income and wealth? Further, we compare our proxy with other well-known measures of uncertainty (EPU by Baker, Bloom and Davis (2015). Macro-uncertainty by Mumtaz (2018) and VIX). The rest of the subsections present the results of uncertainty by state and the responses of consumption, income, housing wealth and financial wealth to a potential twenty percent rise in uncertainty by state.

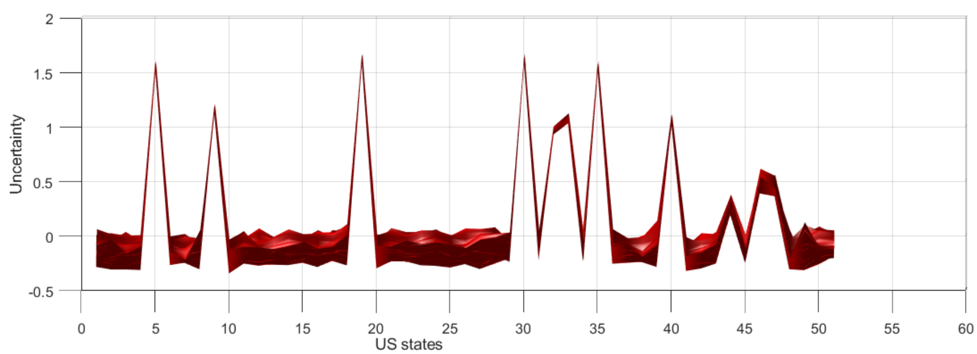
In some cases, we provide evidence of the consequences of the crisis of 2008 on the US states in order to explain the behavior of our proxy of uncertainty and not to analyze the 2008 crisis itself as it is the most recent crisis concluded in our data.

4.4.1 US uncertainty

Figures 4.1, 4.2 and 4.10 (in Appendix) plot the logs of estimated uncertainty for each state as described above. Negative numbers indicate measures of uncertainty under 1%. High levels of uncertainty are observed in California, District of Columbia, Louisiana, New Hampshire, North Dakota, New Mexico, New York, Rhode Island followed by Texas, Vermont, and Virginia. Low uncertainty states are Florida, South Carolina, Hawaii, Alaska, Washington, South Dakota, Arkansas, and Connecticut.

Figure 4.1: US states Uncertainty in logs.



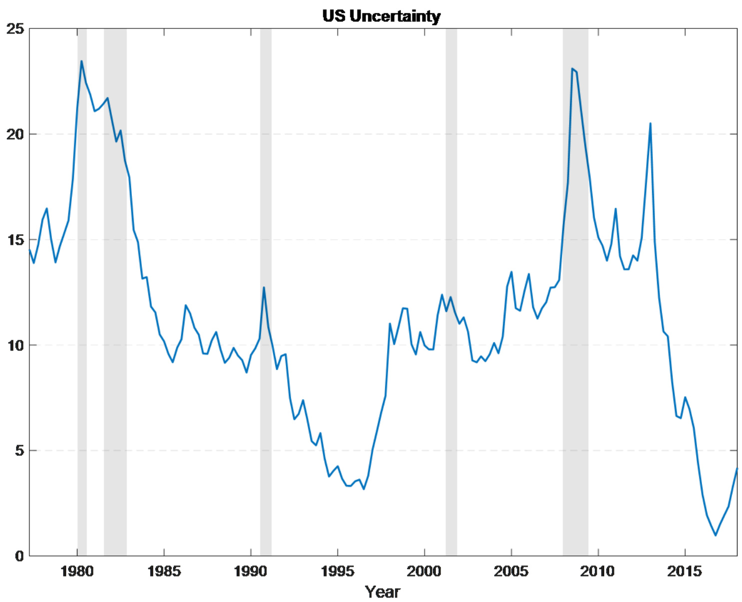


To estimate US uncertainty, we give every state the equal weight and take the averages of individual uncertainty. Figure 4.2 presents US uncertainty. It indicates three peaks in 1980, 2008 and 2012 which coincide with high prices of crude oil.

The correlation between our proxy of uncertainty and crude oil prices (fig. 4.3) is 0.653. This feature explains much of the heterogeneity of states.

Uncertainty also increases after major economic and political shocks, the OPEC I oil-price shock, Gulf war I and II, the 9/11 terrorist attacks. Since 1990 until

Figure 4.2: US uncertainty from 1977q2-2018q1



the Great Recession of 2008, figure 2 shows elevated levels of uncertainty contrary to relatively low oil prices. Particularly in December of 1998 the oil price dropped to $ 19.11 per barrel which was its lowest level up to now (1975-2020). This was reflected in the uncertainty index illustrated in figure 4.2 that presents low levels of uncertainty.

We also compare our proxy to other uncertainty measures, to shed more light on that period and to check the validity of our proxy. Table 4.1 presents the correlation of our proxy with three others popular uncertainty measures, real output growth and the 10-year treasury constant maturity rate, which is strongly associated with Fed's announcements and consequently monetary policy (Swanson 2015, Wölfel & Weber 2017). Further, the 10-year treasury rate is an important determinant

Figure 4.3: The crude oil prices

Source: https://www.macrotrends.net/1369/crude-oil-price-history-chart
Notes: Fig. 4.3 shows the price of crude oil prices in dollars per barrel and the recessions. The price of oil shown is adjusted for inflation using the headline CPI.

of consumer decisions (Swanson 2015; Williams 2013; Wright 2012). Hence, it is of particular interest to compare this rate with our proxy due its connection with consumer spending.

The results confirm the macroeconomic uncertainty is countercyclical along with institutional and political events. We also confirm that our proxy is highly correlated (correlation is about 0.87) with the macroeconomic uncertainty developed by Jurado et al. (2015). Hopefully, our proxy exhibits the highest negative correlation (correlation is about -0.54) with the 10-year treasury rate of all the other uncertainty measures, which means that the uncertainty index we construct represents personal consumption more than the other measures. Hence the correlation

Table 4.1: Uncertainty Measures, Real Output Growth, 10-year rate and correlations

	Our proxy	**EPU**	**Macro-uncertainty**	**VIX**	**Real Output Growth**	**10-year rate**
Our proxy	1.000	0.535	0.867	0.494	-0.459	-0.541
EPU	-0.535	1.000	0.561	0.425	-0.365	-0.459
Macro-uncertainty	-0.867	0.561	1.000	0.442	-0.560	-0.435
VIX	-0.494	0.425	0.442	1.000	-0.494	-0.183
Real Output Growth	-0.459	-0.365	-0.560	-0.494	-1.000	0.250
10-year rate	-0.541	-0.459	-0.435	-0.183	0.250	1.000

Notes: Our proxy refers to the macroeconomic uncertainty proxy constructed in this paper with Jurado et al. (2015) methodology and data, expanding the estimated period from 1977q2-2018q1 and adding household data. EPU refers to Economic Policy Uncertainty constructed by Baker, Bloom and Davis (2015). The macro-uncertainty refers to the macroeconomic uncertainty constructed by Jurado, Ludvigson and Ng (2015) and modified by Mumtaz (2018). The estimated period is 1990q1-2015q3 for the data availability. VIX represents the stock market volatility and is commonly used as proxy for uncertainty.

between our proxy and 10-year rate is 25% larger than that between the latter and the macroeconomic uncertainty by Jurado et al. (2015). Further VIX is very little associated with 10-year treasury indicating its short-term temperament (correlation is about -0.18).

We now explore the response of our variables of interest to an uncertainty shock using the gibbs algorithm. Figure 4.11 (Appendix) shows the impulse response functions (IRFs) of consumption, personal income, housing wealth and financial wealth to a 20 percent increase in uncertainty in an average of US state. It also shows these responses with the 95% and 68% highest posterior density interval (HPDI).

The levels of consumption, personal income, housing wealth and financial wealth fall by about 0.03%, 0.025%, 0.06% and 0.13% respectively as a response to the shock. Uncertainty expands in a horizon of 40 quarters. The impact of uncertainty on consumption, personal income and financial wealth will not be completely offset even after the whole estimated horizon. In the first year, there is an awkward response to the shock. After the first fall, consumption, and wealth point out some kind of sharp increase and diminish the initial fall. But in the end of the first year they fall again and this fall appears to be long term, without dissipation even in the end of the estimated horizon. Instead, housing wealth seems to have no response to the shock and reveals a heavy behaviour to macroeconomic changes, though the median impact falls 0.06% That is, that uncertainty plays a negligible role for housing wealth. Additionally, the confidence intervals of housing wealth are definitely larger in magnitude compared to those of consumption, income and financial wealth. Another feature of results is that the line of consumption towards the shock tends to be linear after 5 quarters (fig. 4.11). This may indicate homogeneous response of households towards uncertainty over a long horizon.

4.4.2 Consumption Response to Uncertainty by State

Figure 4.12 (Appendix) shows the impulse responses of consumption in US states. New Hampshire exhibits the most negative impact of consumption to a 20% increase in uncertainty of -0.13% while California and Idaho follow with -0.058% and -0.050% top average decrease respectively. The rest of the states' top average impact ranges from -0.049 - -0.02 percent.

Economists say that energy costs could affect New Hampshire's economy since the state has some of the highest per-unit energy costs in the country. The residential sector uses the greatest amount of the state energy, while transportation and commercial sector use much less energy and industrial sector consumes only one-eighth of the energy used in the state. Many New Hampshire households rely on fuel oil for heat in the winter. Initially, the share of households that use fuel oil as energy source for home heating was 42.1% in 2019 with the average of US at 4.4% (https://www.eia.gov/). According to 5-Year Estimates Data Profiles of Census Bureau 52.3% households used fuel oil for home heating during the period 2006-2010. We use that period as indicator of uncertainty due to the 2008 crisis.

Table 4.2: House Heating Fuel in New Hampshire (2006-2010)

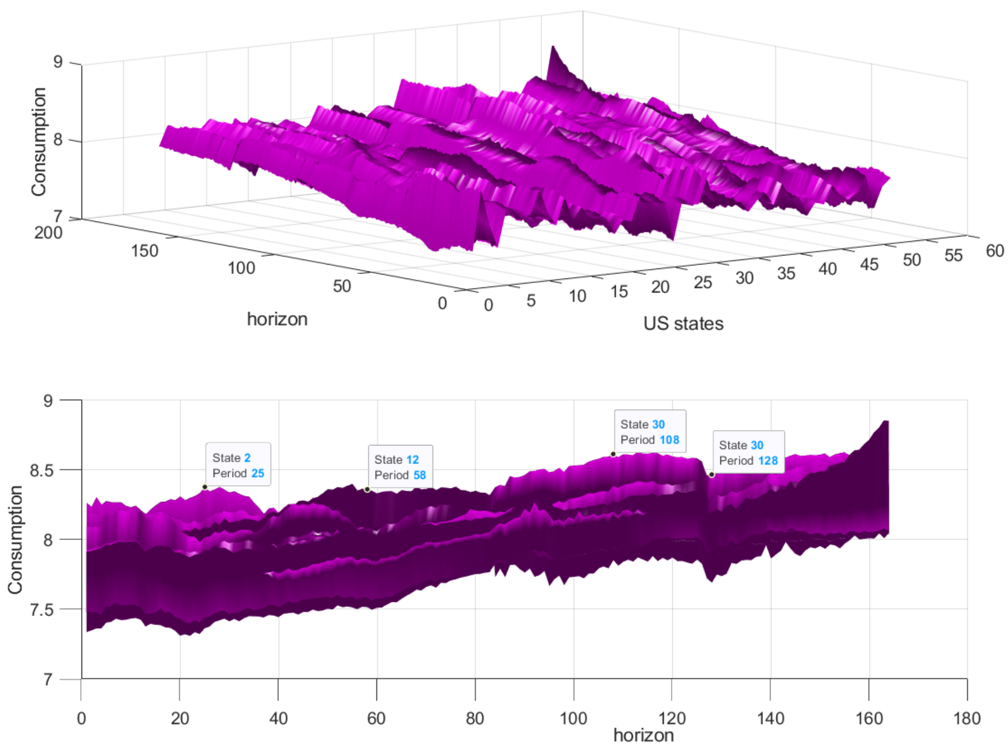
House Heating Fuel	**Percent**
Utility gas	19.7
Bottled, tank, or LP gas	12.8
Electricity	7.7
Fuel oil, kerosine, etc.	52.3
Coal or coke	0.1
Wood	6
Solar energy	0
Other fuel	0.9
No fuel used	0.5

Source. US Census Bureau
https://data.census.gov/cedsci/table?tid=ACSDP5Y2010.DP04&g=0400000US33

Fuel oil or heating oil is a middle-distillate refined petroleum product which taxation and air emission regulations differ based on use, and availability which is seasonally dependent and subject to price volatility. For instance, during the winter of 1999-2000 the heating oil prices were doubling because of the sharply lower storage levels of middle distillate stocks (Andrews 2013). In this paper we estimate consumption through the proxy of retail sales therefore consumption is not related with housing expenditures. However, the high costs of heating oil in New Hampshire reduce the daily consumption of households as their disposable income decreases.

Figure 4.4 shows that New Hampshire (state with number 30) consumption is the highest in US during the period of 2008 crisis until 2017. While Alaska (state with the number 2) has the highest consumption during the periods 1983 and 1991.

Figure 4.4: US states consumption



Note: Fig. 4.4 shows the average consumption in logs by state. Labels indicate the state number and the period number. State (2) is Alaska and state (30) is New Hampshire. Periods 25, 58, 108 and 128 refer to April, 1983, July, 1991, January, 2004 and October, 2008, respectively.

Another issue that could affect New Hampshire's economy is demographics as one in three residents is a baby boomer (https://stateimpact.npr.org/). The state, like neighbours Vermont and Maine, has the nation's oldest median age. This ageing population could create a potential economic crisis: Workers retire and economic productivity declines also, as appears difficult for businesses to attract new workers. (The Guardian, 19.11.2018)

Johnson (2010) supports that it is domestic migration that is driving the demographic changes underway in New Hampshire and during 2008 recession more people left than move to the state. Particularly, the recession deepened migration as nine of New Hampshire's ten counties lost population or grew more slowly than the previous year. Massachusetts used to provide migrants, but during the recession of 2008 migration from Massachusetts to New Hampshire has declined by 34 percent. Boston areas as Rockingham and Stafford received considerable migration growth when the housing market was booming, but that growth slowed dramatically when the recession hit. One explanation is the housing booming and their inevitable decline. Households leaving metro cores tend to be in their thirties and forties with children, so the housing market, particularly selling houses, had a big influence on them. The collapse of the U.S. housing bubble had a direct impact on domestic migration as nearly 52 percent of the population of the state was born elsewhere in the country and later migrated to New Hampshire (Johnson 2019). Bookman and Biello (2017) state that NH needs to attract younger residents to see stronger sustained economic growth.

Therefore, the state exhibits the most dramatic impact of consumption when we impose a 20% rise in uncertainty since New Hampshire's workforce is aging and domestic migration dwindling.

The Milken Institute (2014) states that in California the combined forces of a housing market correction, soaring oil prices, a weak labor market, overextended consumers and turmoil in the credit markets outweigh any gains seen in the export markets. The impact on California could be more pronounced than in other states because of the high concentration of mortgage originations, targeted job losses in the construction and financial services sectors, and decreased import activity in the state's ports and logistics operations.

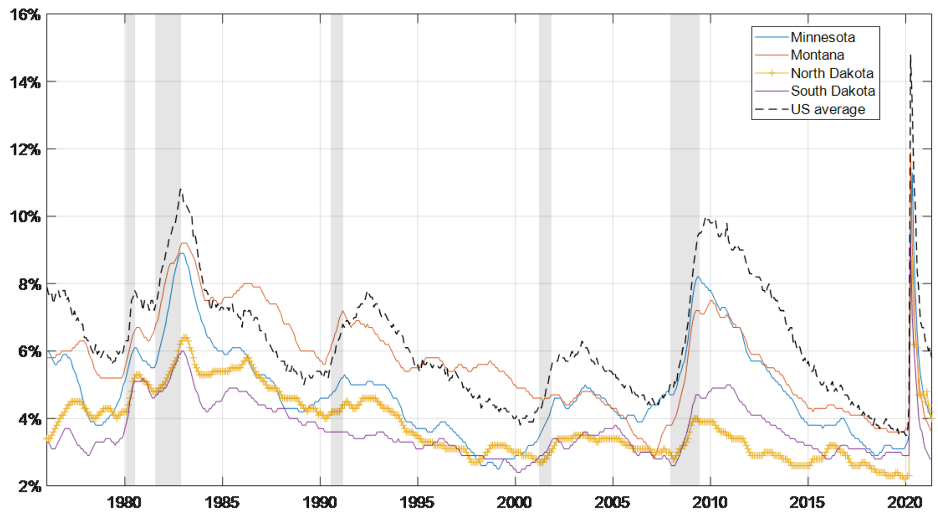
4.4.3 Personal Income Response to Uncertainty by State

Figure 4.13 (Appendix) shows the impulse responses of personal income in US states. New York would experience the largest impact of personal income if uncertainty rises with the top average impact to get at -0.1338%. DC and California follow NY with the top average impact to get at -0.132 and -0.09 percent, respectively. On the other side the personal income in North Dakota seems to increase with the rise of uncertainty.

Jackson, Caton, Williams and Christianson (2018) provide evidence of North Dakota growth and prosperity even during recession of 2008, while it experienced rapid expansion from 2009 to 2012 with growth rates of 8.1, 11.1, and 19.1 percent, respectively. In addition, labor force in North Dakota grew from 275,558 in 1976 to 420,903 in 2017. North Dakota and the states in the region display lower unemployment rates than the national average. The average unemployment rate from 1976 to 2021 is 3.8% which is lower than US (6.3%), Minnesota (4.8%), Montana (5.7%)

and slightly higher than South Dakota (3.8%). Figure 4.5 shows the unemployment rate for those states and US. During recession of 2008 the average unemployment rate of North Dakota is 3.1%, US (5.8%), Minnesota (5.4%), Montana (4.7%) and South Dakota (3.1%). And the years 2008-2010 tthe average unemployment rate of North Dakota is 3.6%, US (8.2%), Minnesota (6.9%), Montana (6.3%) and South Dakota (4.2%). The slow labor force growth and the low unemployment rate even in the recession years are evidence of the state's struggles to attract workers. The state attracts workers mainly during the boom of oil prices. Labor force growth increased after 2008 when the boom began and then dropped when oil prices fell in 2013. High-paying oil jobs attracted workers to the state, causing labor force growth. in North Dakota to greatly exceed regional and national norms. Additionally, agriculture is a large industry in North Dakota, while many other industries in the state service agriculture by manufacturing and selling farm equipment, and undertaking other activities. Despite the decline in the price of wheat, the oil boom and the state's energy sector (the second-largest industry) helped the state to overcome and increase individual income. (Jackson et al. 2018)

Figure 4.5: Average Unemployment Rate

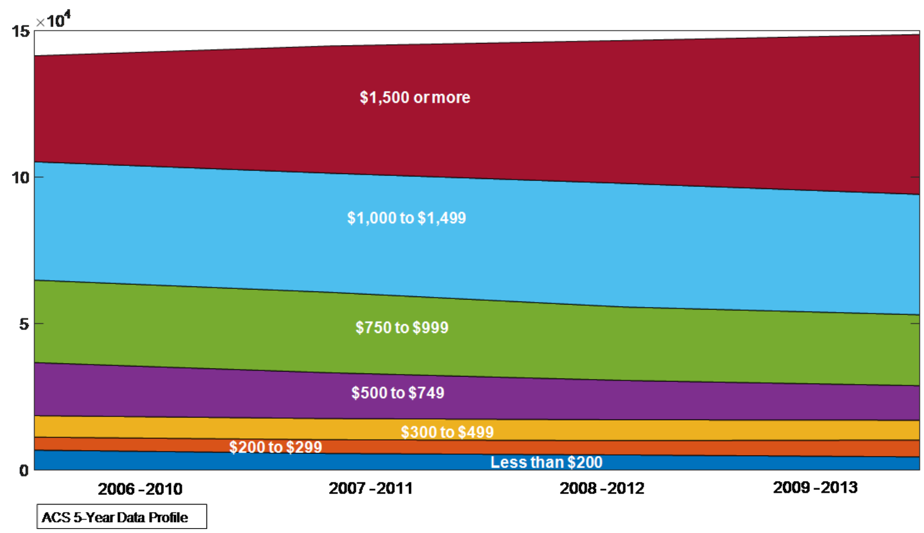


Note: Fig. 4.5 shows the average unemployment rate from January of 1976 to May of 2021 in monthly frequency. The grey areas display recession years recognized by the National Bureau of Economic Research. Source: U.S. Bureau of Labor Statistics, Unemployment Rate in Minnesota [MNUR], North Dakota [NDUR], Montana [MTUR], South Dakota [SDUR] and US [UNRATE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/, July 13, 2021.

4.4.4 Housing Wealth Response to Uncertainty by State

Figure 4.14 (Appendix) shows the impulse responses of housing wealth in US states. DC, North Dakota, Vermont, Hawaii, New Hampshire, Rhode Island, New York and Mississippi have a pronounce impact to uncertainty, regarding housing wealth. DC would experience the most severe negative response of housing wealth in US to a 20% rise in uncertainty. Kijakazi, Atkins, Paul, Price, Hamilton, and Darity Jr. (2016) provide evidence that in DC, construction of cheap homes fell sharply during the 2008 crisis, while expensive homes fell slightly and increased rapidly a year later. This has to do with the dramatic wealth disparities between White communities and communities of color. Importantly racial wealth inequalities were extreme, since half of Black, Lation and Asian households' wealth was erased. Though the racial and ethnic differences in net worth, long predate the dramatic economic downturn in DC, home values are significantly lower for Black families. Houses priced under 800 dollars from 65200 units decreased to 35000 units from 2005 to 2010 and didn't increase in the next two years. Houses priced between 800 and 1500 dollars had a mild loss in units, while houses priced higher than 1500 dollars had almost no loss at that time and a rapid increase thereafter. Figure 4.6 summarizes the number of rental units by rent in DC from 2006 - 2013. Data include five year estimation at that period.

Figure 4.6: Number of rental units by rent in DC



Note. Fig. 4.6 summarizes the number of rental units by rent in DC from 5 periods (2006-2010, 2007-2011, 2008-2012, 2009-2013), to cover the most basic data on the topic. Source: US Census Bureau.American Community Survey (ACS).www.census.gov/

Furthermore, the economic conditions of residents in DC depend on the education level and other variables (age, gender etc.). Tompson and Suarez (2019) provide evidence that the gap between white and nonwhite families is driven by the differences in human capital, demographics, and family financial support. However, an unexplained portion that contributes to this gap is still unaccounted though greater at the top of the wealth distribution. A survey related to urban dwelling racial inequalities show that racial wealth gap may be also the key to other inequities but no details are presented here.

North Dakota is the second state that housing wealth displays a dramatic response in a potential 20% uncertainty. Gunning (2016) provides strong evidence that the key factors of homeownership probability are wage occupations and employment mobility. The largest decreases in housing wealth due to the 2008 crisis occurred to households with low incomes and high job mobility. Uncertain job tenures may be on top of the factors of the dramatic response of housing wealth. During the bubble, easy credit was appreciating quickly home values to seduce buyers with low or high income. Afterwards when the market balanced, the homeownership recovered to normal standards only for high income households. Hence, uncertainty hit households of low income more than those who could afford a loss. It's obviously common sense that poorer and richer households would have been impacted differently to a rise in uncertainty. Further, North Dakota ranks seventh in the nation for the highest proportion of individuals aged 85 years and older (North Dakota Census Office 2014). Older population is a demographic group with limited time to recover from economic shocks and hence, suffers much more than those at younger age. Similarly, inequality in wealth is quite large for non-native households, emphasizing the importance of demographic factors when a shock occurs (Amuedo-Dorantes and Pozo 2015).

Vermont is the third state with the most severe impact of housing wealth in a supposed 20% rise in uncertainty. One explanation is Vermont's chronic housing condition definitely related with households with poor zip-codes. Indicatively, almost 70% of Vermont resident households received tax credit because of their low income (less than 138,250 dollars) in 2019. (Annual report 2020, Department of Taxes in Vermont) The main problems of houses in Vermont are related to affordability, availability, and suitability. In fact, 60% of housing units built before 1980 and 25% built before 1939. A great number of them are expected to be lost to destruction or conversion. As a result, many families buy or rent houses far away from their works while uncertainty aggregates the bad situation. Another characteristic of housing in Vermont is the property transfers to out-of-state buyers that intuitively increased in bad times. Table 4.3 shows that the land sales doubled from 2010 to 2020 resulting in less land for housing development.[1]

Generally, the dramatic response of housing wealth to uncertainty meets the essential problems in the state driven by demographics. (Smith and Barton 2021)

In Louisiana, the housing response has a positive sign to an impending increase in uncertainty, probably related to the land loss rates, because as land is reducing the house prices are increasing. The factors which contribute to land loss

[1] Land Gains Tax is a tax on the gain from the sale or exchange of land that has been held for fewer than six years. The main purpose of a Land Gains Tax is to discourage "speculation," the holding of land for a short period and selling at a profit. Thus, the tax rate is on a sliding scale based on the seller's holding period and the percentage of the gain to the basis. The longer the holding period and the smaller the percentage, the less tax is paid. https://tax.vermont.gov/sites/tax/files/documents/PVR%20Annual%20Report%202020.pdf

Table 4.3: Revenue from Land Gains Tax in Vermont

Fiscal Year	**Land Gains Tax Revenue**
2020	$ 1,252,439
2019	$ 1,664,666
2018	$ 1,660,764
2017	$ 1,422,754
2016	$ 1,237,153
2015	$ 1,459,231
2014	$ 1,245,566
2013	$ 1,158,712
2012	$ 783,868
2011	$ 880,056
2010	$ 600,065

Source. Annual Report 2020. Vermont Department of Taxes, January 2021, Fig. 2, p. 16.
https://tax.vermont.gov/sites/tax/files/documents/PVR%20Annual%20Report%202020.pdf

are subsidence, storm induced erosion, channelization of streams and rivers. However, the land loss rate has decreased almost 60% during the years 1956 – 1990 and the percentage of land being lost is also decreasing per year in a stable rate (Britsch and Dunbar 1993). Louisiana is still vulnerable to sea level rise and flooding. Hence people leave risky areas and move to higher ground districts, affecting real estate markets (The CNN journal 2021). Therefore, it seems that when we impose a 20% rise in uncertainty, the housing wealth indicates a top average response after ten periods of about 0.4% and resets after 30 periods. Our findings show a small variability of housing wealth response in Louisiana during the estimated period of 40 periods, implying similar behavior trends.

4.4.5 Financial Wealth Response to Uncertainty by State

Figure 4.15 (Appendix) shows the impulse responses of financial wealth in US states. New Hampshire, New Mexico, Nevada, North Dakota and Louisiana would experience the most intensive impact of financial wealth in a rise of uncertainty. The top average impacts of those states are -1.172%, -0.345%, -0.29%, -0.28% and -0.25% respectively, and appear at the fifth period of estimation, although the financial impact has an immediate response from the first period to the majority of states. New Hampshire appears to have the largest financial impact to uncertainty at the fifth estimated period. One possible explanation is that New Hampshire has one of the highest median household incomes in the country. Inflated house-price expectations led households across all income groups, especially the middle class, to increase their demand for housing and mortgage leverage. The drop in collateral values increased defaults affecting the stability of the financial markets. The 2008 crisis is that it was not a subprime crisis but a middleclass crisis. Richer households have larger mortgages and the dollar value of mortgage defaults was most pronounced among middle-and high-income borrowers. *"Thus, the largest increase in defaults came from a group of mortgage holders who previously had never defaulted at high rates and constituted good credit scores at the time the mortgages were originated.'* (Adelino, Schoar, and Severino 2018, p. 28).

Furthermore, many households own second or vacational homes in New Hampshire. Adelino et al. (2018) support that second homes shot up during the boom period, especially in areas that experienced rapid house-price increases increasing the demand for mortgage leverage.

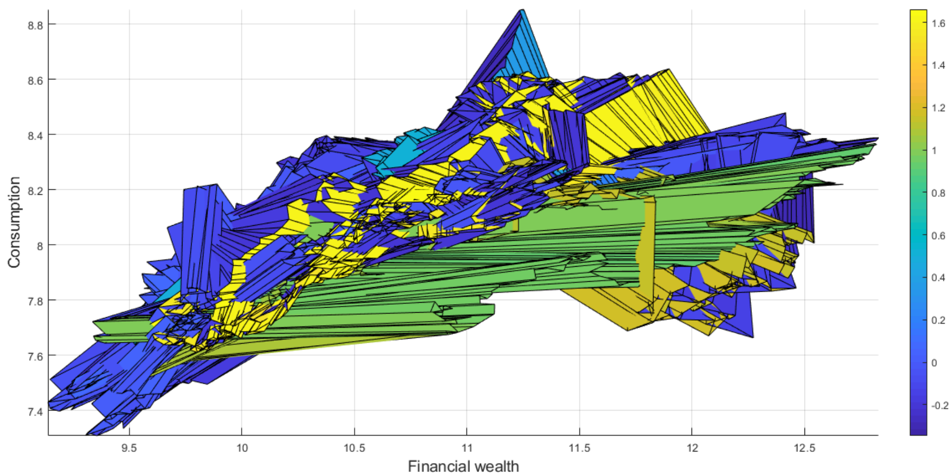
After the recession, the people who recovered fastest and first were higher-income households. The estimated financial wealth includes corporate equities, mutual funds and pension reserves hold by households. Another explanation for the high negative impact of financial wealth of N. Hampshire in a potential increase in uncertainty may be the connection of corporate equities with the drop of industrial sector. The correlation between business sector with financial sector is 93% [2]. These explanations of the reasons of 2008 crisis may shed light on a potential economic and financial crisis in a 20% rise of uncertainty. Additionally, uncertainty is more connected with financial wealth than with consumption, personal income or housing wealth (fig. 4.1). Figures 4.1 and 4.10 show that states with high uncertainty are California, DC, Louisiana, New Hampshire, New Mexico, North Dakota and Rhode Island. The next figures confirm this connection.

Figure 4.7 presents the rise of consumption with respect to financial wealth. Uncertainty seems to connect consumption with financial wealth. Colors of yellow and green are more pronounce in figure 4.6, indicating a great deal of uncertainty for consumers which are holders of financial wealth. The green color (medium uncertainty) is spreading allover the shape and covers mostly medium and low consumption. On the other side it is difficult to know how high uncertainty (yellow colour) affects the behaviour of households.

Further, our data expand from 1975 to 2018, including the period of the ex-

[2]For the calculation of correlation, we used the gross domestic product for each industry sector for New Hampshire. The data were annual from 1997 to 2018, provided by Bureau of Economic Analysis with the code SAGDP9N. The calculations were done under the Pearson correlation formula.

Figure 4.7: Consumption, Financial wealth and Uncertainty

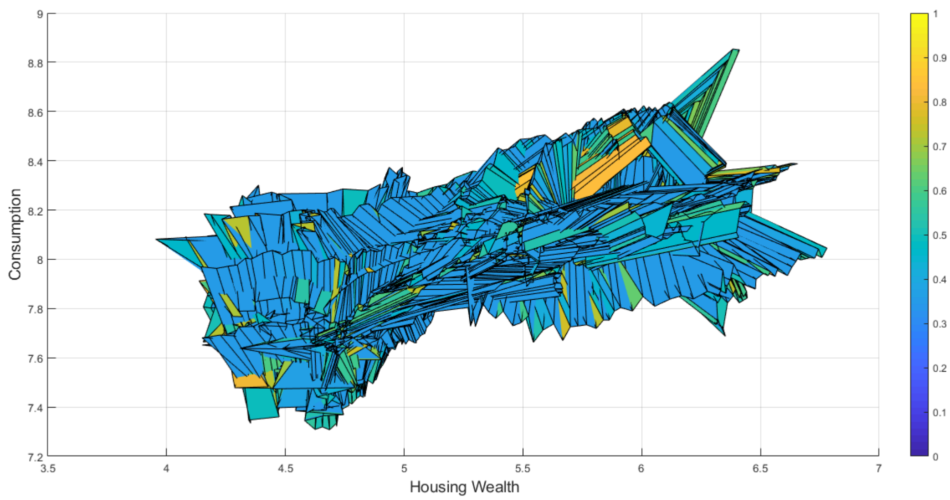


Note. Fig. 4.7 shows the relationship of consumption with financial wealth. The colors indicate the level of uncertainty. High uncertainty levels are yellow colored. Low uncertainty levels are blue colored.

pansion of computers and new technologies, and the rise and drop of stock market, named the New Economy of 1990s. The expansion of new technologies, the internet rush and the related investments shot up a rapid productivity growth, highlighting the New Economy of the 1990s. Its implications were associated with income inequalities, the rise in job insecurity, more rapid job creation and destruction, a move away from long term employment towards short term contracts, and a general increase in managerial pressure on workers. (Temple 2002). Equally, the evaluation of old economy firms declined in the financial market. Bond and Cummins (2000) provide evidence for the beginning of a wide market irrationality at that time, implying that financial market valuations rarely reflected expert profit forecasts. Hence, economists predicted a crash for the NASDAQ high technology index in the late 1990s. The new economy has encouraged many to revise the mean of future rates of productivity growth upwards, but also to emphasize that the degree of uncertainty has risen considerably. (Temple 2002).

Figure 4.8 presents the rise of consumption with respect to housing wealth.

Figure 4.8: Consumption, Housing wealth and Uncertainty



Note. Fig. 4.8 shows the relationship of consumption with housing wealth. The colors indicate the level of uncertainty. High uncertainty levels are yellow colored. Low uncertainty levels are blue colored.

Households which are holders of housing wealth don' t face high uncertainty. Uncertainty is limited to low levels for middle and low-wealth households. Light blue color prevails the figure 4.8, indicating low levels of uncertainty for homeowners.

Although the mortgage and housing markets were at the heart of the 2008 crisis, the financial sector and the ensuing upheavals ended in the great recession. The financial sector significantly reduced the credit flows and other financial functions in the economy, resulting in the slowdown of economic activity. (Adelino et al. 2018)

4.5 Discussion of the results

While economic theory predicts sudden, sharp pullbacks of household purchases following increases in uncertainty, the empirical results suggest that household spending reductions are modest and may only appear after a considerable time has passed. High levels of uncertainty are mostly connecting with high consumption. Owners of housing wealth feel more secure in times of uncertainty. In general uncertainty affect consumers holding financial wealth.

Our results suggest that the uncertainty effect is heterogeneous. Louisiana, N. Hampshire, North Dakota and California appear to be the states most affected by uncertainty. States differ substantially in terms of the type and concentration of industry, the banking sector, and the degree of credit frictions. These differences make it likely that their response to U.S.-wide uncertainty shocks may also differ. (Mumtaz et. al 2018). But which state-specific characteristics can explain the heterogeneous impact of uncertainty shocks? Firms that face higher borrowing costs are likely to reduce their investment. (Schwartzman, 2012).

In 2019, the largest industry in Louisiana was nondurable goods manufacturing. In 2005, the contribution of the basic Chemical Manufacturing in Louisiana to percentage change in real GDP was 5.9%, the biggest in the US states among all the industries. This sector of economy experiences a U-shape of recovery, that is a sharp decline since 2000's recession (fig. 4.9).

Louisiana is the nation's number two producer of oil, producing almost 1.6

Figure 4.9: All Employees: Manufacturing Non-Durable Goods Basic Chemical Manufacturing in Louisiana

Source: https://fred.stlouisfed.org/series/SMU22000003232510001SA

million barrels a day in October 2017. This represents 16.1 percent of the nation's crude oil production, behind Texas, with North Dakota in a close third place. (Scott and Rouge, 2018). Therefore, one explanation of the high uncertainty in these states is connecting with the prices of crude oil as the correlation of our proxy with the prices of crude oil is obvious (fig. 4.3& fig.4.4).

Moreover, the largest industries in the states with high uncertainty were finance, insurance, real estate, rental, leasing and professional and business services. On contrary statistics in BEA reveal that states with advanced retail trade and government and government enterprises or other industries experienced less uncertainty. For example, in Connecticut the largest contributor to real GDP growth was professional and business services while the second largest contributor was information (BEA, 2019). Connecticut experienced low uncertainty compared with the other states in all estimated period. Therefore, financial service industries played an important role in market risk as financial markets gained lending advantages over banks as the size of their borrowers increased (Slovin et al. 1992). These financial supermarkets offered services approximating banking services including a wide range of "financial products" for consumers as if they were commodities and a full menu of capital markets services for midsized and large businesses. (Wilmarth, 2002).

Another explanation regarding the heterogeneity of the states' uncertainty could be the correlation of the main industries among the states. For example, finance, insurance, real estate, rental, leasing and professional and business services are highly correlated. In North Dakota which exhibits high level uncertainty, the correlation of these industries is above 99%. "Accordingly, the trend toward cross-industry consolidation increased the concentration and potential correlation of credit risk and market risk in the U.S. financial system" (Wilmarth 2002:453). On the other side, the main industries in Great Lakes region exhibit low or negative correlations except financial and business services. Government and government enterprises correlation with financial services is -0.526, with professional business services is -0.29 and with information industry is -0.67. Hence Illinois, Indiana, Michigan, Minnesota, Ohio, Pennsylvania and Wisconsin are among the states with low level uncertainty. New York is an exception in this case - with high uncertainty - though its main industry (financial sector) correlation with professional and business services is 0.84, with retail trade 0.77 and government enterprises 0.45. The economy in this region is very diverse.

States of low uncertainty such as South Carolina and Connecticut present high correlation between finance, insurance and real estate sector with government and government enterprises (0.96 and 0.70 respectively). Their connection of the financial and real estate sector with the government may be the key explanation of the low levels of uncertainty. In South Carolina all the sectors are highly correlated, in Connecticut all the other sectors present low correlation except that of financial sector with government enterprises (0.70). Florida experiences low uncertainty and the same time the sectors of its industries present high correlation (0.96). For example, the financial and real estate sector is correlated with retail trade sector and business sector of 0.97.

One explanation for this contradiction may lie on the fact that Florida has adopted electric vehicle infrastructure legislation in order to alleviate its dependence on oil prices (https://www.spglobal.com/).

For the calculations of correlations we used the gross domestic product for each industry sector by state. The data were annual from 1997 to 2018, provided by Bureau of Economic Analysis with the code SAGDP9N. The calculations were done under the Pearson correlation formula.

4.6 Conclusion

In this paper, we introduce a new US uncertainty index which is more relevant for consumer spending and therefore affects households' decisions, based on a very rich set of data. We find evidence that macroeconomic uncertainty shocks impose significant negative effects on income, consumption and financial wealth held by households. In contrast, housing wealth is not affected statistically significantly. The significant variation in the housing wealth response probably reveals demographic factors that explain state heterogeneity.

Further, we show significant heterogeneity in the size of uncertainty among the US states. First, we suggest their relationship with oil prices is an important source of uncertainty (those through which the pipelines pass have greater uncertainty) Second, it seems that the diversity of industries declines the uncertainty in each state and vice versa. We conclude that although the construction of the new financial service industries during the period 1975-2000 was for the favor of large economies of scale and scope they didn't achieve a safer diversification of risks. On contrary we support that their connection with other industries as business services raise the risks and uncertainty.

4.7 References

Adelino, M., Schoar, A., Severino, F. 2018. ”The Role of Housing and Mortgage Markets in the Financial Crisis.” *Annual Review of Financial Economics* 10 (1): 25-41.

Amuedo-Dorantes, C., Pozo, S. 2015. “The impact of the recession on the wealth of older immigrant and native households in the United States.” *IZA J Labor Policy* 4 (6).

Andrews, A. 2013. ”The Northeast Home Heating Oil Reserve and the National Oilheat Research Alliance.” Congressional Research Service 7-7500, R43235.

Bernanke SB., J. Boivin, P. Eliasz. 2005. ”Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach.” *The Quarterly Journal of Economics* 120 (1):387–422.

Bloom, N. 2009. ”The impact of uncertainty shocks.” *Econometrica: Journal of the Econometric Society* 77 (3): 623– 685.

Bloom, N., S. Bond, and J. Van Reenen. 2007. *Review of Economic Studies* 74: 391-415.

Bond, S., & J.G. Cummins. 2000. The Stock Market and Investment in the New Economy: Some Tangible Facts and Intangible Fictions.*Brookings Papers on Economic Activity* 2000(1), 61-107.

Bookman, T., and P. Biello. “Just how well is New Hampshire’s economy doing,” New Hampshire Public Radio (Sept. 13, 2017).

Britsch, L.D, and J.B. Dunbar. 1993. “Land loss rates: Louisiana coastal plain.” *Journal of coastal research* 9(2): 324-338.

Carriero, A., EC. Todd, and M. Massimiliano. 2018. ”Measuring Uncertainty and Its Impact on the Economy.” *The Review of Economics and Statistics* 100 (5): 799-815.

Gunning. 2016. “Lecturers on Modular Forms.” (AM-48). Volume 48. Princeton University.

Johnson, K.M. 2019. ”New Hampshire Demographic Trends in an Era of Economic Turbulence”. *The Carsey School of Public Policy at the Scholars’ Repository.* 380. https://scholars.unh.edu/carsey/380

Jurado, K., S. Ludvigson, and N. Serena. 2015. ”Measuring uncertainty.” *Amer.Econ. Rev.* 105 (3): 1177–1216.

Kijakazi, Atkins, Paul, Price, Hamilton, and Darity Jr. 2016. The Color of Wealth in the Nation’s Capital. The Insight Center. http://www.insightcced.org/.

Mumtaz, H., L. Sunder-Plassmann, and A. Theophilopoulou. 2016. ”The State Level Impact of Uncertainty Shocks.” Working Papers 793, Queen Mary University of London, School of Economics and Finance.

Mumtaz, H., K, Theodoridis. 2017. ” Common and country specific economic uncertainty.”

*J. Int.Econ.*105: 205–216.

Mumtaz, H. 2018. " Does uncertainty affect real activity? Evidence from state-level data." *Economics Letters* 167: 127-130.

Schwartz, A.F. 2021. *Housing policy tin the United States.* Routledge.

Schwartzman, F. 2012. "When do credit frictions matter for business cycles?" *Economic Quarterly.* 98 (3): 209–230.

Scott, C. L., and Rouge, B. 2018. The Energy sector: Still a giant economic engine for the Louisiana Economy. Grow Louisiana Coalition, LA.

Slovin, M.B., Sushka, M.E. and J.A. Polonchek. 1992. "Informational externalities of seasoned equity issues: Differences between banks and industrial firms." *Journal of Financial Economics* 32 (1): 7-101.

Stanfield, J.& Watson, M. Electric Power, "Analysis: Oil price war increases power utilities' uncertainty over EV infrastructure plans". S & P Global plants:Oil Commodity, 12 Mar 2020, available at https://www.spglobal.com/platts/en/market-insights/latest-news/electric-power/031220-oil-price-war-increases-power-utilities-uncertainty-over-ev-infrastructure-plans#article0 Accessed on April 14, 2021.

Stanfield, J.& Watson, M. Electric Power, "Analysis: Oil price war increases power utilities' uncertainty over EV infrastructure plans". S & P Global plants:Oil Commodity, 12 Mar 2020, available at https://www.spglobal.com/platts/en/market-insights/latest-news/electric-power/031220-oil-price-war-increases-power-utilities-uncertainty-over-ev-infrastructure-plans#article0 Accessed on April 14, 2021.

Swanson, E. 2015. "Measuring the Effects of Unconventional Monetary Policy on Asset Prices." Working Paper 21816. National Bureau of Economic Research.

Thompson, J. P.; and G.A. Suarez. 2019. "Accounting for racial wealth disparities in the United States," Working Papers, No. 19-13, Federal Reserve Bank of Boston, Boston, MA, http://dx.doi.org/10.29412/res.wp.2019.13.

Temple, J. 2002. The assessment: The New Economy. *Oxford Review of Economic Policy*, 18(3), 241-264.

The Milken Institute, published on April 1, 2014. Available at https://milkeninstitute.org/article/us-recession-here-impact-california-be-more-severe-rest-us-according-milken-institute. Accessed on July 14, 2021.

U.S. Energy Information Administration (EIA). "New Hampshire Profile and Energy Estimates." 16-07-2020. Accessed at 13-7-2021 https://www.eia.gov/state/analysis.php?sid=NH

Williams, J. 2013 " Lessons from the Financial Crisis for Unconventional Monetary Policy", Panel discussion at the NBER Conference on Lessons from the Financial Crisis for Monetary Policy. http://frbsf.org/our-district/press/presidents/speeches/williamsspeeches/2013/october/research-unconventional-monetary-policy-financial-crisis. Accessed 4 October 2020.

Wilmarth, E. A. 2002. ”The transformation of the U.S. financial services industry, 1975-2000: Competition, Consolidation an Increased Risks.”

Wölfel, K., and C.S. Weber. 2017. ” Searching for the Fed’s reaction function.” *Empirical Economics* 52:191.

Wright, J. 2012. ”What Does Monetary Policy Do to Long-Term Interest Rates at the Zero Lower Bound?” *Economic Journal* 122: F447–F466.

4.8 Appendix

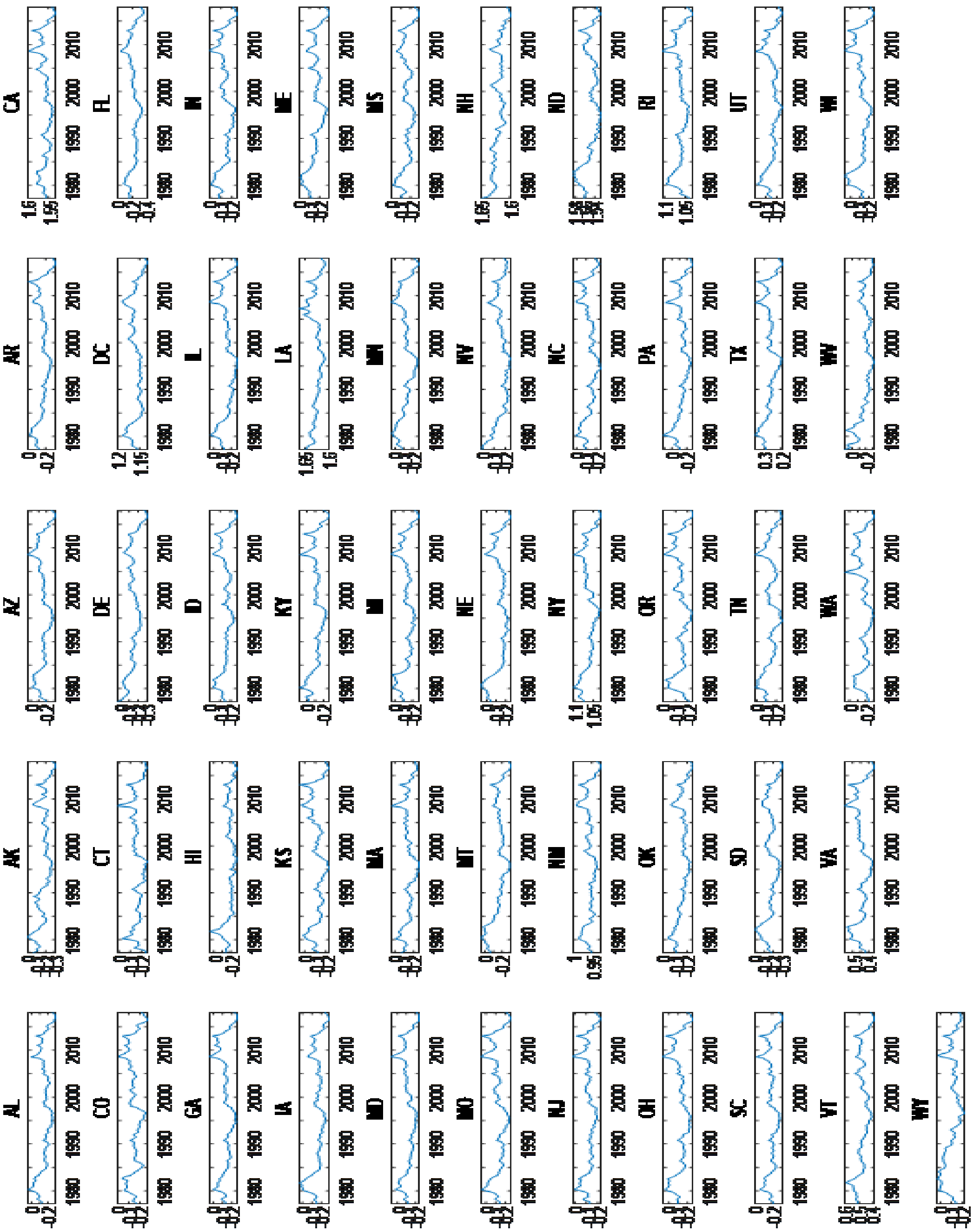
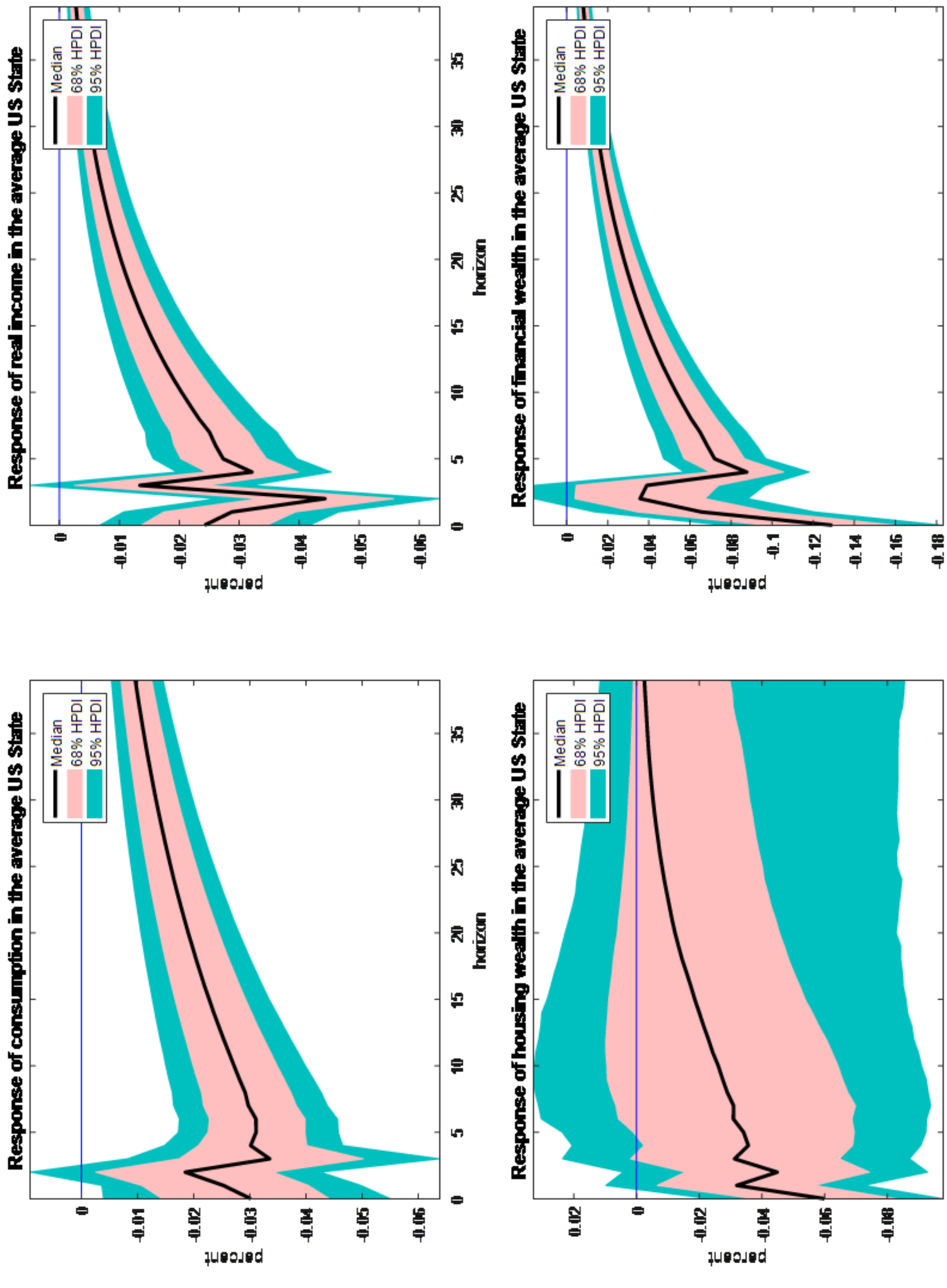


Figure 4.10: US Uncertainty by State

Figure 4.11: Responses of consumption, personal income, housing wealth & financial wealth



Impact of 20% increase in uncertainty

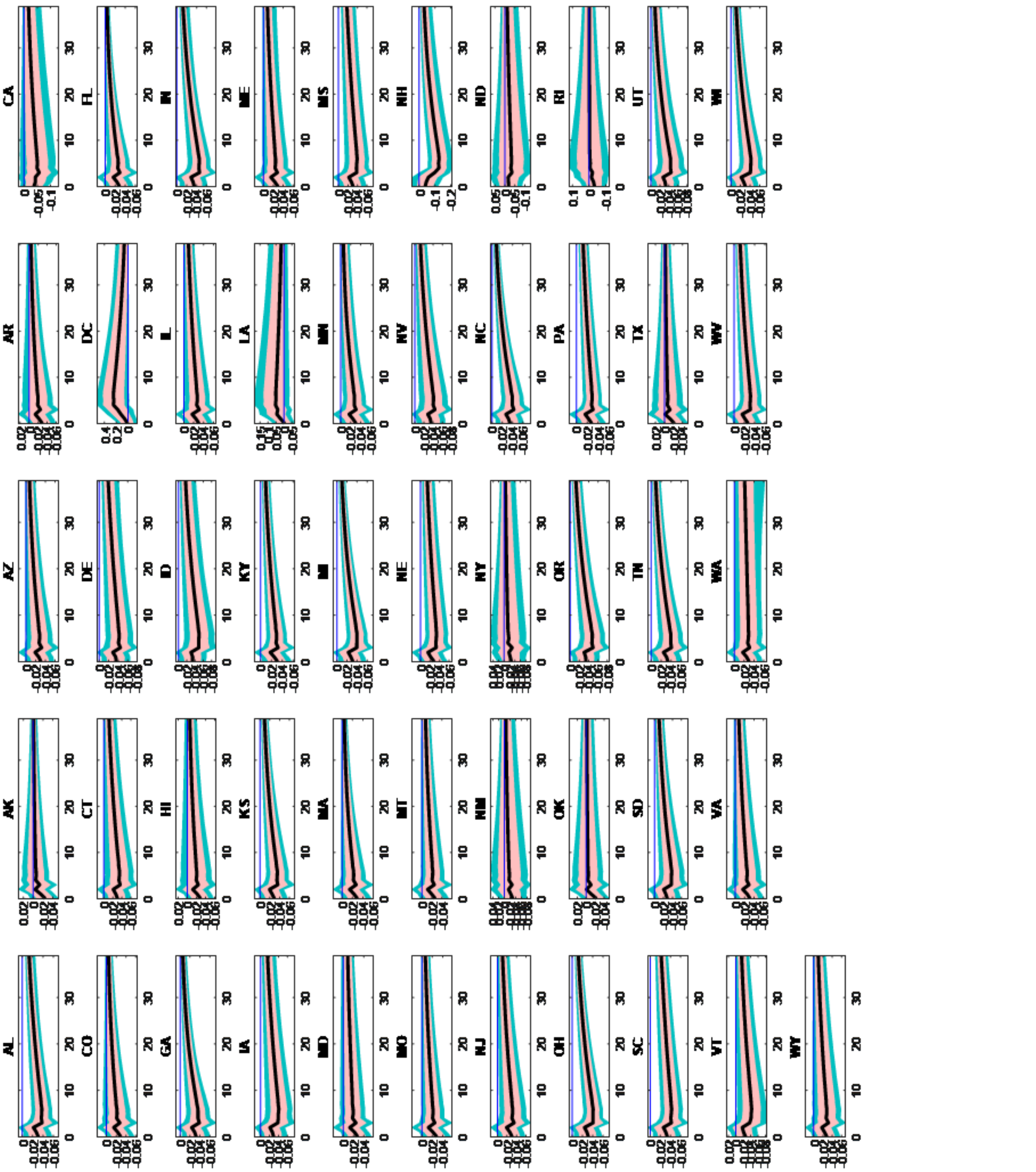


Figure 4.12: Consumption response to Uncertainty by State

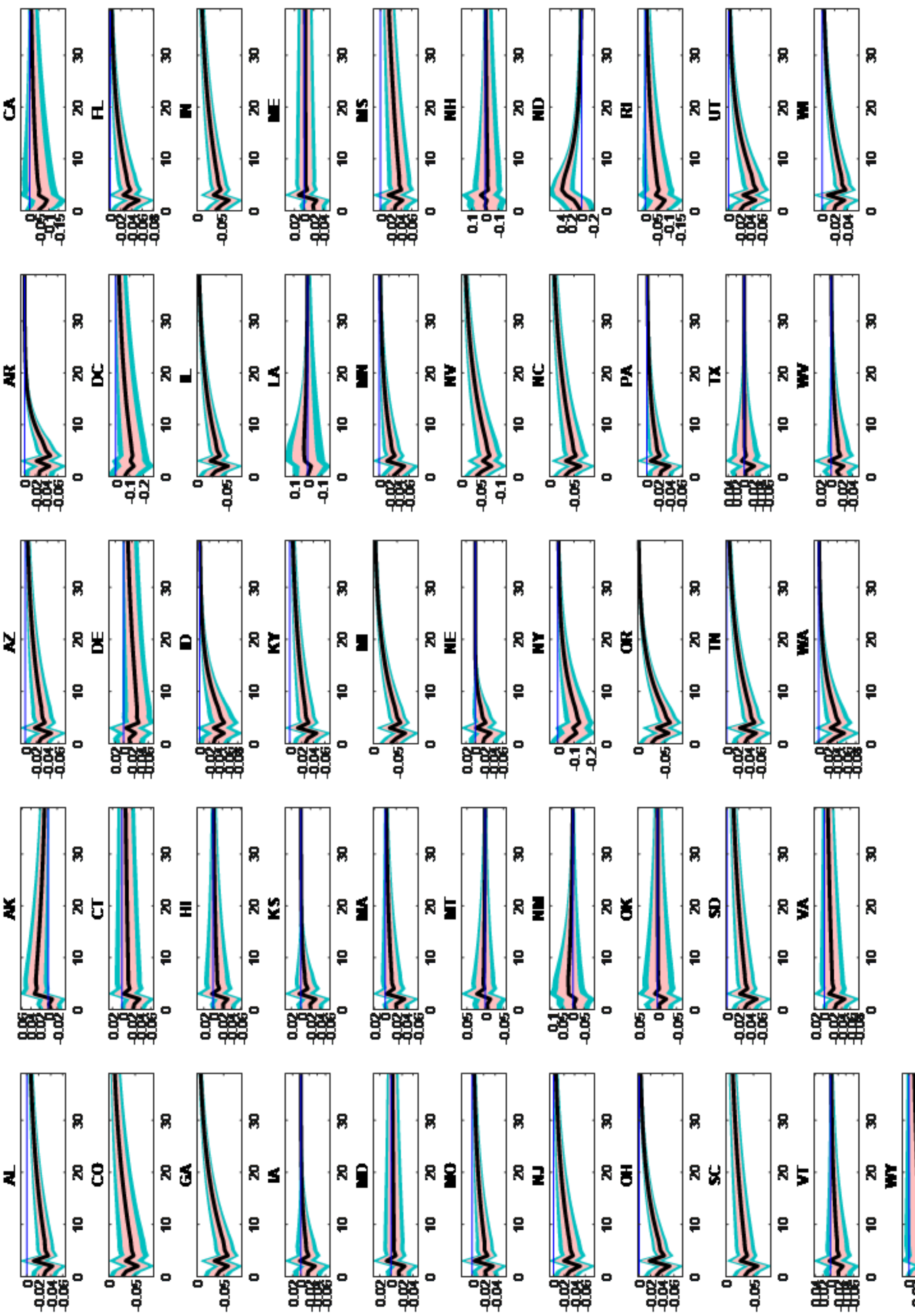


Figure 4.13: Personal income response to Uncertainty by State

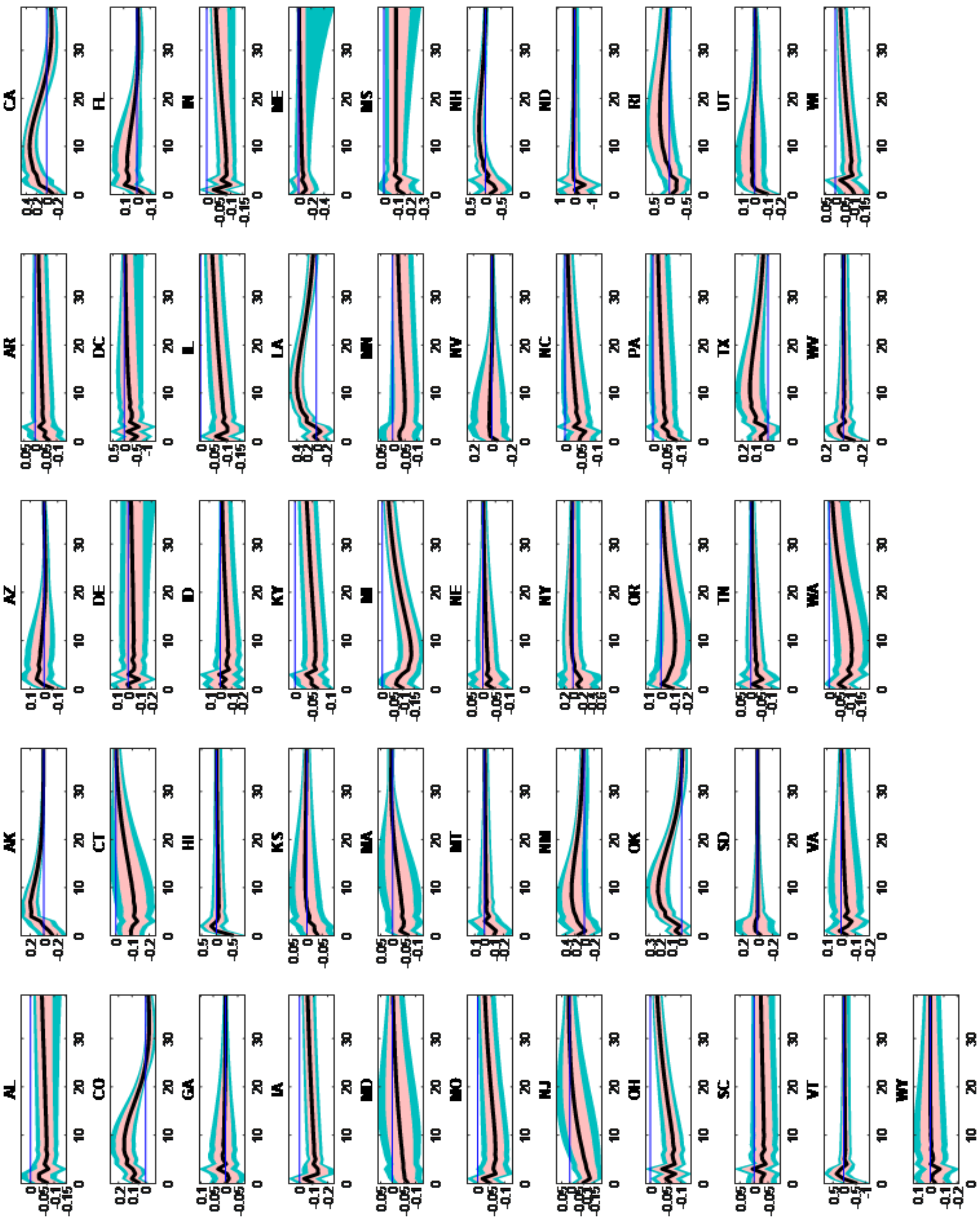


Figure 4.14: Housing wealth response to Uncertainty by State

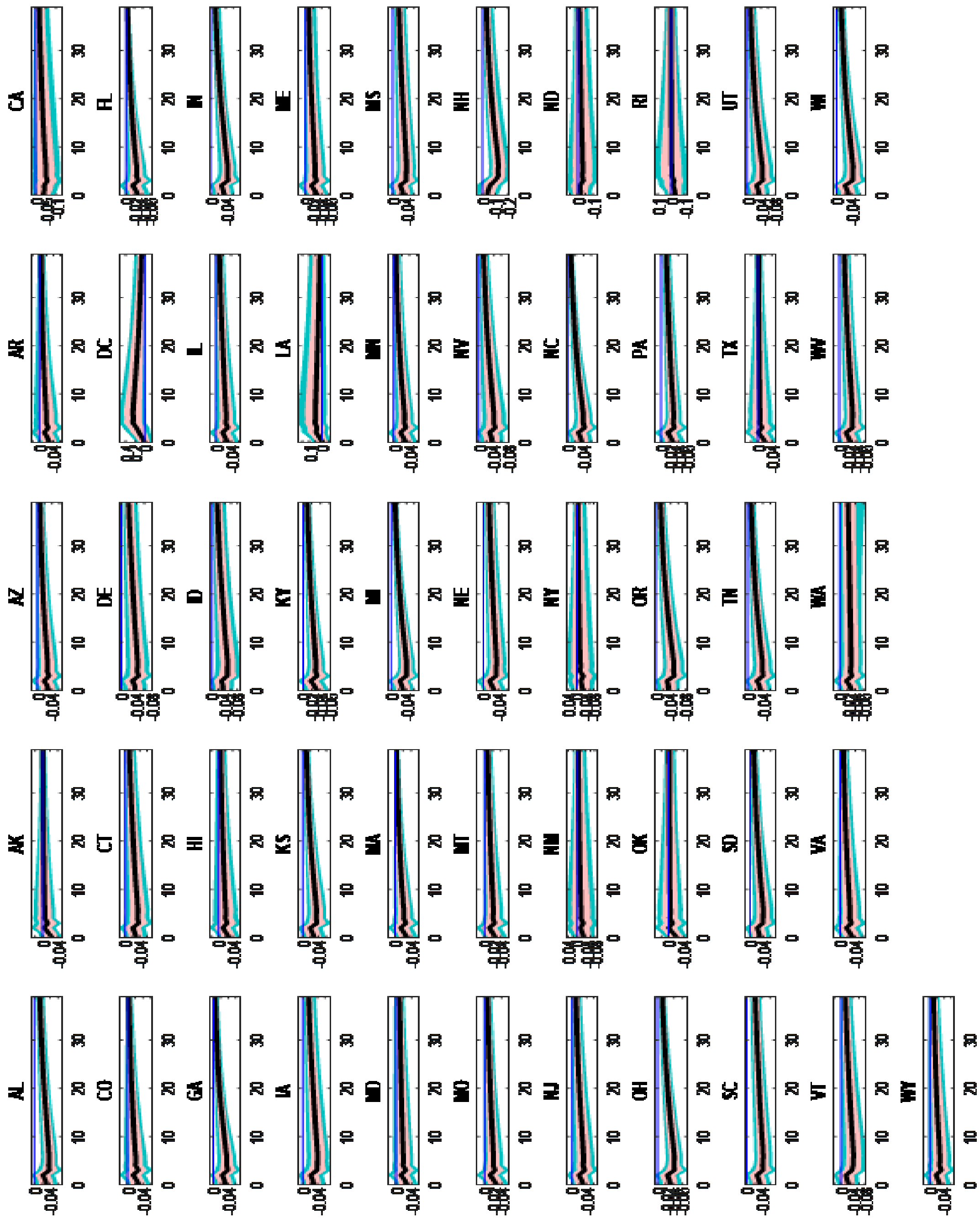


Figure 4.15: Financial wealth response to Uncertainty by State

Chapter 5

The run of US consumption: A functional data analysis approach

Abstract

This chapter uses consumption fluctuations to identify permanent innovations to GDP by employing two techniques. First, by using functional data analysis techniques we demonstrate the patterns and the growth rate of US consumption in the 1939-2020 period. We especially focus on the two derivatives of consumption index to provide evidence about its acceleration and force. Evidence supports the dramatic reduction in the volatility of the derivatives over the years. In all times the market tries to find its balance. Consumption is slowing down after a great deal of growth and is increasing its speed after a crisis. The autumn-winter period is a single cycle with the greatest intensity in consumption. Second, in an attempt to avoid unimportant large fluctuations, we apply a moving average filter to get a smoother index for further investigation. The Covid pandemic obviously changed the consumption pattern and as we are on the threshold of the end of the crisis, we believe in a huge increase in consumption rate that will increase the rate of inflation in the absence of the appropriate policy responses.

JEL codes: E21; E30; H31
Keywords: Consumption; Consumption growth; Seasonality; Functional Data Analysis; Moving Average Filter; Covid-19

5.1 Introduction

Researchers have developed several economic models to analyse consumption fluctuations and shed light on many macroeconomic aspects over the years. These fluctuations reflect the behavior of consumers and follow a dynamic process because consumers very often change their habits, attitude, preferences etc., or because of the diversity of economic conditions. Barsky and Miron (1989) show that seasonal fluctuations display some characteristics, in some cases even more crucial for the economy than those of the business cycle.

Moreover, the world's population has grown over the years and obviously consumption has also increased. Consumption patterns and prices change radically in so many dimensions that no single index can capture the reality while the growth rate of consumption seems to matter most (Piketty, 2014). In some cases, we do better when consumption is both lower and more variable over time because utility and well-being seem to be related more to changes in consumption rather than consumption levels. (Scitovsky, 1992).

For all these reasons, a first feature of this paper is our focus on the change of consumption rather than its overall level. A second feature of our analysis is the emphasis on seasonality as an important characteristic representing habits, preferences, consumer tastes, and crucial characteristics of the business cycle. Some economists (Neusser, 1992) support the misleading role of seasonal adjustment methods and underline the importance of a correct treatment of seasonality. To the best of our knowledge, we are the first to analyze the dynamics of a monthly non-seasonally adjusted index of consumption using the Functional Data Analysis (FDA) techniques pioneered by Ramsay and Silverman (2002). FDA is the analysis of information on curves or functions rather than the investigation of the levels of the variables. We analyze the data in terms of differential operators to cover a much broader class of dynamic behavior. Differential operators' analysis has many advantages, some technical, some substantive. They provide evidence about acceleration and force. The relationship between acceleration and force is fundamental for all dynamical systems and not only in physics. Change in production and consequently in consumption involves acceleration. Therefore, the analysis of consumption involves at least two derivatives, representing acceleration and force, to model the variation in consumption. By analyzing the derivatives of consumption, we aim to explain the dynamical behavior of consumption during the period 1939-2020. Moreover, we use a gentle technique to smooth the seasonal trend index obtained by the FDA approach to investigate the co-movements of consumption with the economy's innovations. We attempt to answer the following questions: What is the change in the dynamics of potential consumers over the last 82 years? Has the pattern of consumption changed? How do consumers respond to structural changes in the economy? What is the consumption behavior during recessions?

We also contribute to the existing literature in many ways. Our analysis is based on monthly non-seasonally adjusted time series data from 1939 to 2020 and avoids the dynamic misspecification arising from seasonally adjusted series. It is obvious that the time series over 82 years has a unit root. We avoid literature controversies over the empirical plausibility of two important classes of statistical univariate time series models: trend stationary and difference stationary models. (Christiano and Eichenbaum, 1990). Second, we use the phase plane plots to analyze consumption changes from the aspect of seasonality. We also aim to contribute to the gap of research in the area of holiday shopping. Finally, we construct the 13-term moving average index of consumption to measure the cycle trend, maintaining crucial turning points of the economy.

Our results show a dramatic reduction in the volatility of the derivatives over the years. In all times the market tries to find its balance. It is slowing down after a great deal of growth, as it did after World War II, and it is increasing its speed after a crisis. The autumn and winter period make the most important cycle of consumption which used to start in November while nowadays starts one month earlier. In the holidays of Thanksgiving, consumption growth reaches its highest speed. The end of January finds the index in the opposite site and the growth rate at the lowest level. Consumers probably respond only to the recessions which affect their permanent income.

The rest of the paper is organized as follows. The second section of this paper presents the related literature. The third section describes the data and the methodology. The fourth and the fifth section present and discuss the results, respectively. The paper ends with a summary and conclusions.

5.2 Literature

A large literature (Barsky and Miron 1988; Dijk, Strikholm and Timo Teräsvirta 2003; Lucas 1977; Canova and Ghysels 1994) provides evidence about the importance of the seasonal cycle and supports that changes are linked to the stages of the business cycle. Lucas (1977) states that the seasonal cycle is just like the business cycle as movements of variables that constitute the business cycle are behind the changes in prices, technology and tastes. Campbell and Deaton (1987) and Campbell and Mankiw (1987) argue about first difference stationary data characterized them as 'too smooth' to provide reliable results. Hence, seasonally unadjusted data is much preferable to avoid the potential for dynamic misspecifications.

A number of researchers (Wuger and Thury, 2001); Hylleberg, Jorgensen, and Sorensen, 1993; Harvey and Scott 1994; Ghysels 1994) improve their results by adding seasonal components in their models, representing by dummies or fixed seasonal effects because they capture a substantial portion of the existing seasonal fluctuations. Barsky and Miron (1988) provide evidence that stochastic seasonal fluctuations represent a relatively small percentage of the fluctuations in real output. On the other hand, 85% of the seasonal variation in the rate of growth of real output is due to deterministic fluctuations. Moreover, seasonal fluctuations demonstrate deterministic patterns in every major component of GNP.

Barsky and Miron (1988) proved that the seasonal patterns of consumption are similar in timing and greater in amplitude than those in output. The patterns of seasonal fluctuations indicate that Christmas plays a great role in economic activity.

Consumption spending reveals also large increases in the fourth quarter and is almost certainly related to Christmas. On the opposite side, the large decreases in the first quarter plausibly reflect the end of the Christmas season.

Early literature (Kuznets, 1946) revealed permanent income as the main component that defines consumption. Moreover, Hall and Mishkin (1982) provide evidence that consumption reacts only to the new information about permanent income indicating a cause of consumption fluctuation. Decreased consumers' income expectations determine the observed consumption drop (Nardi and Benson, 2011). Blanchard (1993) suggests that consumption shocks are a mirror, not a cause, and reflect the anticipations of other shocks and their effect on future income. So, consumption shocks must reflect foresight of shocks with permanent effects or even sudden realizations of past overborrowing, that inevitably minimize the permanent income. Policy makers are often more interested in the underlying trends of an economic time series than in investigating the deseasonalized monthly values. This suggests that more attention should be given than at present to the estimation of current and recent trend levels. (Kenny and Durbin, 1982).

5.3 Data and methodology

5.3.1 Data

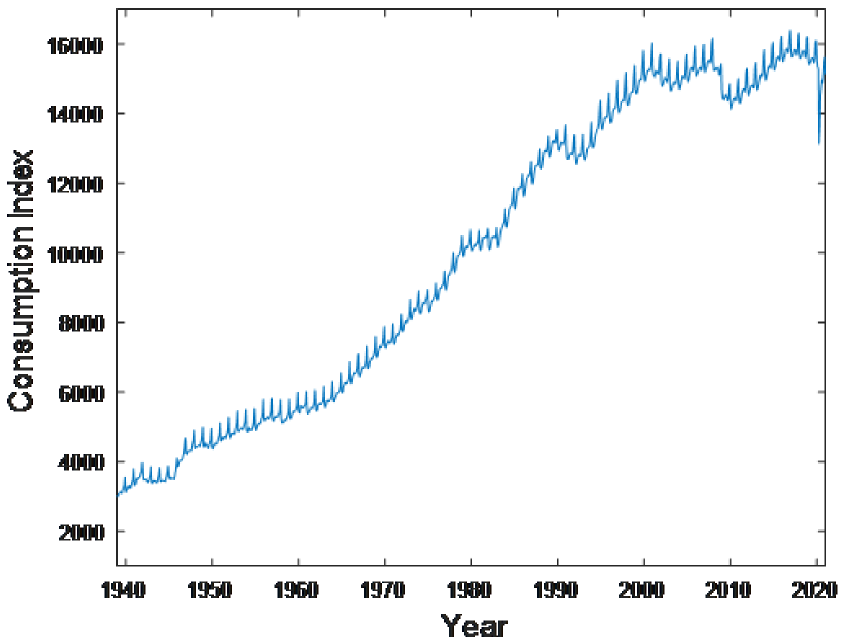
The basic class of models for dealing with time series with seasonal components is ARIMA models. The disadvantage is the presence of unit roots in the longer-term part of the model and seasonal unit roots in the seasonal component. Therefore, ARIMA models may be uninformative or even misleading.

FDA focuses on the seasonal variation that changes over time in response to economic conditions and therefore is a substantial component in a variable (Ramsey and Cheng-Ping, 1993; Ramsey and Keenan, 1996). Moreover, there is evidence that business cycle oscillations and seasonal components are interrelated (Ramsay and Ramsey, 2002).

We use as a proxy of consumption the number of all employees working in US retail trade. The number of employees appears in many empirical works, as a proxy for the firm size or the size of the actual market (Dang, Li and Yang, 2018; Kumar, Rajan, and Zingales, 1999). On the other hand, the data for expenditures include housing expenditures (rent payments, mortgage payments, etc). Therefore, these expenditures do not capture individual behaviour and hence they do not represent a good proxy for everyday activity. Thus, given that we are interested in seasonality, we prefer the use of the number of employees to expenditures to proxy consumption. According to OECD, the retail sector includes all resale activities of new and used goods mainly to the general public for personal or household consumption or use (https://www.oecd.org/). We use a monthly seasonally unadjusted time series which runs from January 1939 to December 2020. The series comes from the 'Current Employment Statistics (Establishment Survey), produced by the US Bureau of Labour Statistics and is sourced at the Federal Reserve Board (https://fred.stlouisfed.org/) with the code CEU4200000001.

The U.S. index of private consumption is plotted in Figure 5.1.

Figure 5.1: The consumption index over the period 1939 to 2021

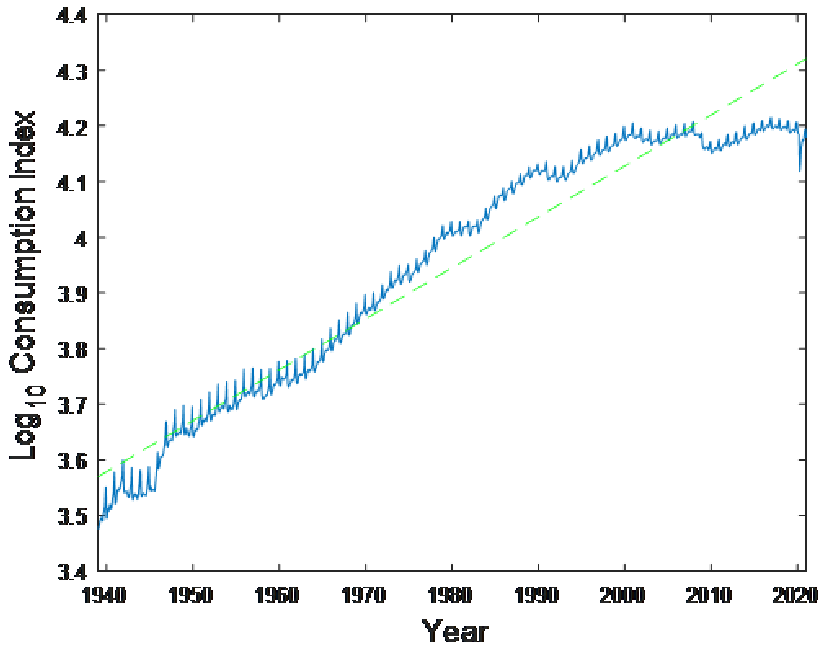


The frequency of the data is monthly and follows the year from January to December. Its plot can represent a year and follows the calendar year. The record for each year may be thought of as an individual functional datum.

Like most economic indicators, the consumption index increases in size and volatility, and the big fluctuations during World War II seem to be small compared to nowadays. Therefore, it is preferable to use the logarithm of the index in our investigation. Fig. 5.2 presents the logarithms (base10) of the series.

This seasonal variation is affected by changes in the economy at various time scales. It is a matter of interest to study how the economy evolves in normal times, and how it reacts to times of crisis and structural change. The seasonal pattern

Figure 5.2: The consumption index in logs



The logarithm of the monthly consumption index: the dotted line is a linear least-squares regression fit.

changes as a response to innovations. In Figure 5.2 the seasonal variation weakens through the years, especially after 1967, and weakens even more after 1980. Times of crisis as the war of six days in June 1967 and technical innovations such as the development of the personal computer in the early 1980s may affect consumption.

5.3.2 Methodology

In this section, we present the methodology used in this study. In the first part we describe the functional data analysis pioneered by Ramsey (2002) which stands behind the phase plane plots and the development of the seasonal trend of our data. In the second part we present the 13-term moving average filter pioneered by Henderson

(1916). We aim to investigate the seasonal cycles through consumption fluctuations and construct an index based on the 13-term moving average filter to allow us identify permanent innovations to GDP. As our data exhibits a strong seasonal component with periodicity 12, we apply the 13-term moving average filter for estimating the trend-cycle. We aim to reduce the noise and maintain the original signal in the best way. The weight for the first and last terms is 1/24 and for the interior terms is 1/12. Weights slowly increase and then slowly decrease, resulting in a smoother curve than another with full weights. Observations at the beginning and end of the series are lost. The moving average has window length 13, so the first and last 6 observations do not have smoothed values.

5.3.2.1 Functional data analysis

In functional data analysis (FDA) we estimate observations on a continuous and in our case differentiable process at discrete points in time t_j. The following equation describes this procedure. This could be written as:

$$\mathbf{y}_j = x\left(t_j\right) + e_j, \tag{5.1}$$

where e_j is the unobserved error term and y_j is the outcome of the process and the function $x(t_j)$ is differentiable to some order.

We describe a part of the procedure to obtain the derivatives of the function

$x(t)$. The reader can refer to Ramsay (2002, 2017) for more complete development of this model and the main ideas. To obtain the derivatives of the function $x(t)$ we use the procedure of smoothing an objective function. In the process of smooth functions, two competing objectives have to be reconciled. We require good fits to the observed data points, y_j, but we also require the fitted function to be smooth. Further, we aim to estimate the derivatives of our function, not just the levels. Therefore, we require our function to have reasonably smooth second derivatives as we use the first and second derivatives to analyze consumption. The following equation describes the fitting equation:

$$\mathbf{fitEq}_\lambda\left(x|y\right) = \sum_j \left[y_j - x\left(t_j\right)\right]^2 + \lambda PEN_4\left(x\right), \tag{5.2}$$

where,

$$\mathbf{PEN}_4\left(x\right) = \int \left\{D^4 x(s)\right\}^2 ds = \|D^4 x\|^2$$

The phase plane plots presented in the next session are based on eq. (5.2) developed in the original papers (Ramsay, 2002 & 2017).

5.3.2.2 The Henderson moving average filter

Having presented the phase plane plots and how seasonality influences consumption behavior and determines different periods of habits, we aim to remove the major seasonal components from our detrended data. In other words, we apply the 13-term moving average filter to our detrended data and obtain a smoother index without the loss of significand turning points of economics. We use the Henderson (1916) method in this respect. This method is described by the expression "graduation by adjusted average ".

A graduated value of a function is determined by adding together a number of adjacent terms each multiplied by a numerical factor. The graduated value is determined by fitting an algebraic function of the third degree to the ungraduated values. Let the algebraic function takes the following form:

$$a + bx + cx^2 + dx^3$$

where, a is the graduated value of the ungraduated value (U_0) of the function we need to adjust. Let also W_x denote the weight to be assigned to the term U_x for all the values of x. We have the following four equations in a, b, c and d:

$$\sum_{-n}^{+n} (a + bx + cx^2 + dx^3) W_x = \sum_{-n}^{+n} W_x U_x,$$

$$\sum_{-n}^{+n} (ax + bx^2 + cx^3 + dx^4) W_x = \sum_{-n}^{+n} xW_x U_x,$$

$$\sum_{-n}^{+n} (ax^2 + bx^3 + cx^4 + dx^5) W_x = \sum_{-n}^{+n} x^2 W_x U_x,$$

$$\sum_{-n}^{+n} (ax^3 + bx^4 + cx^5 + dx^6) W_x = \sum_{-n}^{+n} x^3 W_x U_x.$$

We define $\sum_{-n}^{+n} x^r W_x U_x$ as s_r and the equations take the following form:

$$s_0 a + s_1 b + s_2 c + s_3 d = \sum_{-n}^{+n} W_x U_x,$$

$$s_1 a + s_2 b + s_3 c + s_4 d = \sum_{-n}^{+n} W_x x U_x,$$

$$s_2 a + s_3 b + s_4 c + s_5 d = \sum_{-n}^{+n} W_x x^2 U_x,$$

$s_3a + s_4b + s_5c + s_6d = \sum_{-n}^{+n} W_x x^3 U_x.$

We take for the graduated values a, b, c, d:

$a = h\sum_{-n}^{+n} W_x U_x + j\sum_{-n}^{+n} W_x x U_x + k\sum_{-n}^{+n} W_x x^2 U_x + l\sum_{-n}^{+n} W_x x^3 U_x$

$= \sum_{-n}^{+n} (h + jx + kx^2 + lx^3)\, W_x U_x$

We designate $(h + jx + kx^2 + lx^3)\, W_x by V_x$ and let U_0' denote for the graduated value of U_0. So, provided h, j, k and l are determined, we have:

$U_0' = \sum_{-n}^{+n} V_x U_x$, where,

$\sum_{-n}^{+n} V_x U_x = 1$

$\sum_{-n}^{+n} V_x x U_x = 0$

$\sum_{-n}^{+n} V_x x^2 U_x = 0$

$\sum_{-n}^{+n} V_x x^3 U_x = 0$

We assume that all the values of W_x are positive and symmetrical about W_0, so that $W_x = W_{-x}$

The four equations reduce to:

$s_0a + s_2c = \sum_{-n}^{+n} W_x U_x,$

$s_2b + s_4d = \sum_{-n}^{+n} W_x x U_x,$

$s_2a + s_4c = \sum_{-n}^{+n} W_x x^2 U_x,$

$s_4b + s_6d = \sum_{-n}^{+n} W_x x^3 U_x.$

We see that a appears only in two equations. Following the same procedure and assuming that V_x values are also symmetrical, we have:

$V_x = (h + kx^2)\, W_x$

Then the method determines the relative weights which would produce certain summation formulas. The investigation shows that in order that W_x should always decrease as x increases numerically. In case the values of V_x are not symmetrical the summation will vanish where $V_x = 0$.

Furthermore, for the smoothest possible graduated series with a graduation formula extending from -n to n inclusive, for the values of x, the relation of the differentials of the form is as follows:

$$\Delta^6 V_{x-3} = \kappa + \lambda x + \mu x^2 + \nu x^3$$

Thus, it is proved that V_x must be an algebraic function of not more than the nineth degree and as V_x vanishes for six values of x the final form is equal with the initial formula. The reason behind the fact we obtain the same formula is that only relative weights affect the final result. *"We thus see that the smoothest possible graduated series from a formula of given range is obtained by assigning the smoothest possible series of weight to the successive terms."* (Henderson 1916:48).

5.4 Empirical results

In this paper, we examine the rate of change of the consumption index at any point as we find it more interesting than its actual size. We pay particular attention to a construct called the phase-plane plot, which plots the acceleration of the index against its rate of growth (velocity). Our ability to construct phase-plane plots at all depends on the possibility of differentiating functional data. The estimates of the first three derivatives in Equation (2) are used to discover how the derivatives are interrelated. A plot of this nature is called a phase-plane plot. It plots the second derivative (D2), or the curvature of the fitted function against its first derivative (D1), or slope. Velocity lies on the X axis and shows the action of the first derivative and acceleration lies on the Y axis and shows the action of the second derivative of consumption. In other words, the 1st derivative is a measure of how fast consumption is changing, and the 2nd derivative shows how fast consumption speed changes or the rate of change of velocity. The phase-plane plot shows consumption energy exchange nicely, with potential energy being maximized at the extremes of Y and kinetic energy at the extremes of X.

In economics, potential energy corresponds to the available capital, wealth, or income that consumers spend. In general, it may mean the resources that are at hand to bring about some economic activity. Kinetic energy corresponds to the consuming process in full swing. Consumers increase the rate of growth as their spending increases or decreases.

Figure 5.3 shows phase-plane plots for 1939, 1959, 1979 1999 to examine how the patterns change over several years.

Briefly, the cycles shrink over the years and the biggest cycle of winter begins from the middle of September instead of one month later.

In figure 5.4 we see how seasonality has smoothed out through years. From 1939 and after the II World War the consumption was very high mainly in December compared to the other months, but it is slowly decreasing. From the 1980s to the 1990s we have the greatest normalization of seasonality, which began to increase again with the fall-winter cycle appearing to prevail once more.

Figure 5.3: Phase-plane plots for the years: 1939, 1959, 1979, 1999.

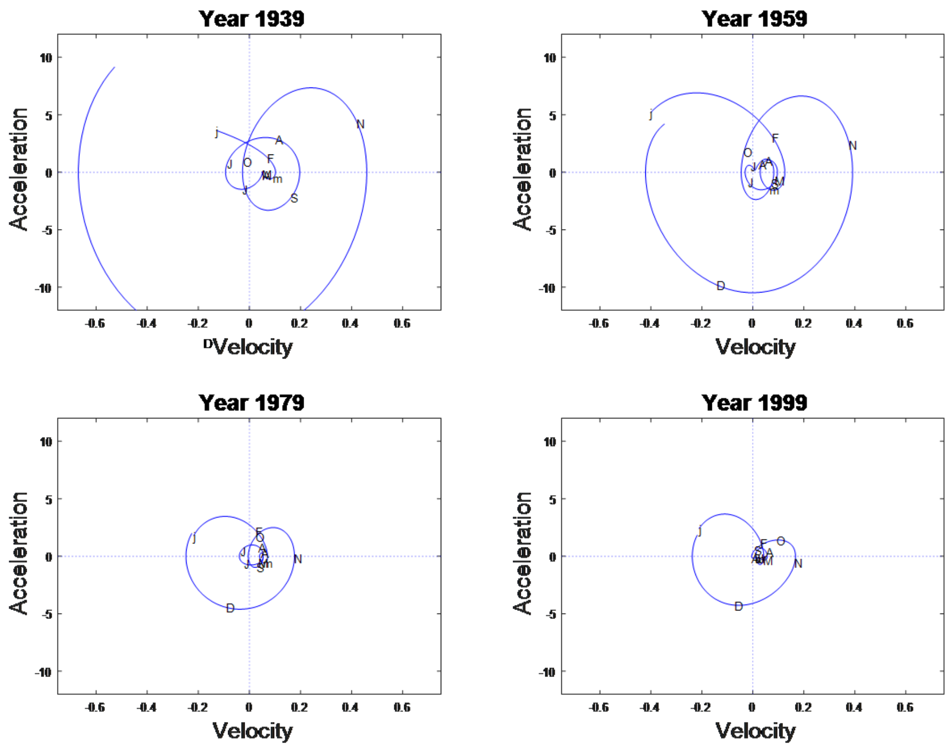
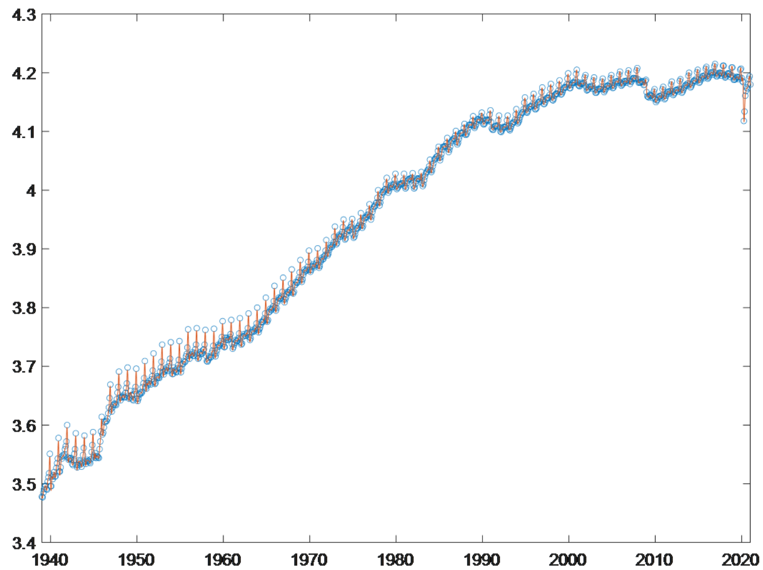


Figure 5.5 shows the cycles of consumption during a crisis or structural changes of the economy. In 1945 (the end of World War II) the cycle is moving to the right. Consumption is in full swing in November indicating the high increase in growth rate.

In figure 5.6 two small cycles shape in spring and summer while the big season starts in October and includes the whole winter. The whole year corresponds to three cycles. Fig. (5.6) presents the years from 1964 to 1967 and fig.(5.7) the years from 2008 to 2011. We see that in the early years the big cycle begins in October through January, while the late years (2008-2011) extends from September

Figure 5.4: The logarithm of the monthly consumption index

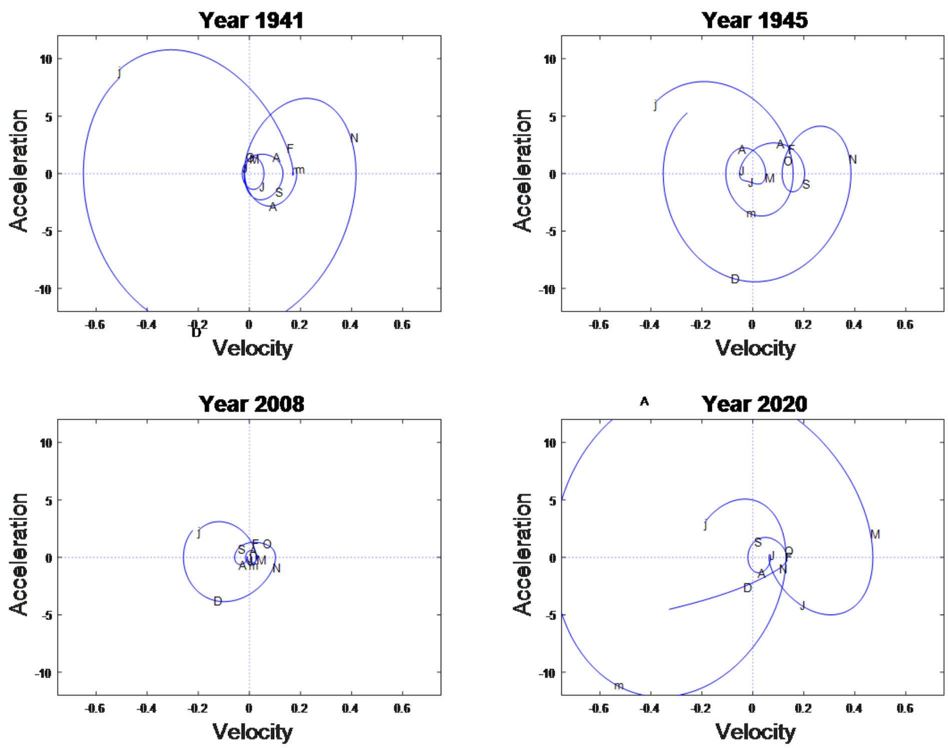


Cycles indicate the months.

passing through October, November, December, January. Fall and winter represent two seasons in one big cycle. March, May, and July are near zero in both periods.

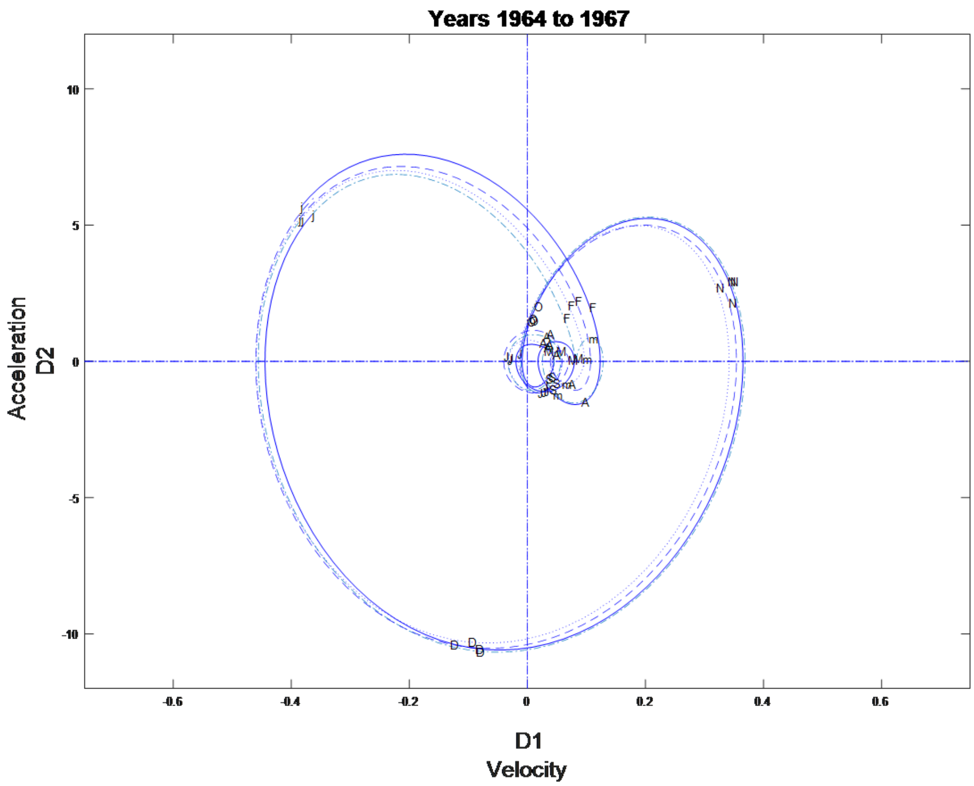
In fig. 5.7 the cycles shift to the right as the overall slope becomes more positive indicating that the economy recovers after the 2008 financial crisis. There is a dramatic reduction in the volatility of the derivatives over the years and the cycles shrink. The summer cycle is normalized and drifted away from the winter, while by the end of August the big cycle of the winter period begins. There is a cusp through June, July, and August near the point at which both derivatives are zero. Consumption is stuck. Next, we present the phase plot of recent years in fig. 5.8. In 2020 the volatility of the derivatives has extremely increased.

Figure 5.5: Phase-plane plots for the years: 1941, 1945, 2008, 2020



Notice in fig. 5.6 that the cycles shift slightly to the left. We have reported that the edges of the horizontal line mark the maximum of mobility. How steep is the change of curve? So here we see that in a period of full growth the curve becomes steeper in its descent slowly. At the same time, the dynamics are reduced. The cycles shrink in height. We can say that consumption reduces local lows while local lows are maintained during periods of high consumption. In other words, consumers are beginning to adopt the habit of shopping altogether at certain times, such as on the two days of Thanksgiving – Black Friday and Cyber Monday, while other cycles are beginning to show negative patterns. That is, we see that the small cycles have

Figure 5.6: Phase-plane plots for the years 1964-67

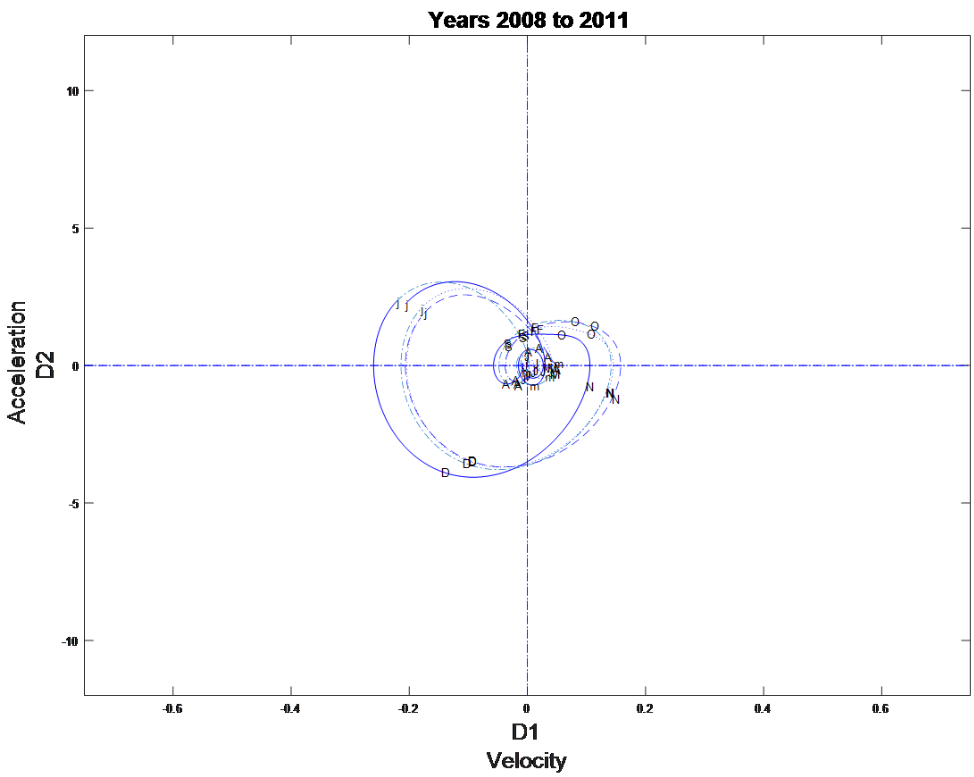


A phase plane plot of the first (D1) and the second (D2) derivatives of the smoothed log consumption index. The solid line is for 1964, the dash-dot line is for 1965, the dotted line is for 1966, and the dashed line for 1967.

a more significant shift to the left than those of large ones. This means that the curve becomes steeper in its descent, meaning the deceleration speed increases. We observe the opposite in Figure 5.7, where the cycles shift to the right, while again the dynamics remain the same. During this time, we had a financial crisis, since then market accelerates to find its balance. This means that the market is slowing down after a great deal of growth, increasing its speed after a crisis.

In 2019 (fig. 5.9) consumption is on the decline, while February forms a local

Figure 5.7: Phase-plane plots for the years 2008-9



A phase plane plot of the first (D1) and the second (D2) derivatives of the smoothed log consumption index. The solid line is for 2008, the dash-dot line is for 2009, the dotted line is for 2010, and the dashed line for 2011.

minimum, similar to that of September. Shortly before March, a small consumption cycle begins. In March, the growth rate is slightly increasing. The market reaches its peak in May. Consumption is doing the biggest push to stop in July where it has already reached its greatest potential energy. From there, the curve goes down sharply. In September, the biggest cycle of consumption begins. Consumers start shopping and consumption is increasing. In the middle of October, the growth rate of consumption is the highest of the year. Then, the growth rate is falling as the

Figure 5.8: Phase-plane plots for the years 2017-20

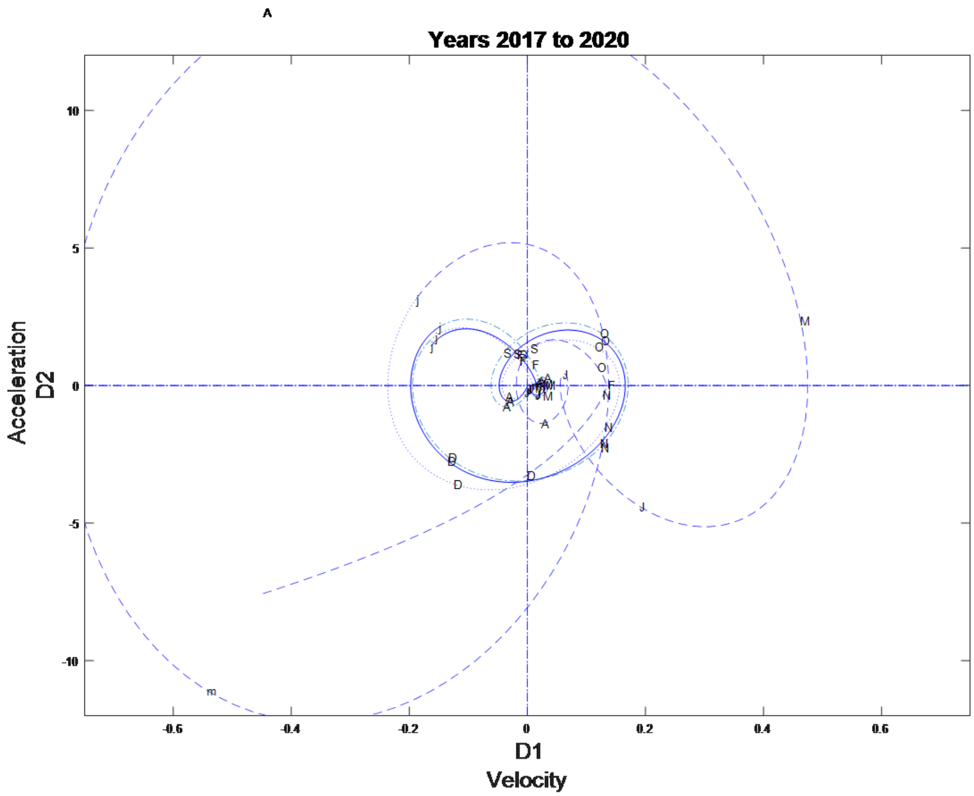
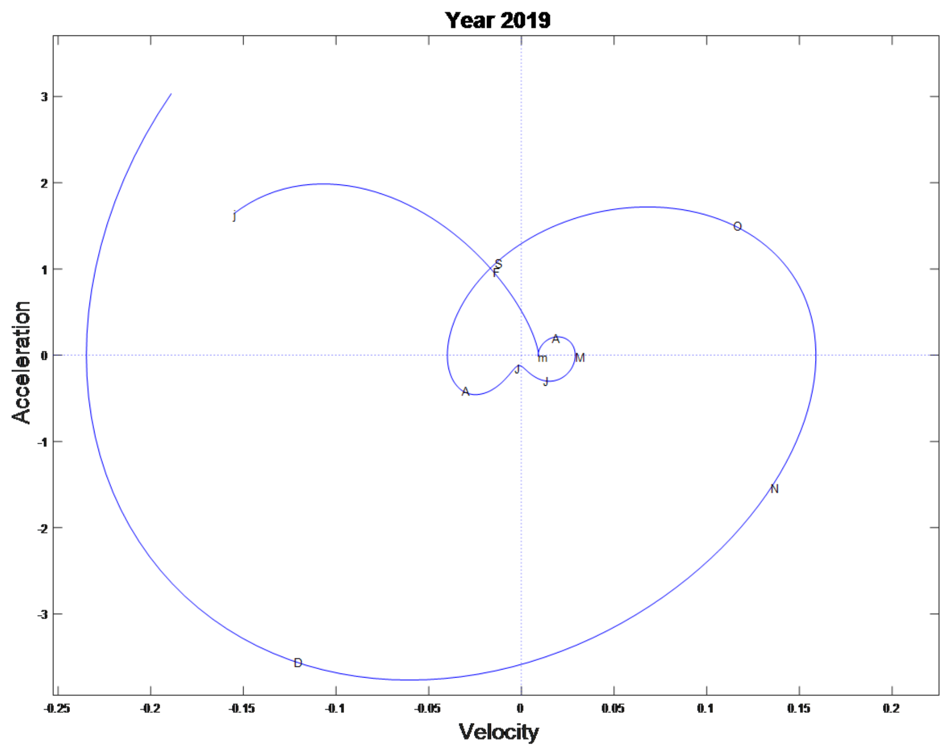


Fig. 5.8 shows the phase plane plot of the first (D1) and the second (D2) derivatives of the smoothed log consumption index. The solid line is for 2017, the dash-dot line is for 2018, the dotted line is for 2019, and the dashed line for 2020.

scale increases. Consumption growth is high just before December, in the days of Thanksgiving and Black Friday. Towards the Christmas holidays, consumption's kinetic is maximized on the decline. January 2020 finds the market at a slightly lower level than the previous year.

It is noteworthy that the point of maximum dynamics does not change in contrast to that of minimum dynamics, meaning the level of capital depletion changes.

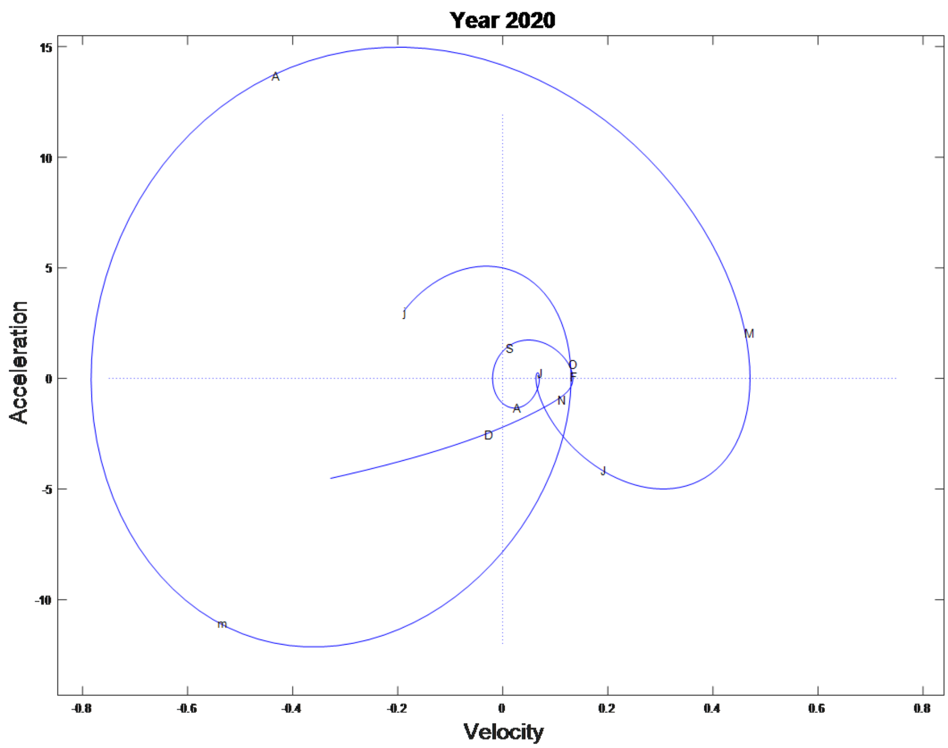
Figure 5.9: The phase plot of 2019



What is happening now? Figure 5.10 shows the 2020 cycle and figure 5.11 the smoothing variation of the index from 2018 to 2020.

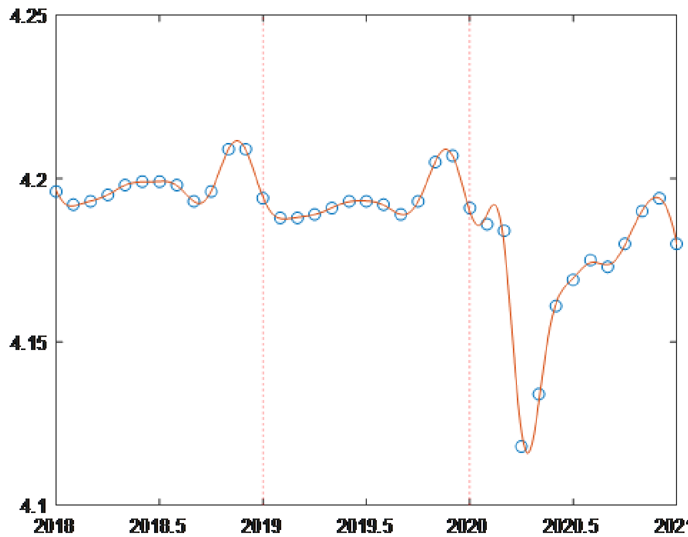
Since last year's Black Friday, the consumption race started to fall in January 2020 until the beginning of February, when the cycle of the winter season ends like every year. At this point, the consumer's money has been spent. Another cycle started in February with a relatively high growth rate. Around the middle of February, it showed its maximum potential energy and then consumption began to fall. Since mid-March, which coincided with the lockdown, the growth rate has been rising while the consumption line is falling. We observe the sharp drop in

Figure 5.10: The phase plot of 2020



consumption which shows the maximum acceleration from the lockdown and then where its lowest dynamics is signalled. Consumption begins to recover in April. The growth rate is high. What characterizes 2020 is the sudden dip of consumption just before March at a very high speed from the middle of that month and onwards. The growth rate is the highest that has been noted as shown in fig. (5.10). May is the month when the economy is accelerating forward and seems to want to regain lost ground. This high-speed stops in June. The line continues to increase at a low rate and stopped in August. October, also, shows almost zero energy and the peak of Black Friday is not what the market expected.

Figure 5.11: The seasonal variation of 2018, 2019, and 2020.



Note: The blue cycles correspond to the months of the year, starting from January to December.

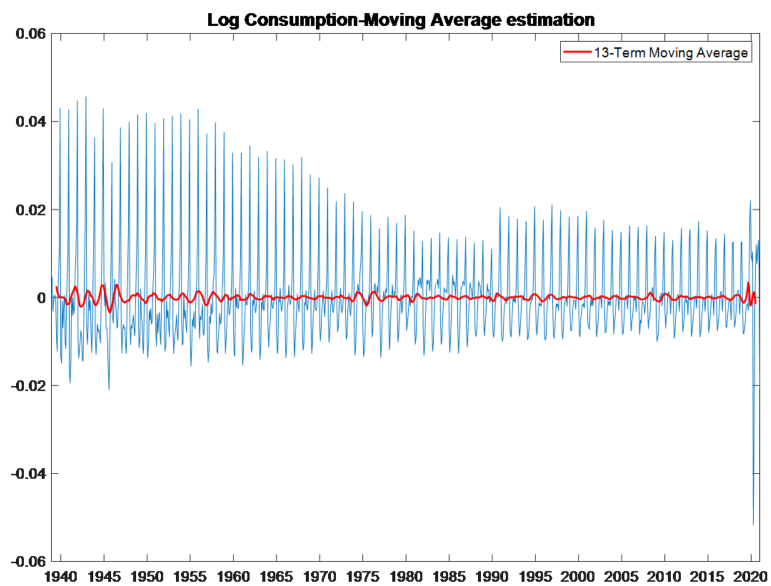
Having presented the phase plane plots and how seasonality involves in consumption behavior and determines different periods of habits, our research objective is to detect permanent innovation in GDP. By subtracting the trend component from the unseasonal adjusted data, we obtained the seasonal trend in the first place. Then we eliminate the huge oscillations of seasonal trend by using a centered moving average with a length equal to the length of the seasonal cycle. We apply the 13-term moving average filter to seasonal trend and obtain a smoother index without the loss of significant turning points of economics. That is, while seasonality is very useful in constructing the annual cycles, as an index it contains very large oscillations and we cannot look at it further and find its sensitivity to crises, economic or political changes, or at any point. Even the reader can discern the dates that interest him and see the behavior of consumers. We naturally expect a reduction in consumption when the economy is facing a recession.

As our data exhibits a strong seasonal component with periodicity 12, we apply the 13-term moving average filter for estimating the trend-cycle. We aim to reduce the noise and maintain the original signal in the best way. The weight for the first and last terms is 1/24 and for the interior terms is 1/12. Weights slowly increase and then slowly decrease, resulting in a smoother curve than another with full weights. Observations at the beginning and end of the series are lost. The moving average has window length 13, so the first and last 6 observations do not have smoothed values.

In Figures 5.5 - 5.7 and 5.11 there is a surge in the index in the last part of each year, followed by a low period starting at the end of January and the beginning of February. Consumers spend more at the beginning of fall and during Thanksgiving and Black Friday. This seasonal variation is also affected by changes in the economy at various time scales, and so we also want to study how the within-year variation evolves.

Perhaps the evolution of seasonal variation can tell us something interesting about how the economy evolves in normal times, and how it reacts to times of crisis and structural change. Seasonal variation in recent years shows bigger than that in the 80s and 90s but smaller than the years around the II World War and the proceedings years. We remove from the index of consumption the nonseasonal trend by using the functional data analysis methodology to get the seasonal trend.

Figure 5.12: Seasonal Trend & 13-term moving average of consumption

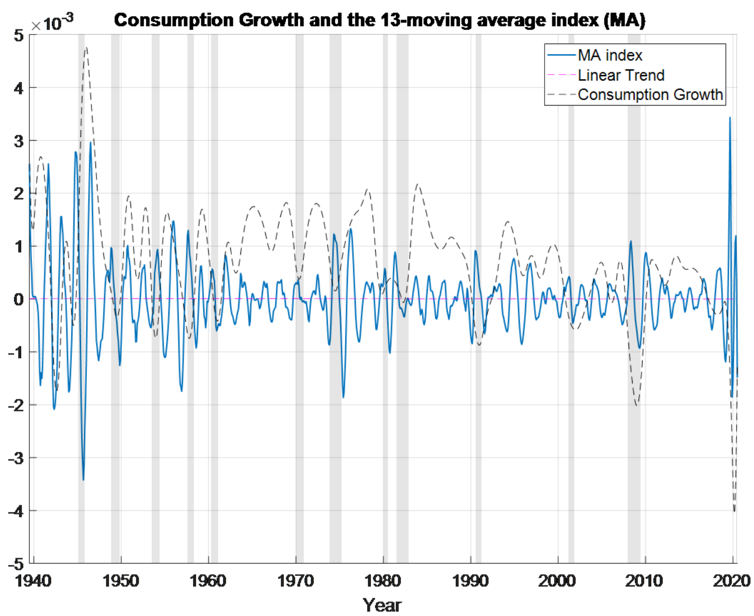


The index of a 13-term moving average is the red line and the seasonal trend is the blue line.

The seasonal fluctuations in consumption are large and regular. It may be preferable to smooth the seasonality using trend-cycle filters, which suppress as much as possible the irregulars without affecting the cyclical component. Many researchers (Kenny and Durbin 1982; Moore, Box, Kaitz, Stephenson, and Zellner 1981; Dagum and Laniel 1987) suggest the estimation of trend-cycle variations instead of seasonal adjustment.

We use the 13-moving average filter pioneered by Henderson (1916) for monthly time series to do so. It is used in preference to simpler moving averages because it can reproduce polynomials of up to degree 3, thereby capturing trend turning points. In moving average procedure, the first and last points of the consumption index cannot be smoothed and therefore are removed from the series. Figure 12 presents the line of the seasonal trend and the estimated 13-term Moving Average. Additionally, figure 13 presents consumption growth and the moving average index of consumption. The main turning points follow the same pattern in both series but the later provides much more information than the consumption growth about consumption behavior which is obviously our main objective.

Figure 5.13: Consumption growth and MA index during recessions



Consumption growth obtained by the log difference of the monthly time series of consumption from July of 1940 to July of 2020. The solid blue line represents the MA index and the black dashed line represents the Consumption growth.

Figure 5.13 shows MA and the recessions. Shaded areas represent years in a recession. In expansions consumption shifts up and in recessions shifts down. During the recessions of 1960, 1970, 1980, and 2002, consumption fluctuations are not very intensive. But high fluctuations occurred in 1945 and 1975.

The traditional view of consumption over the business cycle implies that when output declines, consumption declines but is expected to recover; thus, it implies that there are predictable movements in consumption. Hall's extension of the permanent income hypothesis, in contrast, predicts that when output declines unexpectedly, consumption declines only by the amount of the fall in permanent income as a result it is not expected to recover (Romer, 1996).

5.5 Discussion of the results

Our results of the phase plane plots reveal the two largest shopping days—Black Friday and Cyber Monday as the days which growth rate of consumption takes the highest speed. After those days, although consumption increases, the rate decreases to reveal decreasing returns to scale. Towards Christmas the growth rate is not so high as one would have expected. Prior research (Swilley and Goldsmith, 2013) suggests that Black Friday represents the mall shopping and offers consumers an enjoyable shopping experience. Cyber Monday offers consumers a different experience to continue their weekend gift shopping as includes mostly online purchases. Interestingly, consumers on those days purchase gifts for Christmas. Retailers promote those days to do so, offering photos with Santa and many activities for children. Hence, one explanation for the low speed of consumption rate during Christmas might be that consumers have already finished their shopping of Christmas gifts.

From our point of view the most important finding of this research is the connection of consumption rate with the economy. After a crisis the rate increases and vice versa. The CNBC Markets Editor, Patti Domm (The CNBC Journal 2021) supports that the economy's boom period is on the run following the lockdown in April 2021. Particularly, she states that 2021 could be the strongest year since 1984. Thus, consumers, producers and policymakers must be vigilant for inflation, something the economy has succeeded to fight since 2000.

Further, consumption responds much more strongly to permanent than to transitory movements of income (Halls et al., 1982). Therefore, the high variation in figure 13 reflects the immediate response of consumption to changes in permanent income. In other words, permanent income did not change in the recessions of low variation in consumption. Figure 13 presents a low variation of consumption in the years 1960, 1970, 1980, and 2002.

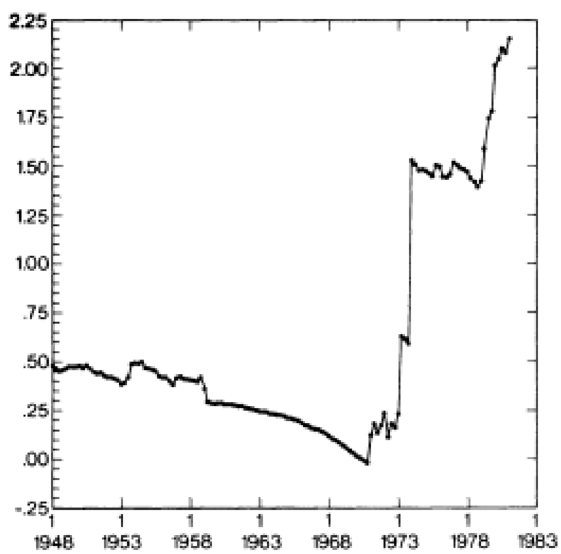
But what were the characteristics of these recessions, that consumers did not treat them as recessions, that is, as periods of uncertainty, so that consumption does not show the fluctuations one would expect? A feature of these recessions is that they were followed by long periods of growth. The recession of 1960 preceded the third-longest economic expansion in U.S. history, from February 1961 until the beginning of the Recession of 1969–1970 in December 1969—to date, only the 1990s and post-financial crisis (2009-2020) have seen a longer period of growth. Therefore, the possible ability of families to distinguish innovations in lifetime income from innovations in transitory income may lead them not to react spontaneously. Otherwise, if they cannot make the distinction at all, they are forced to react equally to both innovations.

The US economy experienced negative growth during the last two quarters of 1990 and the first quarter of 1991. However, this period was preceded and followed by positive growth of 0.7% on average, which was low enough, for example, compared to 2.2% in 1973. (Blanchard, 1993). Recessions are associated with large negative ”consumption shocks,” such that these shocks have long-lasting effects on output. This explains why the recovery – after the 1990-91 recession – has been so slow.

For the 2008 recession, Nardi and Benson (2011) find that the decline in assets can explain 1/3 of the gap between actual and potential consumption, while declines in permanent income expectations explain the other 2/3 of the gap.

For the recessions between the early 1960s to 1970s, consumption fluctuations seem to be mitigated perhaps due to the fall of imported oil price, as illustrated in figure 14 (Darby, 1982:783). One possible explanation for the mild consumption fluctuations is that oil prices apparently remained low and so permanent income was not affected. Later on, with the sharp rise of oil price, consumption fluctuations increase rapidly.

Figure 5.14: Logarithm of the U.S. real price of imported oil.



Source: Darby, 1982, pp. 783, figure 1.

The 2001 recession was different and relatively short compared with the previous recessions. Consumption seems unaffected by the 2001 recession as its fluctuations presented in figure 13 remain the same with the preceding years where no recession occurred. The mildness of the 2001 recession is reflected in consumption fluctuations and implies that the permanent income didn't change, given the jarring economic developments that preceded it. According to the NBER's Business Cycle Dating Committee, the average recession lasted 11 months during the post-World War II period. The 1980 recession was the shortest and has lasted 6 months, while the longest have lasted 16 months (1973-75 and 1981-82). Eliminating these extremes shows that recessions tend to average about 9 months. Hence, the 2001 recession, was shorter than the 9-month average (Kliesen, 2003). Further, by allowing the country to borrow in 'bad' times and lend in 'good' times domestic households smooth their consumption path over time. *'This 'counter-cyclical' role of world capital markets is particularly important if shocks are temporary in nature.'* (Agenor, 2003: 1092). Consumption fluctuations seem to differ according to the persistence of the shock and confirm the permanent income hypothesis that consumption is less volatile than income, if fluctuations in the permanent income are a relatively small part of overall income volatility, and vice versa.

5.6 Summary and conclusions

This paper employs the FDA method to explore consumption seasonality which is regarded as a valuable component. We construct phase-plane plots that are useful ways to inspect seasonality. The examination of the phase-space plots over time indicates the substantial variation in the dynamical processes underlying consumption behavior over time. Consumers consider two major holiday shopping days, i.e., Black Friday and Cyber Monday, by increasing consumption growth. On the other side, consumption growth begins to fade toward Christmas. Particularly in our characteristic seasonal pattern captured by our model, one period of acceleration occurs through the months of October to December and a second period from March to May. Spring and summer involve a cusp in the phase plane diagram that represents low acceleration and velocity. In general, it follows a parallel pattern with that of production (see Ramsay and Silverman, 2002). When production ends, consumption starts, confirming equilibrium business cycle models, that consumption follows the opposite direction from labour supply. Moreover, the market is slowing down after a great deal of growth, as it did after World War II, increasing its speed after a crisis. Economists support that a deep recession tends to be followed by a strong recovery, but a mild recession tends to be followed by a mild recovery (Kliesen, 2003). By employing the 13-term filter which possesses good properties to detect the upcoming turning points of the series we confirm not only that consumption growth follows the business cycle but it also detects the characteristics of the recessions.

Our findings may imply that this harmony between the pattern of consumption and production may simply indicate the power of production system and not consumption preferences. Scitovsky (1990) explains the variability of consumer tastes because they are easily influenced by example, custom, and suggestion, and constantly changed in the life time or modified by changing prices and depend on the availability of goods. It is obvious that, producers have greater power and influence than that of consumers. Besides, in 2014 the advertising industry is an essential stimulus to the U.S economy as it contributes 19 percent to the nation's GDP (HIS Economics and Country Risk). Therefore, understanding the harmony between consumption and production patterns is crucial for economists in order to have a better judgment of how well the economy performs, and to develop and recommend policies to improve its performance.

In addition, our findings are in line with the forthcoming rapid increase in consumption predicted by economists coinciding with the end of the recent pandemic. We conclude that the new challenge for the economy is to manage to restrain inflation that inevitably follows. A challenge that does not always succeed.

5.7 References

Agenor, P.R. 2003. Benefits and Costs of International Financial Integration: Theory and Facts. *The World Economy* 26(8), 1089–1118.

Attanasio, O. 1998. "Consumption demand." Working paper no. 6466 (NBER, Cambridge, MA) and The handbook of macroeconomics (North-Holland, Amsterdam).

Barsky, R.B., and J.A. Miron. 1989. "The seasonal cycle and the business cycle." *Journal of Political Economy* 97: 503–535.

Blanchard, O. 1993. "Consumption and the Recession of 1990-1991." *The American Economic Review* 83 (2): 270-274.

Campbell, J.Y., and A.S. Deaton. 1987. "Is Consumption Too Smooth?" NBER Working Paper No. 2134.

Campbell, J.Y., and N.G. Mankiw. 1987. "Permanent Income, Current Income, and Consumption." NBER Working Paper No. 2436

Canova, F., E. Ghysels. 1994. "Changes in seasonal patterns: are they cyclical?" *Journal Economic Dynamics and Control* 18: 1143–1171.

Christiano, L., and M. Eichenbaum. 1990. "Unit Roots in Real GNP: Do We know and Do We Care?", Carnegie Rochester Conference Series on Public Policy 32: 7-61.

Dagum, E. B., and N. Laniel. 1987. "Revisions of Trend-Cycle Estimators of Moving Average Seasonal Adjustment Methods." Journal of Business & Economic Statistics, (5)2, 177-189.

Dang, C., (Frank) Li, Z., & Yang, C. 2018. Measuring firm size in empirical corporate finance. *Journal of Banking & Finance* 86, 159–176.

Darby, M.R. 1982. "The Price of Oil and World Inflation and Recession." *The American Economic review* 72(4): 758-791.

Dijk V., B. Strikholm, and T. Teräsvirta. 2003. "The effects of institutional and technological change and business cycle fluctuations on seasonal patterns in quarterly industrial production series." *The Econometrics Journal* 6(1): 79.

Donadelli, M., & Gufler, I. (2020). Consumption Smoothing, Risk-Sharing, and Financial Integration. *The World Economy* 00, 1-45.

Ghysels, E. 1994. "On the periodic structure of the business cycle." *Journal of Economic and Business Statistics* 12 (3): 289–298.

Hall, R. E. and F.S. Mishkin. 1982. "The Sensitivity of Consumption to Transitory Income: Estimates from Panel Data on Households." *Econometrica* 50 (2): 461-481.

Harvey A.C., and A. Scott. 1994. "Seasonality in dynamic regression models." *Economic Journal* 104: 1324-1345.

Henderson, R. 1916. ”Note on graduation by adjusted average.” *Transactions of the Actuarial Society of America* 17: 43–48.

Hylleberg, S., Jorgensen, C., and N.K., Sorensen. 1993. ”Seasonality in macroeconomic time series.” *Empirical Economics* 18: 321-335.

Kliesen, K. L. 2003. ”The 2001 Recession: How Was It Different and What Developments May Have Caused It?,” *Federal Reserve Bank of St. Louis Review* 85 (5): 23-38.

Kenny, P. B., and J. Durbin, 1982. ” Local Trend Estimation and Seasonal Adjustment of Economic and Social Time Series.” *Journal of the Royal Statistical Society* 145(1): 1-41.

Kumar, B.K. and, Rajan, G.R. and L. Zingales. 1999. What Determines Firm Size? NBER Working Paper No. 7208.

Kuznets, S. 1946. *National income: A summary of findings.* National Bureau of Economic Research, New York.

Lettau, M., and S. Ludvigson. 2004. “Understanding Trend and Cycle in Asset Values: Reevaluating the Wealth Effect on Consumption.” *American Economic Review* 94: 276–99.

Lucas, E.R., Jr. 1977. ”Understanding Business Cycles.” Carnegie-Rochester Conference Series, vol. 5.

Moore, G.H., Box, G.E.P., Kaitz, H.B., Stephenson. J.A. and A. Zellner. 1981. Seasonal Adjustment of the Monetary Aggregates: Report of the Committee of Experts on Seasonal Adjustment Techniques, Washington, D.C.: Board of Governors of the Federal Reserve System.

Nardi, M., French, E. and D. Benson. 2011. Consumption and the Great Recession. Working Paper 17688. National Bureau of Economic Research, Cambridge.

Neusser, K., 1992. ”Intertemporal nonseparability, liquidity constrains, and seasonality of aggregate consumer expenditures: An empirical investigation.” *Empirical Economics* 17: 363-382.

Piketty, T. 2014. *Capital in the Twenty-First Century.* The Belknap Press of Harvard University Press, Cambridge, Massachusetts London.

Ramsey, J. B and S. Keenan. (1996). Multi-country Tests for the Oscillator Model with Slowly Varying Coefficients. *Journal of Economic Behavior and Organization* 30(3), 383-408.

Ramsey, J.B., and L. Cheng-Ping. 1993. An exploratory analysis of the growth rates of economic and financial data. *Ricerche Economiche* 47, 31–64

Ramsay, J.O, B.W. Silverman. 2002. *Applied Functional Data Analysis.* Springer. New York, ch. 3.

Ramsay, J.O, J.B. Ramsey. 2002. Functional data analysis of the dynamics of the monthly index of nondurable goods production. *Journal of Econometrics* 107(1-2), 327-344.

Romer, D. (1996). *Advanced Macroeconomics*, Fourth edition, Mc Grow.

Scitovsky, T., 1992. ”The Joyless Economy”. *The Psychology of Human Satisfaction.* Oxford University Press, New York/Oxford.

Swilley, E., & R. E. Goldsmith. 2013. Black Friday and Cyber Monday: Understanding consumer intentions on two major shopping days. *Journal of Retailing and Consumer Services* 20(1), 43-50.

Wuger, M., and G. Thury, G. 2001. ”The treatment of seasonality in error correction model as unobserved component: a case study for an Austrian consumption function.” *Empirical Economics* 26: 325-341.

Chapter 6

Conclusions

The main objective of this dissertation was to provide evidence about consumption behavior in US over a long period through four essays. The first essay presented the Keynesian consumption function including the 10-year constant maturity rate as an important determinant of consumption. Using both cointegration and error-correction analysis we provide evidence that housing wealth impact lasts more than that of financial wealth and personal income. Particularly, the estimated income elasticity varies between 0.62 and 1.08, depending on the model specification and the estimated housing wealth elasticity varies between 0.07 and 0.12. Financial wealth and the long-term interest rate do not seem to affect consumption significantly in the long run. Generally, housing wealth proved to be a more significant determinant of consumption than financial wealth in the long run.

Besides, the long-run causality analysis also shows that sudden shocks arising from variables other than income, i.e., financial wealth, consumption and the 10-year treasury, have an immediate effect on housing but the speed at which will eventually be offset is slower compared to the other systems where the dependent variable is consumption, financial wealth, income or 10-year treasury. Finally, the high significance of housing wealth and its linkage with the 10-year treasury rate in most specifications, confirms that developments in the housing market have a major and predictable effect on real economic activity.

In the second essay we aimed to insert uncertainty in our analysis of household consumption. As we proved that housing wealth is more important in driving consumption preferences than financial wealth and income, we suspect that housing wealth uncertainty should also play a more important role in our analysis of consumption. Obviously, uncertainty has its own role to play in the economy but how uncertainty affects households was our main motivation. We constructed three uncertainty indexes for consumption, housing wealth and financial wealth (the variables that consist the keynesian function from the first essay). First, we preferred to construct the rates of these variables with personal income. Based on these rates we measured the three uncertainties by estimating a GARCH-DCC model. Then, we also use two other popular uncertainty indices, EPU and WUI to obtain the impulse responses of consumption, housing wealth and financial wealth to uncertainty shocks.

We find that the different types of uncertainties reveal different impacts on these variables. Initially, a shock in the housing market decreases consumption and financial wealth in the long run and increases their uncertainties. Housing wealth uncertainty may increase consumption for a short period whereas depresses consumption in the long run. In contrast WUI and EPU have an immediate effect on household decisions which eventually is being offset. WUI is inefficient to transmit new information in housing wealth but efficient enough to shake consumption and household financial wealth only for a very short period. WUI, EPU and housing wealth uncertainty have different impact on macroeconomic variables as these types of uncertainty indices are constructed in a different way. Probably, our findings are related to the fact that household and business credit shocks affect output, consumption, investment, labour and house prices differently. Finally, our proxy of housing uncertainty seems to have a more persistent impact on personal consumption and financial wealth than that of EPU and WUI, indicating the different way of constructing and its accuracy as household uncertainty index.

The third essay was also devoted to uncertainty as the previous essay. However we take a different approach by treating the unpredictable events as the main source of uncertainty. Thus, we introduce a new uncertainty index for US using the Bayesian approach. This index is more sensitive to consumer spending and therefore reflects households' decisions, based on a very rich environment data. We find evidence that macroeconomic uncertainty shocks impose significant effects mostly on financial wealth hold by households. This wealth consists of corporate equities, mutual funds and pension reserves. On contrary housing wealth isn't affected by the same shock while has a small impact on personal consumption.

Further, we show significant heterogeneity in the size of uncertainty among the US states. First, we suggest their relationship with oil prices is an important source of uncertainty (those through which the pipelines pass have greater uncertainty). Second, it seems that the diversity of industries declines the uncertainty in each state and vice versa. We conclude that although the construction of the new financial service industries during the period 1975-2000 was for the favor of large economies of scale and scope they didn't achieve a safer diversification of risks. On contrary we support that their connection with other industries as business services raise the risks and uncertainty.

The fourth essay employed the functional data analysis (FDA) method to explore consumption seasonality which is regarded as a valuable component. We were curious to explore different paths than econometric suggests. For example, most researchers attempt to capture seasonality by means of seasonal dummies. However, if seasonal effects change gradually over time, this approach leads to dynamic misspecification and there is no general agreement on how this problem should be tackled (Harvey and Scott). Therefore, we treat seasonality as worth of study. For this purpose we constructed the phase-plane plots which are useful ways to inspect seasonality. The examination of the phase space plots over time indicates the substantial variation in the dynamical processes underlying consumption behavior over time. Consumers consider two major holiday shopping days Black Friday and Cyber Monday by increasing consumption growth. On the other side the growth rate of consumption is higher when the line is falling than when is increasing. Since 1980s consumers seem to increase their speed or in other words rush to end their shopping towards Christmas. In contrast the early years consumption formed its maximum level towards Christmas. Thus, our analysis showed the October effect. In mid-October the growth rate of consumption is the highest of the year, as the line is increasing. Traditionally the stock market decreases in mid October (i.e. the Monday, October 28, 1929, stock market crash was the biggest single-day drop, the October 19, 1987, crash, etc. (Schiller 2015)), and consumers seem to find buying opportunities. Particularly in our characteristic seasonal pattern captured by our model, one period of acceleration occurs through the months of October to December and a second period from March to May. Spring and summer involve a cusp in the phase plane diagram that represents low acceleration and velocity. In general, it follows a parallel pattern with that of production (see Ramsey, 2002). When production ends, consumption starts, confirming equilibrium business cycle models, that consumption follows the opposite direction from labour supply. Moreover, the market is slowing down after a great deal of growth, as it did after World War II, increasing its speed after a crisis. Economists support that a deep recession tends to be followed by a strong recovery, but a mild recession tends to be followed by a mild recovery (Kliesen, 2003). By employing the 13-term filter which possesses good properties to detect the upcoming turning points of the series we confirm not only that consumption growth follows the business cycle but it also detects the characteristics of the recessions.

By the end of the post–World War II Pax Americana (a long period of peace) fundamental transformations within employment systems emerged highlighted by a variety of macroeconomic and sociological forces. The start of macroeconomic changes (such as oil shocks or increases in price competition in 1974 and 1976) put pressure on the core sectors of the economy. These pressures were accompanied by a decline in protections for workers through labor market institutions, such as unions, minimum wage laws, and protective legislation. This shift from the postwar "age of security" to the "age of flexibility". (Kalleberg 2000) *Improvements in purchasing power and standard of living over the long run depend primarily on a transformation of the structure of consumption: a consumer basket initially filled mainly with foodstuffs gradually gave way to a much more diversified basket of goods, rich in manufactured products and services* (Piketty 2014: 66). The New Economy of 1990s highlighted the period of the expansion of computers and new technologies, and the rise and drop of stock market. Its implications were associated with income inequalities, the rise in job insecurity, more rapid job creation and destruction, a move away from long term employment towards short term contracts, and a general increase in managerial pressure on workers. (Temple 2002).

Equally, the evaluation of old economy firms declined in the financial market. The beginning of a wide market irrationality arose at that time, implying that financial market valuations rarely reflected expert profit forecasts (Bond and Cummins 2000). The new economy has encouraged many to revise the mean of future rates of productivity growth upwards, but also to emphasize that the degree of uncertainty has risen considerably. (Temple 2002).

In recent years the shocks and crises are more often than in the past. Consumers may learn to live with them. It would be worth of study to measure the growth rate of consumption at certain points of the phase plane plots using the functional data analysis to investigate how the fraction of consumption rate/ growth rate (c/g) evolves through the years and to compare with interest rates. What's the quantification of acceleration points and comparison with interest rates. How monetary policy reacts to various phases of accelerating consumption and vice versa.

Piketty (2014) supports that the law of the capital / income ratio tends over the long run toward its equilibrium level, represented by b=s/g (where s=saving rate and g=growth rate), provided that the average price of assets evolves at the same rate as consumption prices over the long run. Examples of extreme shocks as the world wars or the crisis of 1929 arose with the covid-19 indicating the extreme rates of consumption. Piketty (2014) states that the law $\beta = s/g$ does not explain the short-term shocks to which the capital/income ratio is subject, any more than it explains the existence of world wars or the crisis of 1929. Therefore, it would be a challenge to measure the same fraction from the view of consumption, including different types of crises as these of 2008 or covid-19.

Another issue for further investigation is the October effect, when the consumption rate is the highest of the year since the end of 1980. Many researchers support that in both developed and emerging markets calendar anomalies attract investors' attention to chase arbitrage opportunity in the markets and researchers' interest to investigate the movements of macroeconomic variables and give possible answers on its causation. Isiker, Ugurlu and Tas (2021) analyzed calendar effects for a group of 5 developed and 5 developing country indexes for the period between 1988 and 2016. October is inefficient [1] for all indexes in the stock market, indicating similar behavior with that of Monday (the stock markets are falling). Equally, towards Christmas consumption rate is the highest of the year as consumption line is falling. One explanation could be that investors sell their stocks during December for tax-loss purposes and repurchase them in January (Rossi (2015). Therefore, consumers consider October as an opportunity for shopping.

Finally, we' d like to mention the physiological sector that reinforces consumption. Schiller (2015) asked on a questionnaire, "Which of the following better describes your theory about the declines: a theory about investor psychology or a theory about fundamentals such as profits or interest rates?" A great proportion of investors picked a theory about investor psychology. Moreover, consumption rate is high in mid October and towards Christmas, when the consumption line is increasing and decreasing respectively. However, the rate is higher when the line is

[1] The market's efficiency is the ability of prices to reflect all currently available information.

decreasing than when it is increasing. Only in 1945, by the end of the II World War, when the United States became the world's dominant economic and military power (Hogan 1989), the rates look similar. Further, the rate lies at the extremes of the axis during a crisis, indicating massive reactions of consumption in bad times, confirming the psychological phenomenon that individuals react more intensively in bad news than in good news or otherwise losses are larger than gains (Tversky and Kahneman, 1991). Further, we suppose that as the market runs to find its balance after a crisis or a great deal of growth, we can predict how the market will behave, i.e. after a major crash. Therefore, we believe that a great deal of the feedback that reinforces consumption is due to psychological expectations rather than to an actual phenomenon.

6.1 References

Bond, S., & J.G. Cummins. 2000. ”The Stock Market and Investment in the New Economy: Some Tangible Facts and Intangible Fictions.” *Brookings Papers on Economic Activity* 2000(1), 61-107.

Harvey A.C., and A. Scott. 1994. ”Seasonality in dynamic regression models.” *Economic Journal* 104: 1324-1345.

Hogan, M.J. 1989. *The Marshall Plan: America, Britain and the Reconstruction of Western Europe, 1947-1952 (Studies in Economic History and Policy: USA in the Twentieth Century).* Cambridge, New York .

Isiker, M., Ugurlu, U. and O. Tas. 2021. ”Investigation of the Calendar Effect: Second-Order Stochastic Dominance Approach”. *Recent Applications of Financial Risk Modelling and Portfolio Management*. IGI Global.

Kalleberg, A.L. 2000. *Good jobs, bad jobs: The Rise of Polarized and Precarious Employment Systems in the United States 1970s to 2000s.* Russell Sage Fountation, New York.

Kliesen, K. L. 2003. ”The 2001 Recession: How Was It Different and What Developments May Have Caused It?,” Federal Reserve Bank of St. Louis Review 85 (5): 23-38.

Piketty, T. 2014. *Capital in the Twenty-First century.* The Belknap Press of Harvard University Press CAMBRIDGE, MASSACHUSETTS LONDON, ENGLAND.

Ramsay, J.O and J.B. Ramsay. 2002. ”Functional data analysis of the dynamics of the monthly index of nondurable goods production.” *Journal of Econometrics* 107 (1-2): 327-344.

Rossi, M. 2015. ”The efficient market hypothesis and calendar anomalies: a literature review.” *Int. J. Managerial and Financial Accounting* 7, 285-296.

Shiller, R.J. 2015. *Irrational Exuberance: Revised and expanded Third edition.* Princeton Editorial Associates Inc.

Temple, J. 2002. ”The assessment: The New Economy.” *Oxford Review of Economic Policy* 18(3), 241-264.

Tversky, A. and D. Kahneman. 1991. “Loss Aversion in Riskless Choice: A Reference Dependent Model.” *Quarterly Journal of Economics* 107(4): 1039-1061.