ESSAYS ON FINANCIAL AND HOUSING WEALTH EFFECTS ON CONSUMPTION AND THE ROLE OF CONSUMPTION-WEALTH RATIO ON STOCK RETURNS PREDICTABILITY

A thesis submitted for the degree of Doctor of Philosophy

by

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ABSTRACT

This thesis consists of three essays. The first and the second essays are related to the study of the wealth effects on consumption, while the third one studies how a proxy of the consumption-wealth ratio is able to predict excess stock returns.

The first essay, investigated in the second chapter, studies the long-run effects on consumption of financial and housing wealth in Italy and the UK, using quarterly data over the period 1972q4-2012q4, and two different methods of estimation. It also attempts to evaluate how financial and housing wealth effects evolved over the sample period via rolling exercises. The empirical results show that: i) total wealth effect on consumption is larger in the UK than Italy; ii) housing wealth plays no role in Italy, while it is significant in the UK; and iii) in both countries, financial wealth exerts a positive and significant impact on consumption of about the same magnitude. As for the dynamics of wealth effects, the related results show that while in Italy the housing wealth effect is insignificant over time, in the UK this kind of effect is relatively increasing over large part of the sample. Further, financial wealth effects in the two countries feature opposite trends over time: slightly increasing in Italy and declining in the UK.

The second essay, investigated in the third chapter, examines the long-run financial and housing wealth effects on consumption using panel annual data over the period 1970-2012 for 14 OECD countries. It applies recently developed nonstationary panel methodologies that assume cross-section dependence through common factor models. The analysis is repeated for two groups of bank-based and market-based economies. This essay offers three main results. First, both housing and financial wealth exert a positive and significant impact on aggregate consumption. Second, the housing wealth effect is shown to be larger in magnitude than the financial wealth effect for the sample of all countries as well as for the two groups of bank-based and market-based economies. Third, wealth effects tend to be higher in market-based economies than bank-based ones.

The third essay, investigated in the fourth chapter, examines the predictive ability of a macroeconomic indicator, denoted “cay_{it}”, for excess stock returns in a panel setting of 9 Euro countries, using quarterly data over the period 1988q1-2014q4. This indicator, regarded as a proxy for the logarithm of the consumption-wealth ratio, is the series of the residuals from an estimated long-run relationship between consumption, asset wealth and disposable income. The empirical analysis first focuses on the estimation of the cay_{it} series using a panel cointegration approach, which controls for cross-sectional dependence via a common factor structure. Afterwards, the analysis aims to estimate panel regressions to forecast excess stock returns using cay_{it} as a sole predictor, and along with other predictors. The empirical results point to predictability of future excess stock returns for the panel of 9 Euro countries, both in-sample and out-of-sample. Notably, in-sample results reveal that: i) cay_{it} affects positively and significantly future excess returns over each horizon ranging from 1 to 8 quarters; ii) its forecasting power increases over horizons. As for the out-of-sample predictions, results highlight that a model with cay_{it} outperforms two benchmark models: the constant expected returns benchmark and the autoregressive benchmark. Moreover, in line with in-sample results, the model that includes cay_{it} improves over horizons compared to the two benchmarks.

Dedicated to my husband

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Iris Meco

DECLARATION OF AUTHORSHIP

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PUBBLICATIONS AND CONFERENCES

A paper extracted from **Chapter 2** is published in *International Review of Financial Analysis* with the following details: Barrell, R., Costantini, M. and Meco, I. 2015. Housing wealth, Financial wealth, and consumption: new evidence for Italy and the UK. *International Review of Financial Analysis*, 42, 316-323.

Some material from **Chapter 3,** titled ‘‘Consumption, wealth effects and common factors: evidence from 14 OECD countries”, has been presented at The 48th Money, Macro and Finance Research Group Annual Conference, 7-9 September 2016, Department of Economics, University of Bath, UK.

I have presented **Chapter 2** and **Chapter 3** at the annual Doctoral Symposium, in 2015 and 2016, respectively, Department of Economics and Finance, Brunel University London, UK.

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CHAPTER ONE

1.1. INTRODUCTION

Since the life-cycle saving hypothesis by Ando and Modigliani (1963), a large number of studies has investigated the so-called consumption-wealth effect, that is the link between household wealth and consumption behavior. The literature on this topic has mainly focused on different impacts on consumption of diverse forms of wealth, and methods of estimation.

The study of different wealth effects on consumption is based on the idea that components of total wealth are not fungible and are associated with different features in terms of risk, collateral, liquidity and bequest motive (Case et al., 2005). Consumers may also attach certain psychological factors to certain assets whereby some are considered more convenient to be used for current expenditures (e.g. stocks), while others (e.g. residential properties, pension funds) are considered more appropriate for long-term savings (Thaler, 1990).

The literature has predominantly tried to disentangle the relative size of housing and financial wealth effects on consumption. However, there is still no full consensus on how housing wealth effect differs from financial wealth effect. Researchers have always considered important the role exerted by financial wealth to understand movements in consumer spending, and episodes of sharp swings in stock market wealth over the last two decades have led to a revived interest in this field. Comparatively, the role of the housing wealth has been largely emphasized only more recently, as a consequence of striking increases of house prices since the late 1990s in several industrialized countries, and deregulation of mortgage markets.

In order to measure the effects of wealth components on consumption, some empirical works have used asset prices to proxy the level of the relative wealth components in traditional consumption functions (see e.g. Boone et al., 1998; Ludwig and Sløk, 2004; Dreger and Reimers, 2012), while others have used wealth data (see e.g. Davis and Palumbo, 2001; Mehra, 2001; Case et al., 2005; Slacalek, 2009; Carroll et al., 2011a; De Bonis and Silvestrini, 2012).

In terms of econometric techniques, wealth effects on consumption have been largely examined using macro data and unit root and cointegration time-series approaches (see e.g. Davis and Palumbo, 2001; Girouard and Blöndal, 2001; Lettau and Ludvigson, 2004; Donihue, and Avramenko, 2007; Sousa, 2010a; Márquez et al. 2013). More recently, this topic has been also studied using macro panel data approaches (see e.g. Case et al., 2005; Labhard et al., 2005; De Bonis and Silvestrini, 2012; Dreger and Reimers, 2012). This is for two main reasons. First, the large range in the values of estimated wealth effects across countries is not justified on the basis of differences across industrialized countries in the rates of return on wealth and demographic distribution of asset ownership. Second, panel unit root and cointegration techniques are statistically more powerful compared to their univariate counterparts.

The relationship between consumption and wealth has also been explored in the field of financial economics. Indeed, a growing strand of the empirical literature in this field has studied how a proxy for the aggregate consumption-wealth ratio is instrumental for stock returns predictability. Lettau and Ludvigson (2001) is the first work to investigate this area. Starting from the theoretical result by Campbell and Mankiw (1989), they show that, if the aggregate consumption-wealth ratio varies over time, this may be associated with changes in stock returns in the future, and variations in the ratio may be approximated by the series of trend deviations from the long-run relationship between consumption, asset wealth and income.

This thesis investigates the wealth effects on consumption and the predictive power of the aggregate consumption-wealth ratio for excess stock returns. As such, it contributes to the empirical literature in three respects. First, it re-examines the financial and housing wealth effects on consumption in Italy and the UK by using two alternative estimation methods designed for time series analyses. Secondly, it studies financial and housing wealth effects in an international setting using a macro panel cointegration approach that takes into account cross-sectional dependence through a common factor structure. Lastly, this same panel approach is used to estimate an empirical proxy for the aggregate consumption-wealth ratio in order to explore its prediction power for excess stock returns within the Euro area.

Chapter 2 studies the long-run financial and housing wealth effects on consumption in Italy and the UK over the period 1972q4-2012q4, using two different methods of estimation: the DOLS estimator by Stock and Watson (1993) and the approach proposed by Carroll et al. (2011a). The first one is a cointegration-based approach. The second one relies on the sticky-consumption-growth model and, through a procedure involving three steps, it firstly estimates the stickiness of aggregate consumption growth, via instrumental variables regressions, and then it uses this result in order to identify immediate (next-quarter) and eventual (long-run) wealth effects. According to Carroll et al. (2011a), mainly because it is more robust to shocks affecting fundamental aspects for consumption/saving decisions (for example, changes to demography or productivity growth), which would impede to estimate stable cointegrating relationships.

In relation to the method of estimation by Carroll et al. (2011a), it can be highlighted that one of the most significant difference between housing wealth (real estate) and financial wealth (e.g. shares and mutual fund shares) has an implication on the degree of stickiness in consumption growth. Indeed, not only is housing wealth less liquid and more suitable for bequest motive than financial wealth, but it is also more persistent, as the recent developments in housing markets in industrialized countries have shown since the late 1999s. This feature of housing wealth likely contributes to making consumption more persistent, as documented by large values of stickiness in consumption growth estimated in the neighborhood of 0.7 on average across countries (see, for example, Carroll et al. 2011b).

Chapter 2 offers two main contributions. First, using wealth data, this chapter considers the recent period of the financial crisis when examining wealth effects on aggregate consumption in Italy and the UK. This is because the crisis hit the two countries in different ways because of their different financial systems. Second, the study offers a rolling regression analysis so as to evaluate how financial and housing wealth effects evolved over time.

Regardless of the estimation method used, the following results emerge for the entire sample period. First, the total wealth effect is higher in the UK than Italy. Second, housing wealth plays no role in Italy, while is significant in the UK. Lastly, in both countries, financial wealth exerts a positive and significant impact of about same the magnitude on aggregate consumption.

As for the rolling exercise, both estimation methods show that while in Italy the housing wealth effect is insignificant over time, in the UK this kind of effect is relatively increasing over large part of the sample. Further, financial wealth effects in the two countries feature opposite trends over time: slightly increasing in Italy and declining in the UK.

Chapter 3 examines the long-run financial and housing wealth effects on consumption in 14 OECD countries, using annual data over the period 1970-2012. It applies recently developed nonstationary panel methodologies that assume cross-section dependence through common factor models.

This chapter makes contributions to the literature in some respects. First, a newly updated data set for housing and financial wealth is used, making it possible to compute marginal propensities to consume (MPC) out of these wealth components. Second, a recently developed biased-adjusted estimator proposed by Westerlund (2007), that embodies cross-sectional dependence through a common factor structure, is used to estimate financial and housing wealth effects. Third, along with the analysis covering the full sample of countries, an analysis along the cross-sectional dimension is provided for the two groups of bank-based and market-based economies.

The empirical analysis shows three main results. First, both housing and financial wealth are found to exert a positive and significant impact on aggregate consumption. Second, the housing wealth effect is larger in magnitude than the financial wealth effect for the sample of all countries as well as for the two groups of bank-based and market-based economies. Third, wealth effects tend to be larger in market-based economies than bank-based ones.

Chapter 4 examines the predictive ability of a macroeconomic indicator, denoted "cay_{it}", for excess stock returns in a panel setting of 9 Euro countries, using data over the period 1988q1-2014q4. This indicator, regarded as a proxy for the logarithm of the consumption-wealth ratio, is the series of the residuals from an estimated long-run relationship between consumption, asset wealth and disposable income.

The empirical analysis is carried out in two steps. First, cay_{it} is derived using a panel cointegration approach, which controls for cross-sectional dependence via a common factor structure. Second, cay_{it} enters as a predictor in panel regressions to forecast excess stock returns, both in-sample and out-of-sample exercises.

This chapter contributes to the empirical literature in two main respects. First, it is believed to be the first work studying the predictability of cay_{it} within the Euro area. Second, cay_{it} is estimated by using a panel approach that takes cross-sectional dependence into account, on the grounds that the set of Euro countries under investigation are likely to be interdependent, because they not only share the same currency, but also some economic characteristics.

The empirical results point to predictability of future excess stock returns in the panel data examined, both in-sample and out-of-sample forecasts. In particular, in-sample results reveal that: i) cay_{it} is positively and significantly related to future excess returns over each horizon ranging from 1 to 8 quarters; ii) its forecasting power increases over horizons, up to explain 15% of variation in excess returns. As for the out-of-sample predictions, results highlight that a model with cay_{it} performs better than two benchmark models: the constant expected returns benchmark and the autoregressive benchmark. Moreover, consistent with in-sample results, the augmented cay_{it} model improves over horizons compared to the two benchmarks.

Chapter 5 presents some conclusions.

To summarize, the thesis consists of five chapters. The first and the last chapter are devoted to the introduction and conclusions, respectively. The second and the third chapter examine wealth effects on consumption in Italy and the UK, and in a panel of 14 OECD countries, respectively. Chapter 4 investigates the predictive power of the consumption-wealth ratio for excess stock returns in a panel of 9 Euro countries. The thesis contributes to the literature by disentangling the relative size of the long-run financial and housing wealth effects on consumption, and by establishing the role of the consumption-wealth ratio for forecasting excess stock returns, using the best available wealth data as well as different and recent developed econometric techniques.

CHAPTER TWO

HOUSING WEALTH, FINANCIAL WEALTH, AND CONSUMPTION: THE CASE OF ITALY AND THE UK

2.1. INTRODUCTION

The analysis of the influence of wealth on consumption has gained large attention since the study of the life-cycle hypothesis of savings by Ando and Modigliani (1963). The literature has focused on the impact on consumption of different forms of wealth and different methods of estimation of wealth effects. The bulk of the work has mainly looked at US experience (see Poterba, 2000; Davis and Palumbo, 2001; Benjamin et al., 2004; Lettau and Ludvigson, 2004; Klyuev and Mills, 2007; Donihue, and Avramenko, 2007; Carroll et al., 2011a; Paradiso et al., 2012; Caporale et al., 2013 among others), although increasing significant attention has been paid to experiences in other countries (see Boone and Girouard, 2002; Byrne and Davis, 2003; Catte et al., 2004; Ludwig and Sløk, 2004, Fernandez-Corugedo et al., 2007; Slacalek, 2009; Sousa, 2010a,b; Carroll et al., 2011b; Márquez et al. 2013, among others). Most of works have used macro data and time series approaches, mainly unit root and cointegration techniques. A different approach to measure wealth effects is instead proposed by Carroll et al. (2011a). These authors consider a method based on the literature on stickiness of consumption growth in order to identify immediate (next-quarter) and eventual (long-run) wealth effects. Their method, compared to cointegration-based approaches, seems to be more robust to shocks to fundamental aspects of consumption/saving decisions (for example, changes to demography or productivity growth). According to Carroll et al. (2011a), shocks of this kind are so frequent, even in more stable economies such as the US, that it is quite difficult to find evidence of stable cointegrating relationships.

This chapter aims to study the long-run financial and housing wealth effects on consumption in Italy and the UK over the period 1972q4-2012q4, using both the approach proposed by Carroll et al. (2011a) and the dynamic ordinary least squares (DOLS) estimator by Stock and Watson (1993).

The novelty of this study is to consider the recent period of the financial crisis when examining wealth effects on aggregate consumption.

Second, the analysis focuses on Italy and the UK as case studies because these countries feature a different financial system: bank-oriented in Italy and market-oriented in the UK. Since the structure of the financial system plays a crucial role in translating wealth shocks into consumer spending, the analysis aims to verify a potential difference in the strength of wealth effects on consumption in the two countries. Market-based economies are mainly characterized by larger sizes of financial markets, larger scales of stock market participation by households, higher degrees of stock market capitalization, and more deregulated mortgage markets than bank-based economies. Thus, it is reasonable to expect that consumption responds to changes in stock prices and house prices more intensively in the former group of economies.

Moreover, the two countries were affected by the recent financial crisis in a different way, likely due to their diverse financial system. The impact of the crisis on the UK financial system was quicker and more intense due to a higher exposure to the US stock market, in particular to the toxic subprime assets (see Moschella, 2011; Choudhry and Jayasekera, 2014). Furthermore, the high level of indebtedness of UK households also amplified the impact of the crisis in this country. The UK economy flatlined after the 2008-09 recession, and only in 2013 it has returned to grow at pre-crisis rates. On the contrary, the Italian financial system was not dramatically affected by the crisis at the very beginning, though its negative impact on the economy is still in place. A well-grounded structure for financial regulation and supervision in Italy played an important role in weakening the impact of the crisis. As a result, no bank failed in Italy or was rescued by public intervention. Moreover, the fact that the Italian financial system is less sophisticated and risky than the Anglo Saxon one was also crucial. In fact, the financial activities in Italy are mainly bank-based and characterised by a relatively low leverage ratio, a large stable base of depositors, and low exposure to risky activities (see Quaglia, 2009).[1] Italy entered

[1] The banking system in Italy had a low exposure to US subprime mortgages, and its operations in the financial market are relatively limited as compared with other banking systems in Europe (see Quaglia, 2009).

into recession in late 2008, with no recovery until 2015. Nevertheless, the recovery is still weak and slow.

Finally, this study contributes to the literature by offering a rolling regression analysis so as to evaluate how the marginal propensity to consume out of financial and housing wealth evolved over time.

Regardless of the estimation method used, empirical findings over the full sample period show that: i) the total wealth effect is higher in the UK than Italy; ii) housing wealth plays no role in Italy as expected, and in line with previous studies, while the housing wealth effect is significant in the UK; and iii) in both countries, financial wealth exerts a positive and significant impact on aggregate consumption.

As for the rolling analysis, both estimation methods show that in Italy the effect of housing wealth is insignificant over time, as opposed to a slightly increasing trend for the effect of financial wealth. As for the UK, a declining trend for the financial wealth effect is observed, along with a relatively increasing trend for the housing wealth effect, in large part of the examined period.

The rest of the chapter is organized as follows. Section 2.2 reviews the existing literature on wealth effects on consumption in Italy and the UK. Section 2.3 describes the econometric methodology. Section 2.4 presents the data. Section 2.5 discusses the empirical results. Section 2.6 concludes.

2.2. A REVIEW OF LITERATURE

Since the seminal paper by Ando and Modigliani (1963), an extensive empirical literature has been published providing measures of the effects on consumption of total wealth as well as its main components. This is because total wealth consists of several components which are different in terms of risk, collateral, liquidity properties, and bequest motive. As a result, MPCs out of various forms of wealth are expected to reflect these differences.

The role played by stock market wealth in understanding movements in consumer spending has been mainly studied for the US economy by splitting total wealth into stock market and non-stock market wealth (Mehra, 2001; Davis and Palumbo, 2001). This is because stock market wealth in the US is traditionally huge and more widespread among households than in other countries. Some researchers have also highlighted the importance of splitting total household wealth into liquid and illiquid assets, supposing lower marginal propensities for the latter assets and underlining the role of financial deregulation for increasing their degree of spendability (Muellbauer, 1994; Donihue and Avramenko, 2007).

The role of financial wealth on consumption as a whole rather than that of stock market wealth is the focus of more recent works on wealth effects, in order to account for a more widespread household ownership of financial assets beyond equities. The role of housing wealth, along with that of financial wealth, is also explored because of the remarkable evolution of house prices in several countries over the last decades, and the introduction of institutional innovations that have made it easier to extract cash from housing equity. Although financial and housing wealth effects have been broadly investigated, there is still no full consensus on the relative size of the MPCs out of these two main wealth components.

These considerations have implications for the analysis in this chapter which focuses on financial and housing wealth effects on consumption in Italy and the UK. In fact, previous related works have studied the role of these two main forms of wealth, with some also measuring the effects of liquid and illiquid financial assets (Byrne and Davis, 2003; Aron et al., 2012). While the studies related to Italy commonly estimate a smaller housing wealth effect than financial wealth effect, the evidence for the UK is a bit more controversial. In fact, some UK-related works estimate a larger housing wealth effect than financial wealth effect, while others find the opposite result.

Most of the studies on Italy and the UK have used linear error correction models to investigate wealth effects on consumption. However, as pointed out by current research (Márquez et al. 2013; Jawadi et al., 2017), consumption may not react in the same way to positive and negative wealth shocks. In particular, consumption seems to react quicker to negative financial wealth shocks than positive ones (Márquez et al. 2013). This is because declines in stock prices increase the uncertainty in the market and lenders are much less able to discern good and bad borrowers. The resulting credit restrictions make the consumption adjustment to the equilibrium stronger. As for housing wealth, it is more likely to observe a quicker response of consumption to positive shocks than negative ones, likely because of the housing equity withdrawal (HEW) mechanism (Márquez et al. 2013). Above considerations imply that appropriate econometric techniques should be considered for the study of wealth effects on consumption in presence of asymmetric adjustment to the equilibrium (Márquez et al. 2013).

In line with the focus of this chapter, this section reviews the empirical literature on financial and housing wealth effects on consumption that considers Italy and/or the UK. More specifically, the section looks at those studies that use macro data and time series approaches, paying particular attention to common themes which have characterized this research over the last two decades.

Studies in the late 1990s and early 2000s use cointegration techniques to estimate a consumption function based on the life-cycle/permanent income theoretical framework by Ando and Modigliani (1963) and Friedman (1957). Examples are: Boone et al. (1998), Girardou and Blöndal (2001), Boone and Girouard (2002), Bertaut (2002), Byrne and Davis (2003), and Catte et al. (2004).

Boone et al. (1998) study the influence of stock market fluctuations on the US economy and the G7 countries, focusing on wealth effects on consumption. The consumption equation includes stock market index, house price index, short real interest rate, inflation rate and unemployment rate.[2] A single dynamic consumption equation is estimated using half-yearly data. The estimated elasticities for stock price market index are all positive and significant at 5% level, with the exception of Italy, which exhibits the lowest value (0.008), significant at 12.5%. The Unites States has the largest estimated value, followed by the UK. Boone et al. (1998) also find for the UK that the impact of real house price index on consumption is significant, with the estimated elasticity being equal to 0.09.

The main goal in Girouard and Blöndal (2001) is to investigate the role that house prices may play in affecting private consumption and residential investment in 6 OECD countries. This is on the grounds that deregulated mortgage markets in most of the OECD countries since the 1970s have enhanced the withdrawal mechanism. The analysis for wealth effects is conducted by using co-integration techniques. In this respect, both the Granger-Engle two-step estimation strategy and the Johansen co-integration technique are used, the latter aimed at checking for the robustness of the Granger-Engle findings. Estimation results for the US, Canada, the UK, Italy, and Japan, when wealth is split into housing, financial, and other wealth, point to a significant and positive housing wealth

[2] The house price index is considered only for the UK.

effect, with Italy being the only exception.[3] The related MPCs range from 0.02 cents for the United States to 0.18 cents for Canada, with MPCs for the UK and Italy being equal to 0.027 and -0.03 cents, respectively. The financial wealth effects are found significant for all the countries, with MPCs ranging from 0.037 cents for the UK to 0.083 cents for Canada, with Italy at 0.05 cents.

Boone and Girouard (2002) take a further step in the analysis of wealth effects compared to Boone et al. (1998) looking at the role that both financial and housing wealth may play in determining private consumption for the G7 countries.[4] This goal is achieved using co-integration techniques and error correction models.[5] A significant total wealth effect is estimated for all countries, with long-term elasticities ranging between 2% (for the UK) and 6% (for Canada). Italy has an intermediate position at 3%. When wealth is disaggregated, the long-run MPC out of financial wealth varies between 4% (for the UK and the US) and 10% or more (for Canada and Japan), with Italy at 8%. By contrast, the estimated long-run MPC out of housing wealth varies between 3% and 5% for France, the UK (4%) and the US, but is larger than 10% for Canada and Japan. Only for Italy a negative housing wealth effect is estimated. Boone and Girouard (2002) also investigate whether the financial deregulation that began in the late 1970s might be the cause of a structural shift in consumption, especially with respect to wealth effects. This is done by augmenting the long-run equations with dummies. According to the empirical results, the relevance of wealth effects has increased for some countries over the last decades, due to the fact that deregulation and competition among financial institutions have eased household liquidity constraints.[6]

Bertaut (2002) investigates wealth effects in 6 OECD countries.[7] Single-country error-correction equations for different periods of time are estimated. Total wealth is taken into account in the first model which is estimated for Australia, Canada, the UK and the US. The second model, which is estimated for France and Japan, incorporates financial

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[3] The empirical analysis is carried out for different periods across countries: Canada (1973q1-1998q2), France (1970q1-1997q2), Italy (1980q1-1996q2), Japan (1975q1-1998q2), UK (1982q1-1999q2) and US (1970q1-1999q2).

[4] Germany is not included in the data set.

[5] In the two specifications used for estimating both the long-term level of consumption and its growth rate, where aggregate and disaggregate wealth enter alternatively, regressors are in levels and expressed as ratios to disposable income, whilst the dependent variable, expressed in log, is the ratio of private consumption to disposable income.

[6] Statistics for testing the presence of structural breaks yield significant results for Canada, the UK and the US, while for the other countries there is much less evidence of structural changes.

[7] The countries are: Australia, Canada, France, Japan, the UK and the US.

wealth. The third model, estimated for Canada, the UK, and the US, embodies financial and non-financial wealth. Finally, the forth model, estimated for Canada and the US, considers equity wealth and all the other wealth, as wealth components. For each country, a long relationship between consumption, income and wealth is first estimated using the DOLS estimator. Then, consumption growth is regressed on lagged values of consumption growth, real disposable income growth, real wealth growth, change in interest rate and change in unemployment rate. The empirical results for the UK show that the long-run elasticity of consumption out of total wealth is equal to 0.195 and is significant; the estimated values for financial wealth and non-financial wealth are also significant and equal to 0.088 and 0.092, respectively. When coming to the related MPCs, findings show a value of 0.043 and 0.042 for financial wealth and non-financial wealth, respectively.

Byrne and Davis (2003) use a backward looking approach for aggregate consumer expenditure to study the impact of financial wealth on consumption for the G7 countries, distinguishing between liquid and illiquid assets. A long-run relationship between consumption, income and financial wealth is estimated using an error correction model. Byrne and Davis (2003) use several formulations for the consumption equation. When considering the equation with total financial wealth and real personal income (see equation (2) in Byrne and Davis, 2003), they find that the MPC out of wealth is equal to 0.01 in Japan, 0.02 in Germany, Italy, and the UK, while it is sensibly higher for the US (0.06). For the specification with illiquid and liquid financial assets (see equation (7) in Byrne and Davis, 2003), the results show that the liquid effect is significant only for Canada, with a value being equal to 0.04, while illiquid wealth is significant for all the countries but Germany (Italy and the UK take values equal to 0.01 and 0.03, respectively).

Catte et al. (2004) examine the linkage between housing markets and the business cycle in ten OECD countries. They specifically focus on transmission channel from housing wealth to consumption using the approach by Ando and Modigliani (1963). They apply an error correction model in order to estimate a consumption equation, which includes real labour income, real net financial wealth, real net housing wealth, unemployment rate, inflation rate and short real interest rate.[8] The empirical results show that the long-run MPCs out of financial wealth are between 0.01 and 0.02 for France, Germany, Italy (0.01) and Spain, while they vary between 0.03 and 0.07 for Australia, Canada, Japan, the Netherlands, the UK (0.04) and the US (0.07). The estimated long-run

[8] For Italy and Germany, real stock market capitalisation and real house prices were used as proxies for wealth data due to limited availability of these data.

MPC out of housing wealth is in the range of between 0.05 and 0.08 for Australia, Canada, the Netherlands, the UK (0.07) and the US, while it is between 0.01 and 0.02 for Italy (0.01), Japan and Spain, and statistically insignificant in France and Germany. In order to account for the effect on consumption of extracting liquidity from the housing market, Catte et al. (2004) also consider a consumption equation with housing equity withdrawal. The estimation results show slightly larger estimated values for the financial wealth and a very large impact of housing equity withdrawal on consumption in the UK (the estimated coefficient is close to 0.90).

In the second half of the 2000s and early 2010s, some works such as Barrell and Davis (2007), Aron et al. (2012), and Márquez et al. (2013), still relying on the life-cycle/permanent income theoretical framework and cointegration techniques, emphasize the role of financial liberalization for the strength of wealth effects on consumption. In particular, Márquez et al. (2013) also focus on asymmetric consumption responses.

Barrell and Davis (2007) estimate the impact of financial liberalisation on consumption in seven OECD countries, using dynamic error correction models.[9] To this end, they leverage both cointegrating coefficients of the long-run consumption equation and coefficients of the related VECM representation with dummies, which get values larger than zero at a rate linked to the growth rate of mortgage stock up to five years.[10] Their empirical results show a significant increase in the long-run wealth effects as well as smaller long-run income effects in the US, Sweden and France after liberalisation. By contrast, in Canada, Germany and the UK there is no evidence of significant shifts in the long run parameters, while for Japan there is evidence of a shift from long-run wealth to income effect.[11] In terms of short-run dynamics, during the liberalisation process there has been a significant increase in the speed of adjustment to the long run in the US, the UK, France, Sweden and Canada, reflecting the fact that borrowing is enhanced after liberalisation to sustain consumption when income falls. Further, results show a notably decrease in short-run income elasticities and an increase in short-run elasticities out of wealth and interest rate, respectively, for most of the countries.

The impact of the financial liberalisation on consumption is also investigated by Aron et al. (2012), who look at the UK, the US, and Japan. A revision of the consumption

[9] The countries are: the US, the UK, Germany, France, Japan, Canada and Sweden.

[10] This is the time usually required for financial liberalisation to have a complete effect. The dummies are selected on the basis of the dates of financial liberalisation (see Table 3 in Barrell and Davis, 2007).

[11] The long-run estimated elasticity of consumption out of total wealth for the UK is 0.166.

function by Ando-Modigliani (1963) is used, which includes income growth expectations, income uncertainty, housing collateral, and other credit effects. Different specifications of the consumption function are estimated for the examined countries. In line with theory, the empirical results underscore the role played by credit constraints for consumer spending. Financial liberalization in the UK and the US over the last decades seems to have enhanced the positive effect of housing wealth on consumption. By contrast, the lack of credit liberalization in Japan would explain no evidence of any shifts in the parameters of the consumption function over the examined period.

The first estimated specification represents a modified version of permanent income model (see equation (2.9) in Aron et al., 2012).[12] The related results for the UK, over the period 1967q1-2005q4, show that the estimated long-run MPC out of net worth is 2.6 percent (see Table 1 in Aron et al., 2012). When allowing for the estimation of the effects of the ratios to income of net liquid assets (liquid assets minus mortgage debt and other consumer debt), illiquid financial assets, and housing wealth, respectively, in the model specification, the resulting MPC out of net liquid assets is equal to 0.126, substantially larger than 0.026 previously found for the first specification; the value of estimated MPC for illiquid financial assets does not change (0.026), whilst the housing wealth effect becomes larger (the estimated coefficient is 0.047). Two further model specifications are estimated, with parameters being shifted with the general credit conditions index (GCCI) proposed in Fernandez-Corugedo and Muellbauer (2006). As a result, the housing wealth-to-income ratio becomes insignificant for the UK, while its interaction effect with GCCI is strongly significant. The MPC out of housing assets at the maximum value of GCCI is 0.043, that of illiquid financial assets is equal to 0.022, and the MPC out of net liquid assets takes the values of 0.114.

Márquez et al. (2013) study housing and financial wealth effects in the UK, taking into account the influence of financial liberalization and testing for the existence of an asymmetric adjustment of consumption to the long-run equilibrium relationship. To this end, they apply the Enders and Siklos (2001) M-TAR methodology modified in a multivariate framework. A long-run relationship among consumption, income, housing wealth, financial wealth, and credit conditions is found, using the FMOLS method over the

[12]In this specification, consumption is consumer spending, expressed in real per capita term, and includes durables and the imputed rental value of owner-occupied housing. Income is real per capita disposable non-property income. The net worth to current disposable non-property income includes liquid assets minus mortgage and other consumer debt, plus net illiquid financial assets and housing wealth.

period 1976q1-2009q4. The resulting MPC out of financial wealth is 0.06, as opposed to a huge MPC out of housing wealth, at 0.14. Also an asymmetric behaviour for consumption is found. In particular, findings related to the asymmetric error correction movements show that the adjustment of consumption to the new target level occurs when financial wealth decreases more than the estimated threshold, while this does not occur when financial wealth increases by more than the threshold value. On the contrary, as for real estate wealth, UK households adjust their spending when this form of wealth increases more than the estimated threshold, otherwise the response is insignificant. Market liquidity reasons are highlighted to understand the asymmetric adjustment of consumption to both financial and housing wealth shocks.

Differently from above-mentioned studies, Sousa (2010a) and Bassanetti and Zollino (2010) follow a more data oriented approach proposed in Lettau and Ludvigson (2001, 2004) that derives the cointegration property linking consumption, income and wealth from a simple budget constraint identity.

In his paper, Sousa (2010a) shows that the series of residuals derived from the trend relationship among consumption, financial wealth, housing wealth and labour income, denoted "$cday_t$", should predict better US and UK quarterly stock market returns than a variable like "cay_t", defined in Lettau and Ludvigson (2001), which takes into account aggregate wealth instead of disaggregated wealth. Sousa (2010) derives a relationship between temporary deviations from the shared trend in consumption, housing wealth, financial wealth and labour income, that is $cday_t$, and expected future asset returns (see equation (10) in Sousa, 2010a). As for the estimation of the consumption function, Sousa (2010a) uses the DOLS estimator and data over the period 1975q1-2008q4. The empirical results for the UK show that the estimated elasticities of consumption with respect to financial and housing wealth are equal to 0.16 and 0.02, respectively. For the US, the results changes slightly, and the elasticity of financial wealth is equal to 0.10, while that of housing wealth is equal to 0.07. In both cases, the impact of the financial wealth is larger than that of housing wealth.

Bassanetti and Zollino (2010) investigate wealth effects in Italy by extending the approach used in Lettau and Ludvigson (2001, 2004). In particular, they use a log-linear approximation of the intertemporal budget constraint where total wealth is disaggregated into housing and non-housing wealth. This extension implies that total consumption, income, housing and non-housing wealth should be linked by cointegration. Data, spanning over the period 1980-2006, support this condition. Bassanetti and Zollino (2010) also introduce two dummies in the cointegrating relationship, reflecting two major economic events in the sample period, in order to control for a potential shift in the level of the long-run equilibrium.[13] Their long-run estimates for the housing and non-housing wealth effect range between 1.5-2 and 4-6 cents, respectively. In addition, the related estimated VECM suggests that the adjustment process towards the equilibrium is gained through housing wealth, whilst non housing wealth shows insignificant error-correction mechanism. Disposable income also contributes to smooth spending of households, even if significantly less.[14]

This literature review concludes with the work by Slacalek (2009), who does not apply a cointegration-based approach. Indeed, Slacalek (2009) uses an estimation method which relies on the sluggishness of consumption growth to investigate the effect of financial and housing wealth on consumption for 16 OECD countries. The empirical results show that while total wealth effects are quite strong, ranging between about 4 to 7 cents, in Anglo-Saxon and market-based countries, and in economies with better developed mortgage markets and outside the Euro area, consumption expenditures only barely reacts to wealth in most of continental Europe. The magnitude of housing wealth effect is smaller than that of financial wealth effect for most countries, but not for the US, the UK (6.95 cents as opposed to 3.71 cents per dollar, respectively) and Ireland, reflecting the development of financial infrastructure. For Italy, while the estimated financial wealth effect is large and equal to 10.30 cents per dollar (and significance at 10% level), the result for housing wealth is more in line with similar measures from other works, with a related MPC being negative, -1.07 cents per dollar, and significant at 10% level .

Table 2.1 summarizes the evidence reported in the studies cited in this section for long-run MPCs out of wealth components, in Italy and the UK. As can be seen, for each paper listed, the table also reports the sample period, the forms of wealth considered in the analysis, besides the methodology used to estimate wealth effects on consumption.

[13] The two dummies refer to the period of the severe currency crisis, 1992-1993, and the period when Italy joined the single currency area, respectively.

[14] In the fashion of Lettau and Ludvigson (2004), Bassanetti and Zollino (2010) assess which share of quarterly fluctuations in consumption, disposable income and wealth components is due to permanent and transitory shocks. Their results show that permanent shocks dominate consumption, non-housing net worth, and apart from very first quarters, residential wealth.

Table 2.1: Long-run MPCs out of financial and housing wealth. Italy and the UK.

	Sample period	Method	Italy	UK
Girouard and Blöndal (2001)				
MPC (financial wealth)	IT:1980q1-1996q2	Cointegration ECM	0.05	0.037
MPC (housing wealth)	UK:1982q1-1999q2		-0.03	0.027
Bertaut (2002)				
MPC (financial wealth)	UK:1970q1-2000q3	Cointegration	-	0.043
MPC (non-financial wealth)		Dynamic OLS	-	0.042
Boone and Girouard (2002)				
MPC (financial wealth)	IT:1980q1-1996q2	Cointegration	0.08	0.04
MPC (housing wealth)	UK:1982q1-1999q2	ECM	-0.06	0.04
Byrne and Davis (2003)				
MPC (financial wealth)	IT:1972q2-1998q4	Cointegration ECM	0.02	0.02
MPC (liquid financial wealth)	UK:1972q2-1998q4		-	-
MPC (illiquid financial wealth)			0.01	0.03
Catte et al. (2004)				
MPC (financial wealth)	IT:1981q1-2002q1	Cointegration	0.01	0.04
MPC (housing wealth)	UK:1976q2-2002q1	ECM	0.01	0.07
Slacalek (2009)		Instrumental variables OLS regression		
MPC (financial wealth)	IT:1971q4-1999q4		0.103	0.037
MPC (housing wealth)	UK:1970q1-2003q4		-0.011	0.069
Bassanetti and Zollino (2010)				
MPC (financial wealth)	IT:1980q1-2006q4	Cointegration	0.04-0.06	-
MPC (housing wealth)		VECM	0.015-0.02	-
Aron et al. (2012)				
MPC (net liquid wealth)	UK:1967q1-2005q4	Cointegration ECM	-	0.126
MPC (illiquid financial wealth)			-	0.026
MPC (housing wealth)			-	0.047
Márquez et al. (2013)		Momentum Threshold Autoregressive model		
MPC (financial wealth)	UK:1976q1-2009q4		-	0.06
MPC (housing wealth)			-	0.14

Notes: ECM denotes error correction model; VECM indicates vector error correction model. In Byrne and Davis (2003), different MPCs are available only if they are significant. Slacalek (2009) provides eventual MPCs, obtained imposing in both countries a value of 0.60 for the stickiness of consumption.

2.3. ECONOMETRIC METHODOLOGY

This section is dedicated to presenting the two different approaches used in the empirical analysis in order to measure wealth effects on aggregate consumption in Italy and the UK.

2.3.1. COINTEGRATION ESTIMATION APPROACH

The main goal of this method is to estimate the following long-run relationships based on the theory of the permanent income hypothesis or the life-cycle model (Friedman, 1957; Ando and Modigliani, 1963):

$$c_t = \beta_0 + \beta_y y_t + \beta_w w_t + \varepsilon_t, \qquad (2.1)$$

$$c_t = \beta_0 + \beta_y y_t + \beta_{fw} fw_t + \beta_{hw} hw_t + \varepsilon_t, \qquad (2.2)$$

where $c_t = lnC_t$ is the logarithm (log) of real per capita consumption expenditure, $y_t = lnY_t$ is the logarithm of real per capita personal disposable income, $w_t = lnW_t$ refers to the logarithm of real per capita total wealth, while $fw_t = lnFW_t$ and $hw_t = lnHW_t$ denote the logarithm of real per capita financial wealth and housing wealth, respectively. While equation (2.1) aims at measuring the effect of total wealth on consumption, equation (2.2) aims at measuring the effects on consumption of financial and housing wealth.

The estimation procedure requires a preliminary analysis on unit root and cointegration. As for the unit root properties of the variables in equations (2.1) and (2.2), the standard unit root test by Dickey and Fuller (1979) and the test developed by Elliott et al. (1996) are applied.[15]

The unit root test by Elliott et al. (1996) considers the following stochastic process:

$$y_t = \gamma' z_t + u_t, \qquad (2.3)$$

[15] For the Dickey-Fuller unit root test, the reader can refer to econometric textbooks.

$$u_t = \alpha u_{t-1} + v_t, \tag{2.4}$$

where z_t denotes the deterministic components ($z_t = 1$ for the model with a constant; $z_t = (1, t)$ for the model with a constant and a linear trend), and v_t is a zero-mean stationary process. This test, which is shown to be more powerful than the standard Dickey-Fuller unit root test, requires a quasi-difference detrending of the series involved, and the estimation of the following equation:

$$\Delta\tilde{y}_t = \beta_0 \tilde{y}_{t-1} + \sum_{j=1}^{k} \beta_j \Delta\tilde{y}_{t-j} + \varepsilon_t \ , \tag{2.5}$$

where $\tilde{y}_t$ denotes the locally detrended series, which is given by:

$$\tilde{y}_t = y_t - \hat{\gamma}' z_t \ . \tag{2.6}$$

The estimate $\hat{\gamma}$ is obtained using the GLS method by regressing $\bar{y}$ on $\bar{z}$, where:

$$\bar{y} = (y_1, (1 - \bar{\alpha}L)y_2, \dots, (1 - \bar{\alpha}L)y_T)',$$

and

$$\bar{z} = (z_1, (1 - \bar{\alpha}L)z_2, \dots, (1 - \bar{\alpha}L)z_T)',$$

with $\bar{\alpha} = 1 + \bar{c}/T$. Elliott et al. (1996) suggest $\bar{c} = -7.0$ and $\bar{c} = -13.5$ for the model with a constant and for the model with a constant and a linear trend, respectively. The null hypothesis of a unit root, that is $\beta_0 = 0$, is tested against the alternative, $\beta_0 < 0$, by performing the DF-GLS test.

As far as the cointegration analysis is concerned, the Phillips and Ouliaris' (1990) cointegration statistics are applied on the residuals of both equations (2.1) and (2.2). In particular, Phillips and Ouliaris (1990) consider the following linear regression:

$$y_t = \hat{\beta}' x_t + \hat{u}_t, \tag{2.7}$$

and propose several statistics for testing the presence of a unit root in the residuals of this equation.[16] In this chapter the following two statistics are used:

i) ADF statistic, t_{α}, for the regression $\Delta\hat{u}_t = \hat{\alpha}\hat{u}_{t-1} + \sum_{j=1}^{p} \Delta\hat{u}_{t-j} + \hat{v}_t$;

ii) $Z_{\alpha} = T(\hat{\alpha} - 1) - \left(\frac{1}{2}\right)(s_{Tl}^2 - s_k^2)(T^{-2}\sum_{t=1}^{T} \hat{u}_{t-1}^2)^{-1}$, for the regression: $\hat{u}_t = \alpha\hat{u}_{t-1} + \hat{k}_t$, with $s_{Tl}^2 = T^{-1}\sum_{t=1}^{T} \hat{k}_t^2 + 2T^{-1}\sum_{s=1}^{l} w_{sl} \sum_{t=s+1}^{T} \hat{k}_t\hat{k}_{t-s}$, and $s_k^2 = T^{-1}\sum_{t=1}^{T} \hat{k}_t^2$, for some choice of lag window, such as $w_{sl} = 1 - s/(l + 1)$.

Once consumption, income, total wealth and its main components are assessed for unit root and cointegration, then the DOLS estimator by Stock and Watson (1993) is applied in order to estimate the elasticities in both equations (2.1) and (2.2), in a context where variables are likely to be endogenous. The method consists in estimating equations of the following forms by using OLS estimator:

$$c_t = \beta_0 + \beta_y y_t + \beta_w w_t + \sum_{i=-k}^{k} b_{y,i}\Delta y_t + \sum_{i=-k}^{k} b_{w,i}\Delta w_t + \varepsilon_t , \qquad (2.8)$$

$$c_t = \beta_0 + \beta_y y_t + \beta_{wf} fw_t + \beta_{wh} hw_t + \sum_{i=-k}^{k} b_{y,i}\Delta y_t + \sum_{i=-k}^{k} b_{wf,i}\Delta fw_t + \sum_{i=-k}^{k} b_{wh,i}\Delta hw_t + \varepsilon_t , \qquad (2.9)$$

where Δ indicates the first difference operator, and leads and lags of the first difference of regressors are included in order to obtain estimates robust to potential endogeneity.

2.3.2. CARROLL ET AL. (2011a) ESTIMATION APPROACH

Carroll et al. (2011a) derive their method to estimate wealth effects on consumption from the literature on the sluggishness of aggregate consumption growth. This literature has documented that consumption reacts to shocks more slowly than implied by the random walk model by Hall (1978). Works by Flavin (1981), Campbell and Deaton (1989), and Campbell and Mankiw (1989) have marked the beginning of this literature by

[16] For the analysis carried out in this chapter, y_t in equation (2.7) denotes consumption, while x_t denotes a vector whose components are disposable income and total wealth or wealth components, depending on whether cointegration is investigated in equation (2.1) or in equation (2.2). All variables are expressed in log real per capita terms.

testing the main implication of the model by Hall (1978), whereby consumption growth is unpredictable. These studies have found that consumption growth is indeed significantly related to past variables, such as predicted income growth and consumption growth.

Since its original formulation, the theory of the permanent income hypothesis has offered a plausible explanation of why aggregate consumption is less volatile than aggregate income. This is because consumption is determined by permanent income, which is presumably smoother relative to current income. However, Campbell and Deaton (1989) argued that it is not necessarily true that permanent income must be more sluggish than current income. If income is non stationary and its changes follow a stationary process, then consumption should be more volatile than current income. However, Campbell and Deaton (1989) show that the ratio between the variability of consumption to that of income is lower than 1, so the reaction of consumption to unanticipated changes in income is too smooth or sticky (so called "excess smootheness" of consumption). This result might depend on the fact that estimated income innovations do not reflect the true income innovations perceived by the agents on the basis of their larger set of information, which would display a lower variance. So, predictions of income changes should not be limited to past income values, but also to past saving, which really reflects agents' expectations of future changes in income. Analysing the implications of the permanent income theory related to the joint behaviour of income and saving, Campbell and Deaton (1989) provide an explanation of why consumption is so smooth, which links the two puzzles of "excess smoothness" and "excess sensitivity" of consumption (see Flavin, 1981): if consumers overreact to expected income changes, the intertemporal budget constraint induces them to have an excessively sticky reaction to unanticipated income changes.

Some more recent studies suggest that "habit formation" can explain the sluggishness in consumption dynamics (Fuhrer, 2000; Dynan, 2000; Sommer, 2007), while others point to "sticky expectations" referring to the fact that consumers are inattentive to macroeconomic shocks (see, e.g., Carroll and Slacalek, 2007). In sharp contrast with the model by Hall (1978), both the two theoretical frameworks of habit formation and sticky expectations imply serial correlation in the aggregate consumption growth.[17]

[17] These frameworks are indistinguishable in aggregate data.

In Hall (1978), consumption dynamics are expressed by the following equation[18]:

$$\Delta \log C_t = \zeta + \varepsilon_t . \quad (2.10)$$

Equation (2.10) indicates that the log of aggregate consumption follows a random walk model (see Carroll and Slacalek, 2007), and therefore the growth of consumption is unpredictable.

Both the habit formation and sticky expectation models imply that the log-difference of consumption at period t is predictable at time t-1, since it follows a first order autoregressive process:

$$\Delta \log C_t = \zeta + \chi \, \Delta \log C_{t-1} + \varepsilon_t . \quad (2.11)$$

Unlike Hall's (1978) model, the sticky expectation framework (see Carroll and Slacalek, 2007) assumes that consumers are moderately inattentive to macroeconomic news (e.g. changes to productivity growth or the unemployment rate). Moreover, they maximize the discounted sum of time-separable constant relative risk aversion (CRRA) utility. Under these conditions, if consumers update the information about their permanent income with probability Π in each period, the log difference of aggregate consumption approximately follows the AR(1) process in equation (2.11), where $\chi = (1 - \Pi)$ reflects the fraction of consumers who do not have up-to-date information on macroeconomic news. When $\chi = 0$, equation (2.11) reduces to the random walk model by Hall (1978), implying that consumers have all available information when taking consumption decisions.

In the habit formation framework, on the other hand, consumers maximize time-nonseparable utility. This means that consumers derive utility not only from the level but also the change of consumption, implying that they react to news to lifetime resources gradually. The level of consumption they experienced at the previous period represents their habit stock to which their current level of consumption is compared, and $\chi \in (0,1)$ in the utility function is a parameter capturing the strength of habit. When the economy consists of habit-forming consumers with CRRA utility, consumption growth follows

[18] ε_t represents news to lifetime resources and ζ is a constant.

equation (2.11), with χ being the serial correlation coefficient (Dynan, 2000). When this parameter is equal to zero, that is habit persistence plays no role in consumer behaviour, equation (2.11) is equivalent to equation (2.10).

Sommer (2007) proposed instrumental variables regression method to estimate consumption sluggishness χ in equation (2.11). This is because OLS estimation of χ is biased toward zero, caused by measurement errors, effects of temporal aggregation and transitory expenditures (such as those caused by floods or hurricanes).

Once χ is estimated, the second step of this estimation procedure consists of identifying the immediate effect of wealth shocks on consumption, which is smaller than that in the PIH model because consumption responds sluggishly to shocks. [19] Afterwards, the estimation proceeds by combining the immediate MPC with χ in order to derive the so-called eventual (long-run) MPC. More in detail, to achieve these goals, consumption shocks ε_t in equation (2.11) are thought to be driven partially by wealth shocks, ∂W_t, and partially by control variables $\tilde{Z}_t$:

$$\varepsilon_t = \alpha_w \partial W_t + \alpha_{\tilde{z}}^T \tilde{Z}_t, \tag{2.12}$$

where $\partial W_t = \frac{\Delta W_t}{C_{t-1}} = \frac{\Delta W_t}{W_{t-1}} \times \frac{W_{t-1}}{C_{t-1}}$ indicates rescaled wealth growth as an approximation of wealth shocks, and $\frac{\Delta W_t}{W_{t-1}}$, which is wealth growth, is multiplied by the wealth-consumption ratio in order for the parameter α_w in equation (2.12) to have the meaning of the immediate MPC out of wealth. Equation (2.12) aims to determine the contribution of wealth shocks while controlling for the effect of other variables, collected in $\tilde{Z}_t$, which contribute to consumption dynamics.[20] To obtain more precise estimates of α_w, an indirect estimation method based on the following moving average representation of consumption growth is used:

$$\Delta \log C_t = \alpha_0 + \sum_{i=1}^{\infty} \chi^i \varepsilon_{t-i} + \varepsilon_t, \tag{2.13}$$

[19] In this section, the same notation in Slacalek (2009) and Carroll et al. (2011a) is used.

[20] Income growth, unemployment rate, change in short-run interest rate or interest rate spread are good examples of variables that may be collected in $\tilde{Z}_t$.

where $\alpha_0 = \frac{\zeta}{1-\chi}$. Substituting (2.12) into (2.13) gives:

$$\Delta \log C_t = \alpha_0 + \alpha_w \sum_{i=1}^{\infty} \chi^i \partial W_{t-i} + \alpha_{\tilde{z}}^T \sum_{i=1}^{\infty} \chi^i \tilde{Z}_{t-1} + \varepsilon_t ,$$

or

$$\Delta \log C_t = \alpha_0 + \alpha_w \bar{\partial} W_{t-1} + \alpha_z^T Z_{t-1} + \varepsilon_t, \tag{2.14}$$

where $\bar{\partial} W_{t-1} = \sum_{i=1}^{\infty} \chi^i \ \partial W_{t-i}$, $\alpha_z^T = (\alpha_{\tilde{z}}^T \chi, \alpha_{\tilde{z}}^T \chi^2, \dots)$ and $Z_{t-1}^T = (\tilde{Z}_{t-1}^T, \tilde{Z}_{t-2}^T, \dots)$ are control variables. In order to estimate equation (2.14), it is necessary to approximate $\bar{\partial} W_{t-1}$ with a finite sum, $\bar{\partial} W_{t-1} \approx \chi (\Delta W_{t-1} + \chi \Delta W_{t-2} + \chi^2 \Delta W_{t-3} + \chi^3 \Delta W_{t-4}) / C_{t-5}$, and re-scale consumption accordingly with the initial level of consumption, C_{t-5}. As a result, the equation takes the following form:

$$\partial C_t = \alpha_0 + \alpha_w \bar{\partial} W_{t-1} + \alpha_z^T Z_{t-1} + \varepsilon_t, \tag{2.15}$$

where $\partial C_t = \Delta C_t / C_{t-5}$ and $\bar{\partial} W_{t-1} \approx \chi (\Delta W_{t-1} + \chi \Delta W_{t-2} + \chi^2 \Delta W_{t-3} + \chi^3 \Delta W_{t-4}) / C_{t-5}$. It should be underlined that ∂C_t is not equal to consumption growth $\Delta C_t / C_{t-1} \approx \Delta \log C_t$, but the two variables are strongly correlated as C_t and C_{t-5} are very similar.

Once the estimates of χ and α_w are obtained, the immediate MPC is computed as α_w / χ. Finally, the eventual MPC out of wealth is the geometric sum:[21]

$$\sum_{i=1}^{\infty} \chi^i \ \frac{\alpha_w}{\chi} = \frac{\alpha_w}{\chi(1-\chi)} . \tag{2.16}$$

In order to estimate immediate MPCs and eventual MPCs out of financial and housing wealth respectively, the following equation is also estimated:

$$\partial C_t = \alpha_0 + \alpha_{fw} \bar{\partial} FW_{t-1} + \alpha_{hw} \bar{\partial} HW_{t-1} + \alpha_z^T Z_{t-1} + \varepsilon_t. \tag{2.17}$$

[21] For further details on the eventual (long-run) MPC, see Slacalek (2009).

2.4. DATA

This chapter uses quarterly data for Italy and the UK, spanning the period from 1972q4 to 2012q4. The NiGEM database developed by the National Institute of Economic and Social Research (NIESR) is the source of the data, unless differently indicated. The variables of interest for the analysis are briefly described below.

The consumption data (C_t) are total private consumption expenditures, which combine expenditures on durable and non-durable goods and services. This definition of consumption is not common to all previous works which have investigated wealth effects on consumption. Some of them have used expenditures on non-durables and services, as their measure of consumption, on the grounds that conventional theories of consumer behaviour refers to a flow measure of consumption that, in part, can be approximated by expenditures on nondurables and services (see, for example, Ludvigson and Steindel, 1999; Lettau and Ludvigson, 2001). This approach excludes expenditures on durable goods because they cannot be considered as a proxy of the service flow consumers may derive from the existing capital stock. In line with the analysis in this chapter, many other previous papers have used total consumption, defined as the sum of durable and non-durable goods (e.g. Mehra, 2001; Ludwig and Sløk, 2004; Dreger and Reimers, 2012). This is because durable spending is a relatively small part of the total, and because significant resources raised by mortgage refinancing are spent on durables (see Peltonen et al., 2012). Further, as argued in Paradiso et al. (2012), it is likely that the consumption of durable goods is linked to the business cycle pattern and asset market dynamics.

The income data (Y_t) refer to personal disposable income, defined as total market income plus transfers from government less income taxes and social contributions. The financial wealth data (FW_t) correspond to gross financial assets owned by households less their financial liabilities, which include mortgages and consumer credit. The housing wealth data (HW_t) consist of the current value of the stock of housing capital owned by the personal sector. Housing wealth is benchmarked on annual housing wealth data, interpolated in year in line with house prices and quarterly expenditure on housing investment. House prices are from the Bank for International Settlements (BIS) database. All previous series are deflated by personal consumption expenditure price index (PCI) and expressed in per capita terms. The population series are interpolated from annual data, and the sources are ISTAT (Italian National Institute of Statistics) for Italy, and ONS (Office for National Statistics) for the UK.

Other data used as instruments in the regression related to the method by Carroll et al. (2011a) are the following: the interest rate spreads, defined as the difference between the long and the short interest rates; the nominal short-term interest rates referring to the 3-month interest rates; and unemployment rate. The first two variables are taken from the National Central Banks, while the third one, used only in the estimation process related to Italy, is taken from ISTAT.[22]

Figure 2.1 illustrates the dynamics of total wealth and its components for Italy and the UK. The graph highlights the following patterns:

i) The growth rates of per capita wealth components were similar for the two countries until the recent financial crisis, with no substantial difference between the two kinds of wealth. In particular, the growth rates of housing wealth averaged between 1.15% and 1.19% for Italy and the UK, respectively, while those for financial wealth averaged between 1.12% and 1.16%, respectively;
ii) Since the beginning of the crisis to the end of the period, the growth rates of wealth components were more negative in Italy than the UK. More precisely, figures are: -0.51% as opposed to -0.34% for housing wealth, and -0.97% as opposed to -0.005% for financial wealth for Italy and the UK, respectively;
iii) In terms of standard deviations, financial wealth growth for the UK is more than twice as volatile as housing wealth growth, before and after the crisis. By contrast, this is true for Italy only from the beginning of the crisis onwards.

The housing wealth dynamics are mainly driven by house prices, which follow similar trends in both countries. In particular, house prices grew remarkably from the late 1990s to the first quarters of 2008, with a higher growth for the UK, before starting to decrease. However, while in the UK, after a more sharp decrease, real house prices have remained stable since the second quarter of 2009, in Italy they have continued to decrease, even more sharply, over the last quarters of the period.

[22] See Table A2. in Appendix A for the instruments and control variables used for the estimation of MPCs by the method proposed in Carroll et al. (2011a).

Regarding the evolution of the financial wealth, a similar sustained upward trending pattern is observed for both countries during the Internet bubble period. By contrast, during the burst of the bubble (2000-2003), the slump in stock prices and the resulting economic stagnation triggered a downward trend, which was much steeper in the UK than Italy. This difference reflects the higher correlation between financial wealth and stock prices in the UK due to a higher share of quoted equities. After a period of temporary recovery of financial wealth up to 2007 (stronger in the UK than Italy), both countries experienced a reduction in the value of financial assets due to the financial crisis. However, unlike Italy, the UK has seen a reversal of trend since the beginning of 2009.

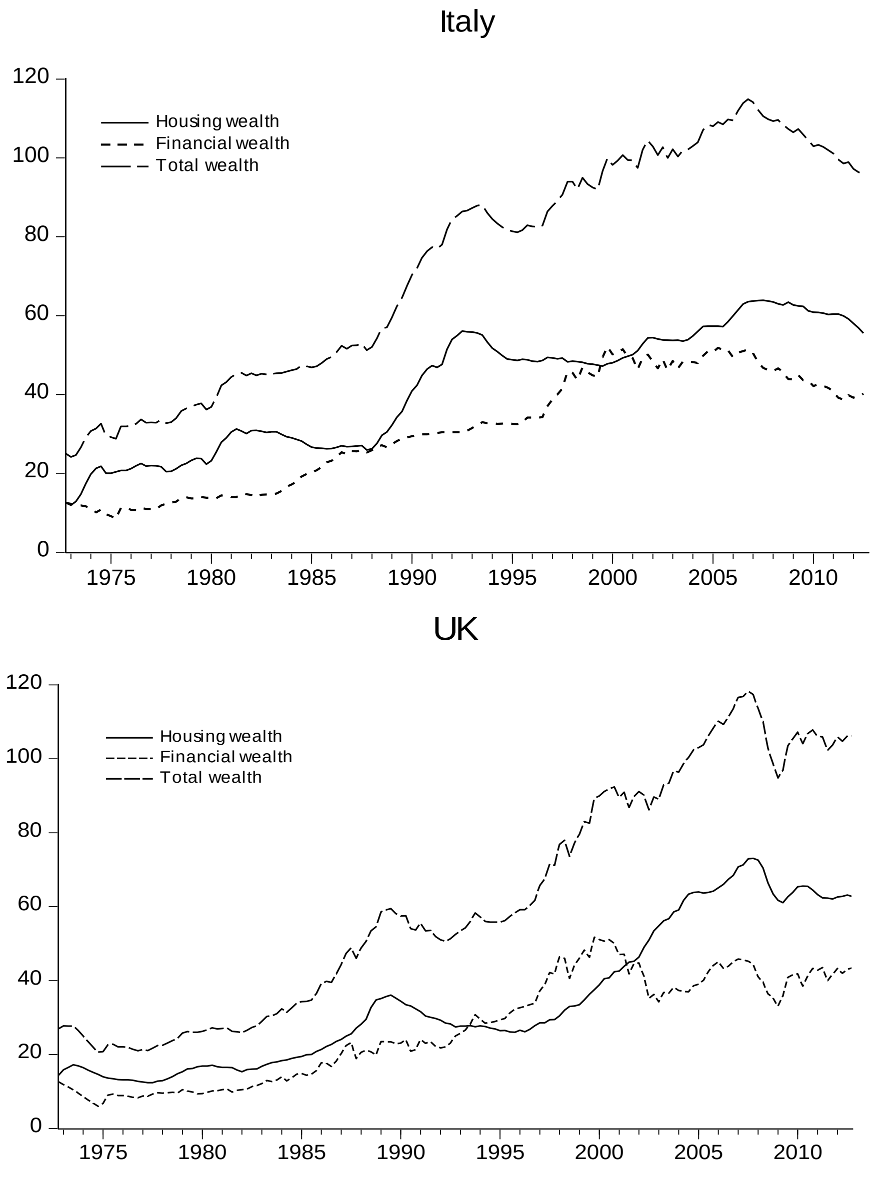

Figure 2.1: Real per capita total, financial and housing wealth. Italy and the UK, 1972q4-2012q4.

2.5. EMPIRICAL RESULTS

This section is devoted to the results of the empirical analysis. After presenting findings for unit root and cointegration, estimation results of long-run wealth effects for Italy and the UK are discussed. Evidence of the dynamics of wealth effects over time is also reported.

The unit root results (see Table 2.2) obtained by using both the standard Augmented Dickey-Fuller (ADF) test and the DF-GLS test by Elliott et al. (1996) show that all the series under consideration are I(1) processes. This occurs for both Italy and the UK.

Table 2.3 reports the Phillips and Ouliaris (1990) cointegration test results. A clear-cut evidence of cointegration is found at 1% significance level for the UK in all the cases (equations (2.1)-(2.2)). As for Italy, related results seem to be less conclusive. While cointegration is found for equation (2.2) at 5% significance level, the null hypothesis of no cointegration cannot be rejected in the case of equation (2.1), although statistics Z_α is not far from being significant at 10% significance level. However, the results of the trace test by Johansen (1995), which we perform for robustness check, clearly show existence of a cointegrating vector at 5% significance level in all the cases (see Table 2.4).

Table 2.2: Unit root results. Level and first difference. Italy and the UK, 1972q4-2012q4.

Variables	**Italy**		**UK**	
	ADF	DF-GLS	ADF	DF-GLS
c_t	0.642	0.209	-1.384	-1.504
y_t	0.255	0.486	-0.056	-0.608
w_t	0.831	0.021	-2.021	-1.469
fw_t	-0.968	-1.489	-1.987	-1.457
hw_t	-2.959	-2.522	-3.035	-2.376
Δc_t	-5.851***	-5.488***	-4.391***	-3.685**
Δy_t	- 10.126***	-10.251***	-16.563***	-7.335***
Δw_t	-6.224***	-2.795*	-9.457***	-9.058***
Δfw_t	-4.150***	- 3.298**	-11.065***	-9.726***
Δhw_t	-6.961***	-3.281**	-4.308***	-2.811*

Notes: Model with constant and trend is considered. ADF indicates the standard Augmented Dickey-Fuller test; DF-GLS indicates the modified Dickey-Fuller unit root test proposed by Elliott et al. (1996). Critical values for the ADF test are -3.144, -3.439, and -4.018, while those for the DF-GLS tests are -2.681, -2.971, and -3.509 at 10%, 5%, and 1% significance level, respectively; ***,** and * denote significance at the 1%, 5% and 10% level, respectively. Lags are selected using the Aikake Information Criterion with a maximum number of lags equal to 5.

Table 2.3: Phillips-Ourialis cointegration test results. Italy and the UK, 1972q4-2012q4.

	Italy	**UK**
Panel A $c_t = \beta_0 + \beta_y y_t + \beta_w w_t + \varepsilon_t$		
Statistics		
t_α	-3.030	-5.051
	(0.238)	(0.001)
Z_α	-18.805	-45.054
	(0.168)	(0.001)
Panel B $c_t = \beta_0 + \beta_y y_t + \beta_{fw} fw_t + \beta_{hw} hw_t + \varepsilon_t$		
Statistics		
t_α	-4.443	-5.368
	(0.024)	(0.001)
Z_α	-36.018	-51.699
	(0.017)	(0.001)

Notes: Panel A and Panel B report the results of Phillips-Ourialis cointegration test for equations 2.1 and 2.2, respectively. The Phillips-Ourialis test is performed on the residuals from a cointegrating equation with a constant, using a Bartlett kernel and Newey-West automatic bandwidth (NW automatic length lag =4). MacKinnon (1996) p-values are in parenthesis.

Table 2.4: Johansen (1995) cointegration test results. Italy and the UK, 1972q4-2012q4.

Panel A

$$z_t = X_t'\phi + \varepsilon_t$$
$$z_t = (c_t, y_t, w_t)'; X_t = (1, z_{t-i})';$$

Italy				**UK**			
$H_0{:}\,r$	λ_{trace}	CV 5%	p-value	$H_0{:}\,r$	λ_{trace}	CV 5%	p-value
r=0	50.20	35.07	0.000	r=0	50.07	35.07	0.000
r=1	12.07	20.16	0.451	r=1	19.41	20.16	0.064
r=2	5.40	9.14	0.251	r=2	7.01	9.14	0.129

Panel B

$$z_t = X_t'\phi + \varepsilon_t$$
$$z_t = (c_t, y_t, fw_t, hw_t)'; X_t = (1, z_{t-i})';$$

Italy				**UK**			
$H_0{:}\,r$	λ_{trace}	CV 5%	p-value	$H_0{:}\,r$	λ_{trace}	CV 5%	p-value
r=0	95.45	53.94	0.000	r=0	79.45	53.94	0.000
r=1	32.77	35.07	0.089	r=1	32.55	35.07	0.093
r=2	14.87	20.16	0.239	r=2	16.29	20.16	0.164
r=3	5.61	9.14	0.231	r=3	4.91	9.14	0.304

Notes: Panel A reports the results of Johansen cointegration test between consumption, disposable income and total wealth, while in Panel B the existence of cointegration between consumption, disposable income, financial and housing wealth is assessed. A VAR(2) is used in the analysis for cointegration ($i = 1,2,$ in z_{t-i}). r indicates the number of cointegrating vectors; CV5 % indicates critical values at 5% level; MacKinnon et al. (1999) p-values are reported.

Table 2.5 reports the results for the long-run MPCs out of total, financial and housing wealth for Italy and the UK, obtained by using the two methods of estimation under analysis.[23] More specifically, for the DOLS estimator, the MPCs are obtained by multiplying the estimated elasticities in equations (2.1)-(2.2) (see Tables A1. in Appendix A) by the average sample ratio of consumption to the respective variable of interest, namely total wealth, and financial and housing wealth (see Catte et al., 2004; Donihue and Avramenko, 2007).[24] As far as the method by Carroll et al. (2011a) is concerned, eventual MPCs are estimated from equation (2.16), once the related estimates for the parameter χ (the stickiness of consumption), and those for the immediate MPC (see equations (2.11), (2.15) and (2.17)) are obtained.[25]

Table 2.5: Total, housing and financial wealth effects (MPCs). Italy and the UK, 1972q4-2012q4.

Eventual MPCs					
Italy			**UK**		
Total	Financial	Housing	Total	Financial	Housing
0.010	0.028***	-0.003	0.020***	0.021***	0.028***
DOLS MPCs					
Italy			**UK**		
Total	Financial	Housing	Total	Financial	Housing
0.018***	0.024***	0.007**	0.032***	0.023***	0.030***

Notes: ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Results for Italy show that the estimation methods under consideration provide slightly different estimates for total wealth effects. Indeed, the MPC out of total wealth takes a value of 0.010 when using the method by Carroll et al. (2011a) compared to 0.018 obtained by the DOLS estimator.[26] These values are in line with those in previous studies (see, for example, Byrne and Davis, 2003; Slacalek, 2009). When splitting total wealth into financial and housing components, the estimation methods provide more similar results.

[23]The marginal propensity to consume out of income is not reported here, as the focus of the analysis is primarily on wealth effects on consumption.

[24]For the DOLS estimator, we use four lags and leads of the first difference of the regressors. Monte Carlo evidence in Ng and Perron (1997) suggests using large lag length to obtain more precise estimates.

[25]The estimation of consumption sluggishness uses instrumental variables regression (see Sommer, 2007; Slacalek, 2009; Carroll et al., 2011a,b). For details about the instruments used in this analysis, see notes in Table A.2 in Appendix A. This table reports the estimates of χ alongside the estimates of the immediate marginal propensities to consume.

[26]Our marginal propensities to consume are expressed in cents per euro for Italy and cents per pound for the UK, and are not annualised values.

Both of them highlight a nil effect for housing wealth, though of opposite sign, compared to a significant financial wealth effect. In particular, for housing wealth, DOLS estimate is equal to 0.007 as opposed to -0.003 by the procedure by Carroll et al. (2011a), while for financial wealth, DOLS estimate is equal to 2.4% compared to a slightly larger 2.8% by the procedure in Carroll et al. (2011a). Girouard and Blöndal (2001), Boone and Girouard (2002), and Slacalek (2009) find for Italy a similar nil effect for housing wealth, but a higher financial wealth effect.

Similarly to Italy, estimates of total wealth effects for the UK differ slightly across the two estimation methods: 0.020 by the DOLS estimator as opposed to 0.032 by the method of Carroll et al. (2011a) (similar results are in Girouard and Blöndal, 2001; Byrne and Davis, 2003). As regards disaggregate wealth effects, even though to lesser extent, estimates by both estimation methods confirm a pattern highlighted in other works related to Anglo-Saxon countries, featured by market-based financial systems and highly deregulated mortgage markets (see, e.g., Catte et al., 2004; Slacalek, 2009; Carroll et al., 2011a). That is, in the UK, the housing wealth effect seems to be more important than the financial wealth effect: estimates for the housing wealth effect are 2.8% and 3.0% by DOLS estimator and by Carroll et al.'s (2011a) procedure, respectively, as opposed to 2.1% and 2.3% for the financial wealth effect. A more incisive role of housing wealth than financial wealth on consumption in the UK is also found in other studies (see Ludwig and Sløk, 2004; Catte et al., 2004; Slacalek, 2009; Aron et al., 2012).

To summarize the results in Italy and in the UK, some clear patterns emerge:

1. The total wealth effect is larger in the UK than Italy, regardless of the estimation method;
2. Although financial wealth dominates in the UK, and direct and indirect households' participation in the financial market is far higher than Italy (see De Bonis et al., 2013), the above findings underscore that the financial wealth effect in Italy is about as important as in the UK. This feature may be due to the different composition of financial wealth in the countries concerned, reflecting a less generous State pension scheme in the UK. Indeed, more than fifty per cent of financial wealth is held in the form of insurance and pension products in the UK, while the same percentage decreases to less than 20% in Italy (see De Bonis et al., 2013). As a consequence, UK consumption may be

less sensitive to the variation of wealth held in these forms because they are thought to be long-term assets. On the other hand, in Italy a higher proportion of shares and other equities (quoted and unquoted shares, mutual funds, and other equity) are held directly by households (about 27% as opposed to about 14% for the UK), which are usually associated with higher MPCs. However, it should be noted that a large proportion of shares are unquoted in Italy (due to the large number of small firms), and therefore less liquid than quoted shares;

3. Although housing wealth is huge and widespread in Italy, it is hard to detect any sizeable incidence of it on consumption, likely reflecting the absence of the mechanism of mortgage equity withdrawal (MEW). On the contrary, findings for the UK reveal a different pattern. Because this country has experienced a substantial credit market liberalization compared to Italy, the housing wealth effect turns to be higher than the financial wealth effect.

In order to study the dynamics of the MPC out of financial and housing wealth, a rolling regression exercise is offered, using a window of 90 observations, as displayed in Figure 2.2. The first rolling estimate covers the period 1972q4-1995q1, whereas the last one is related to the period 1990q3-2012q4.[27]

The most striking aspect of Figure 2.2 is that the two estimation methods seem to provide roughly similar dynamics for the two type of wealth effects considered, both in Italy and in the UK.

In particular, when focusing on the UK, one can observe a common descending trend for the financial wealth effect, starting from the late of 1990s. Both methods provide estimates for the MPCs out of financial wealth at around 3% in the initial period of the rolling exercise, which decrease afterwards until reaching a value of about 1% at the end of period. These declining trends may reflect the increasing importance that consumers might have attributed to real assets for their consumption behaviour relatively to financial assets, in a period when house prices started to increase in the UK as well as in many other

[27] A window of around 90 observations is considered appropriate in order to reduce the impact of the bias on the estimates of wealth effects when using the co-integration estimation method. Indeed, Carroll et al. (2011a) show that the bias is remarkable when using 20/40 observations, and reduces slightly with 60 observations. Therefore, given the features of the two estimation methods used, a window size of around 90 observations is regarded as a good trade-off to consistently estimate with the two methods.

industrialized countries (see, for example, Chamberlin, 2009). This remark is supported by the fact that both methods estimate substantially higher housing wealth effect along the same period, with trends being increasing during large part of the 2000s, when large rises in house prices occurred.

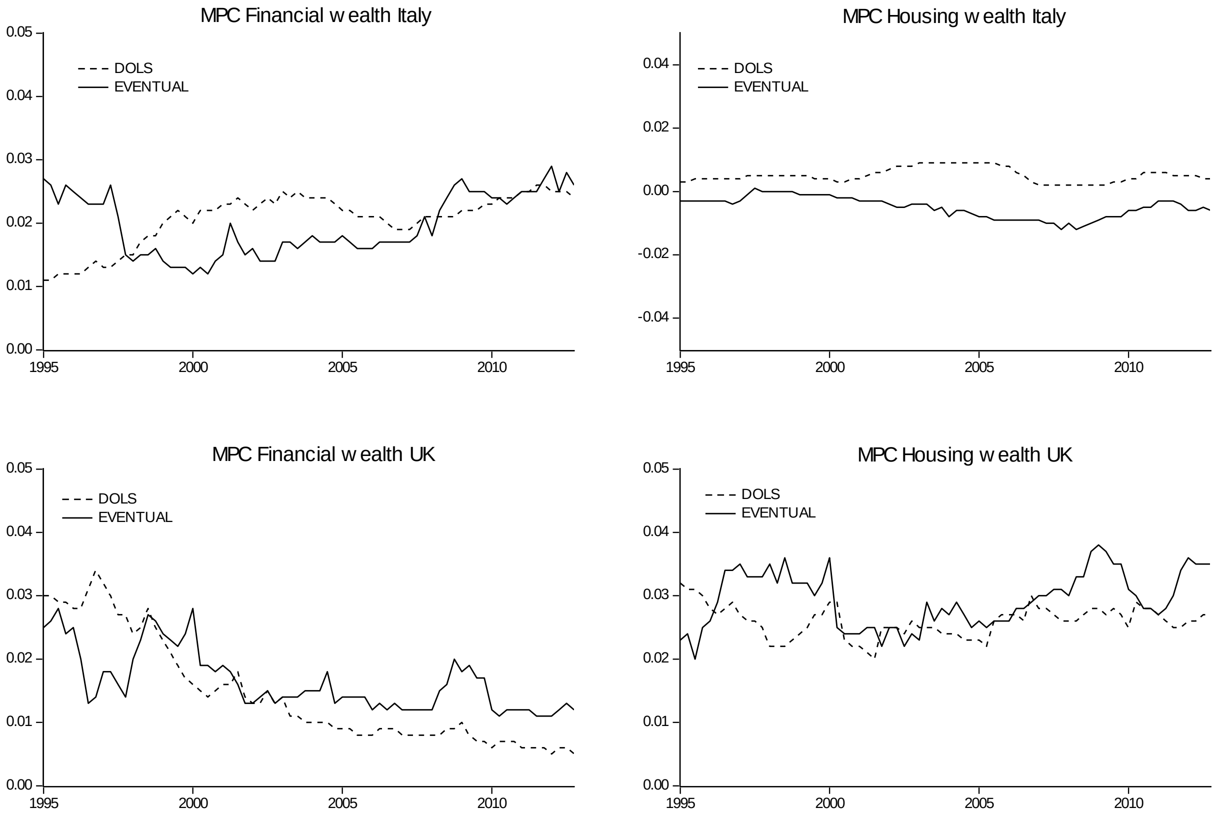

Figure 2.2: Marginal propensity to consume out of financial and housing wealth. Italy and the UK, 1995q1-2012q4.

Looking at the period during the recent financial crisis, it can be noticed that MPCs out of both financial and housing wealth are increasing, and this is particularly true for MPCs resulting from the method by Carroll et al. (2011a). The findings may be attributable to a stronger persistence in consumption habits (see the dynamics of χ in Figure A.1 in Appendix A), as reflecting an increasing reluctance of UK habit-forming consumers to change their consumption path during the financial crisis,[28] which saw remarkable

[28] The literature relying on habit formation (see Muellbauer, 1988; Fuhrer, 2000; Dynan, 2000; Lettau and Uhlig, 2000; Carroll et al., 2000; Sommer, 2007, among others) underlines that habits induce consumers to smooth both the level and the change in consumption. As a result, consumers will respond gradually to shocks.

reductions of the values of assets (see Figure 2.1).[29] As such, higher MPCs out of both financial and housing wealth result in an attempt for consumers to smooth the changes in consumption.

With the respect to Italy, the financial wealth effect displays trends that are slightly increasing over time since the late 1990s. This pattern may reflect the development of the financial market in Italy over the period under consideration, which has allowed financial assets to play a more incisive role relative to the residential property in determining the aggregate demand. By contrast, when dealing with the housing wealth effect, the two methods under consideration confirm that this effect in Italy is practically nil over time. These findings are consistent with an underdeveloped mortgage market featuring the Italian economy.

Regarding dynamics in Italy during the financial crisis, one can observe increasing estimates of the financial wealth effect by the method of Carroll et al. (2011a) compared to more stable DOLS estimates. Similarly to the case in the UK, this result may reflect stronger habit formation behaviour during this period. Nevertheless, the increase is more muted relatively to the UK and it is absent in DOLS estimates. Perhaps, more incisive drops in wealth components and the more negative impact of credit constrains during the financial crisis in the UK than Italy, may explain these differences in the two countries.

2.6. CONCLUSIONS

This chapter focuses on the long-run impact of housing and financial wealth on consumption in Italy and the UK, taking into consideration the recent period of financial crisis.

The impact of the crisis on the two countries has been different, mainly due to their distinctive financial systems, which crucially account for the strength of wealth effects. The impact in the UK has been quicker and more intensive due to a higher exposure to the US stock market and the high level of indebtedness of UK households. By contrast, Italy observed a less dramatic impact, though its negative effect is still in place.

[29] In Chandler and Disney (2014), it is highlighted that the worsening in credit conditions in the UK during the financial crisis may also have played a role in increasing the responsiveness of next-quarter marginal propensity to consume out of real and financial assets. Our rolling results for the immediate MPCs out of both assets for the UK support this claim (see Figure A.2 in Appendix A).

This study contributes to the empirical literature in some respects. First, to the best of my knowledge, this is the first study to thoroughly compare wealth effects in Italy and the UK, using macro data. To this end, marginal propensities to consume out of wealth components over the period 1972q4-2012q4 are estimated, using two different estimation methods: the DOLS estimator by Stock and Watson (1993) and the approach proposed by Carroll et al. (2011a). Second, a rolling analysis to investigate how wealth effects evolved over the examined period is carried out, with a particular focus on the recent period of financial crisis.

The empirical results show that housing wealth plays no role in Italy, whereas it is significant in the UK. Furthermore, in both countries, the financial wealth exerts a positive and significant impact on aggregate consumption. As for the rolling analysis, both estimation methods show an insignificant effect of housing wealth for Italy over time, as opposed to a slightly increasing trend for the effect of financial wealth. As for the UK, a declining trend for the financial wealth effect is observed, along with a relatively increasing trend for the housing wealth effect, in large part of the examined period.

The importance of the housing wealth effect in the UK has strong policy implications for this country. Limits on loan to value and loan to income ratios could contribute to damping the cycle in economic activity in the UK. They may also constrain bad lending by banks and reduce the probability of another banking crisis. These tools are much less needed in Italy, as house prices do not seem to impact on consumption, and hence they are unlikely to contribute to bad lending by banks. Therefore, the difference in housing wealth effects in the two countries should lead to very different policy approaches to the housing market.

Appendix A

Table A.1: DOLS estimates out of total, financial and housing wealth. Italy and the UK, 1972q4-2012q4.

Panel A

$$c_t = \beta_0 + \beta_y y_t + \beta_w w_t + \varepsilon_t$$

	Italy			UK		
Variables	elasticity	t-stat	p-value	coef.	t-stat	p-value
y_t	0.359	3.877	0.000	0.588	7.588	0.000
w_t	0.396	10.870	0.000	0.262	5.949	0.000
Const	-1.059	-15.180	0.000	-0.673	-6.773	0.000

Panel B

$$c_t = \beta_0 + \beta_y y_t + \beta_{fw} fw_t + \beta_{hw} hw_t + \varepsilon_t$$

	Italy			UK		
Variables	elasticity	t-stat	p-value	coef.	t-stat	p-value
y_t	0.397	4.751	0.000	0.668	13.822	0.000
fw_t	0.226	9.836	0.000	0.075	4.110	0.000
hw_t	0.091	2.488	0.014	0.142	10.019	0.000
Const	-0.515	-6.754	0.000	-0.427	-10.459	0.000

Notes: 4 lags and leads of the first difference of the regressors are used in the estimation.

Table A.2: Stickiness of consumption and immediate MPCs. Italy and the UK, 1972q4-2012q4.

Italy			UK		
χ	Immediate MPC Total wealth		χ	Immediate MPC Total wealth	
0.70***	0.001		0.65***	0.005***	
χ	Immediate MPC Financial wealth	Immediate MPC Housing wealth	χ	Immediate MPC Financial wealth	Immediate MPC Housing wealth
0.76***	0.005***	-0.001	0.80***	0.003***	0.004***

Notes: The estimation of consumption sluggishness in equation (2.11) uses instrumental variables method. As for Italy, the instruments involved are: housing wealth, financial wealth, disposable income growth rate, interest rate spread, nominal short interest rate, and changes in unemployment rate. The control variables in the OLS estimation of equations (2.15) are: disposable income growth rate, interest rate spread, and unemployment rate. As for the UK, the instruments are housing wealth, financial wealth, interest rate spread and nominal short interest rate, while the control variables are interest rate spread and nominal short interest rate. Both sets of instruments for Italy and the UK pass the Partial R2- test and F-tests for assessing instrument strength as well as the Hansen test for overidentifying restrictions. Immediate MPCs out of wealth reflect next-quarter effects following £1 or €1 change in wealth. *** denotes significance at the 1% level.

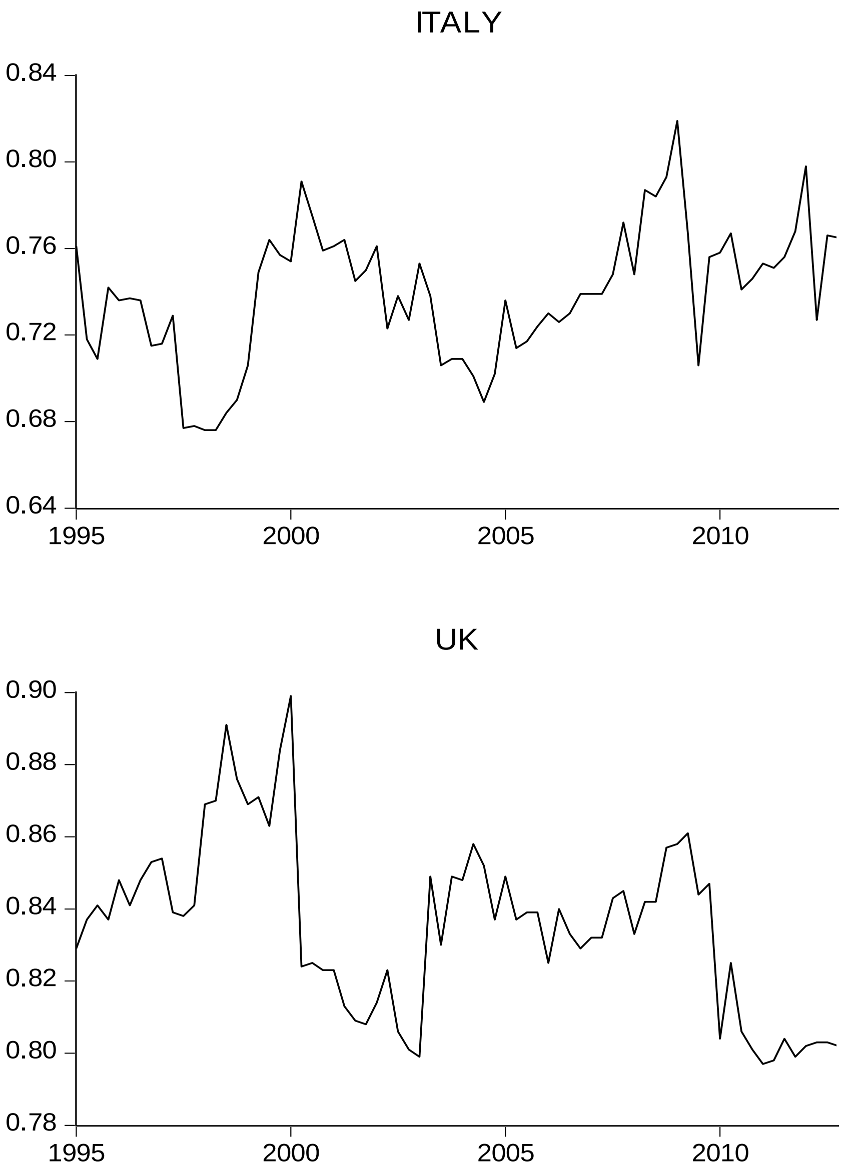

Figure A.1: Rolling estimates for the stickiness of consumption (χ). Italy and the UK, 1995q1-2012q4.

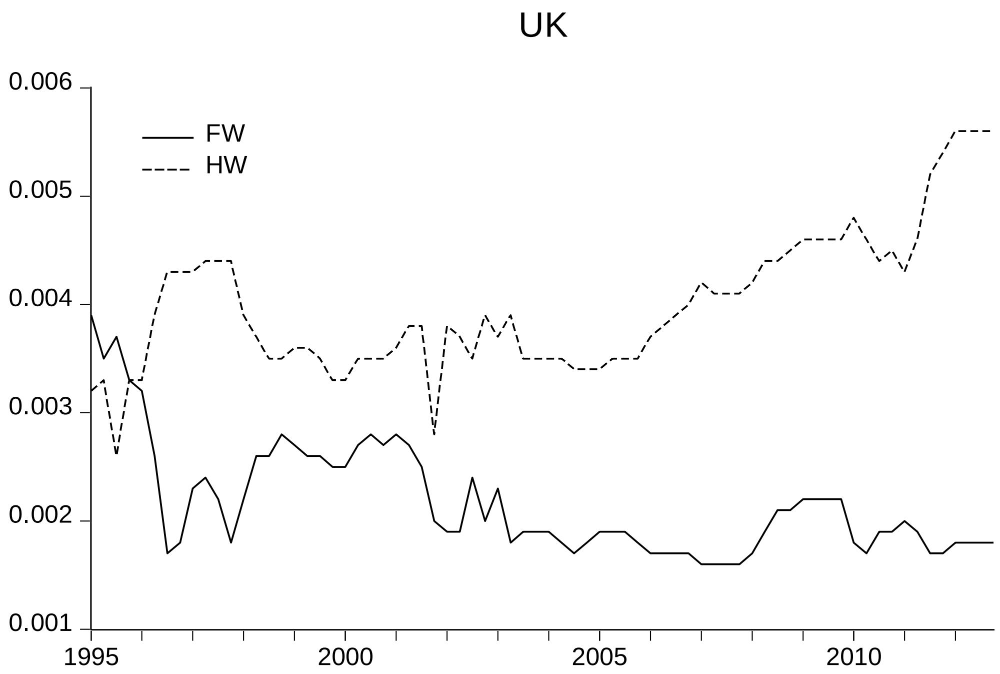

Figure A.2: Rolling estimates for the immediate MPCs for the UK, 1995q1-2012q4.

CHAPTER THREE

CONSUPMTION, WEALTH EFFECTS AND COMMON FACTORS: EVIDENCE FROM 14 OECD COUNTRIES

3.1. INTRODUCTON

The bulk of empirical literature on the wealth effect on consumption has focused on macro data and unit root and cointegration time-series approaches. Notably, most of the works, referring to both country-specific and comparative international analyses, have studied this topic estimating individual country equations for aggregate consumption or vector error-correction models (see e.g. Boone, 1998; Poterba, 2000; Davis and Palumbo, 2001; Girardou and Blöndal, 2001; Boone and Girouard, 2002; Byrne and Davis, 2003; Catte et al., 2004; Benjamin et al., 2004; Lettau and Ludvigson, 2004; Barell and Davis, 2007; Klyuev and Mills, 2007; Donihue, and Avramenko, 2007; Slacalek, 2009; Sousa, 2010a,b; Carroll et al., 2011; Aron et al., 2012; Caporale et al., 2013; Márquez, et al. 2013, among others). Over the last decade, increasing attention has been devoted to the study of wealth effects on aggregate consumption at international level. As there is little theoretical rationale for a large variation in the values of estimated wealth effects across countries (see Altissimo et al. 2005; Labhard et al., 2005), and also across studies related to the same country, some authors have stressed the advantages of pooling data and using panel data approaches in this field of economic research.[30] For example, in Altissimo et al. (2005) and Labhard et al. (2005), it is highlighted that differences across countries in terms of rates of return on financial assets, lengths of planning horizons, distribution of wealth, and demography are not so large to justify such a wide range of discrepancies when it comes to wealth effects estimates. On the contrary, there would be good reasons to believe that data deficiencies due to differences in the methodological approach used to measure wealth across countries could contribute to weakening the comparison of results at international level. In this setting, the use of the pooled mean group estimator (PMG) (see Pesaran et al., 1999) has been recommended because it allows for estimating common long-run marginal

[30]It is widely acknowledged that panel unit root and cointegration tests are statistically more powerful compared to their univariate counterparts.

propensity to consume, while considering potential differences across countries in the adjustment process towards the long-run propensity.

The PMG estimator has been largely applied to estimating wealth effects on consumption (see, for example, Ludwig and Slok, 2004; De Bonis and Silvestrini, 2012; Jaramillo and Choilloux, 2015). However, this approach is based on the assumption of cross-sectional independence, which is very difficult to justify in this context, because economies have become increasingly interconnected over the last decades. This implies that the resulting estimates are likely to be biased and inconsistent (see, Andrews, 2005; Bai and Kao, 2006), besides the fact that unit root and cointegration tests which do not account for cross-section dependence suffer from large size distortions (see Banerjee et al., 2004, 2005).

This chapter draws motivation from the assumption that it is more reasonable and appropriate to investigate wealth effects using a factor structure to characterize cross-sectional dependence when looking at the international dimension of aggregate consumption. This is because increasingly international financial integration, since the 1970s, has led asset prices, risk premia, and price volatility to become highly correlated across countries (see IMF, 2007; Vansteenkiste and Hiebert, 2011; Hoesli and Reka, 2015). As a result, equity markets in advanced and emerging market economies have become highly synchronized, and, though to a rather lesser extent, the same is true for housing markets. As for the latter, what is crucial for them to be not independent to each other is that the main determinants of house prices, such as income and interest rates, tend to co-move at international level (see IMF, 2011).

This study investigates the long-run financial and housing wealth effects on consumption in 14 OECD countries, using annual data over the period 1970-2012. It applies recently developed nonstationary panel methodologies that assume cross-section dependence through common factor models. In particular, the procedure developed in Gengenbach et al. (2006) (see also Urbain and Westerlund, 2011) is used to test for unit root and cointegration, and then the recently developed least square biased-adjusted estimator by Westerlund (2007) is applied in order to estimate the long-run marginal propensity to consume out of financial and housing wealth.

A related work by Dreger and Reimers (2012) considers the impact of international spillovers on consumption responses using a common factor structure. Although in the same spirit, the study in this chapter differs from their work in several respects. First, a newly updated data set for housing and financial wealth is used instead of asset prices. In this way, it is possible to compute marginal propensities to consume out of housing and financial wealth, which represent more appropriate measures of wealth effects than elasticities computed by using asset prices. In fact, asset prices do not account for the scale and composition of asset holdings, which can differ across countries. Second, a recently developed biased-adjusted estimator proposed by Westerlund (2007), which embodies cross-sectional dependence through a common factor structure, is used in order to compute the marginal propensities to consume out of financial and housing wealth. Third, this work carries out a wider analysis along the cross-sectional dimension. To this end, all the OECD countries are first pooled, and then they are split into two groups, namely bank-based and market-based countries (see also Bayoumi and Edison, 2003; Ludwig and Sløk, 2004; Slacalek, 2009). The split is motivated by the fact that the structure of the financial system in the two groups is diverse, and this may exert a different impact on consumption (see Ludwig and Sløk, 2004).

The empirical analysis shows three main results. First, both housing and financial wealth have a positive and significant impact on aggregate consumption. Second, the housing wealth effect is larger than the financial wealth effect for the sample of all countries as well as for the two groups of countries. Third, wealth effects are larger in market-base economies than bank-based ones.

The rest of the study is organized as follows. Section 3.2 discusses previous studies. Section 3.3 presents the econometric methodology. Section 3.4 describes the data. Section 3.5 discusses the empirical results, and Section 3.6 draws conclusions.

3.2. RELATED LITERATURE

This section is devoted to previous studies on wealth effects related to OECD countries using macro panel data techniques. This strand of the literature is relatively scant and has predominantly tried to disentangle the relative size of housing and financial wealth effects. This is on the grounds that wealth components may be associated with different features in terms of risk, collateral, liquidity and bequest motive (Case et al., 2005).

Consumers may also attach certain psychological factors to certain assets whereby some are considered more appropriate to be used for current expenditures (e.g. stocks), while others (e.g. residential properties, pension funds) are considered more appropriate to be earmarked for long-term savings (Thaler, 1990).

In order to measure the impact of wealth components on consumption, some empirical works have used asset prices as proxies of wealth components in traditional consumption functions (Ludwig and Sløk, 2004; Dreger and Reimers, 2012), while others have used wealth data (Case et al., 2005; Labhard et al., 2005; Slacalek, 2009; De Bonis and Silvestrini, 2012; Jaramillo and Chovilloux, 2015). A different approach is used in Bayoumi and Edison (2003) since a mix of the two sources of data is used in the estimation.

In particular, Bayoumi and Edison (2003) use stock market capitalization as a ratio to GDP and house prices, as proxies for equity and housing wealth, respectively, to investigate wealth effects on aggregate consumption on a panel of 16 advanced economies for the period 1970-2000. They also try to study differences of behaviour of wealth effects over different time periods and across financial systems. For these reasons, the analysis is repeated over the sample 1984-2000, and for the market-based and bank-based groups of countries.[31] More in detail, the analysis relies on a two-step panel procedure. In the first stage, a standard long-run relationship between consumption, disposable income and wealth components is estimated, and the related results are then embodied into a dynamic error-correction specification. Unlike housing wealth, consumption, disposable income, and equity wealth are all measured as a ratio of trend real GDP. In order to account for housing wealth to be measured in a different way compared to other variables, the related coefficient is allowed to trend over time in the estimated long-run relationship. The related findings show that both types of wealth are statistically significant in the short-run as well as in the long-run.[32] The wealth effect on equities is higher in market-based countries than

[31] While Anglo-Saxon countries feature market-based financial systems, Continental Europe is characterized by bank-based financial systems. The former type of financial system shows a larger size of stock markets and a higher degree of stock market capitalization than the latter type. This would imply that consumption responds to changes in stock prices more intensively in the former group of countries (see Ludwig and Sløk, 2004).

[32] A preliminary analysis on unit root and cointegration is conducted before estimating the error-correction model.

bank-based countries (4½ cent as opposed to 1 cent per dollar, respectively).[33] Although comparisons are problematic since the coefficient of equity wealth is measured in cents to dollar whilst the coefficient of housing wealth represents elasticity, the housing wealth effect seems to be larger than financial one in both groups. For example, for the market-based group a dollar increase in stock wealth seems to be associated with 4½ cents increase in consumption as opposed to 7 cents for housing wealth. Finally, in both groups these effects had increased over time. This is particularly true in the countries with market-based financial systems, possibly as a consequence of financial deregulation.

Ludwig and Sløk (2004) use quarterly price indices, as proxies of stock market and housing wealth, to investigate the relative importance of these forms of wealth as determinants of private consumption in 16 OECD countries. They conclude that their results do not provide enough evidence of whether housing wealth plays a major role in explaining consumption than financial wealth. Their analysis is conducted for the sample of all countries and for the two groups of countries with bank-based and market-based financial systems. This is because the transmission of changes in asset prices to changes in consumption depends on the type of financial system.[34] Furthermore, the sample period, 1960q1-2000q4, is split into the two sub-periods, 1960-1984 and 1985-2000, in order to investigate a potential increase in the responsiveness of consumption to variations in the price of assets due to increases in the size of stock markets and deregulations of mortgage markets over time. The panel technique involved is the so-called PMG estimator, which pools long-run relationships between countries, while allowing the short-run responses to be unrestricted across countries. Before estimating wealth effects, findings in a preliminary analysis show that consumption, income, stock prices and house prices are nonstationary and cointegrated. Ludwig and Sløk (2004) consider three different cases in the estimation process. First, they apply the panel technique developed by Pesaran et al. (1999) which is based on the assumption of cross-sectional independence. Second, they consider a specification that allows for the presence of cross-sectional dependence in the examined panel data through a common factor structure. Finally, while controlling for the common factor problem, they use stock market capitalization data instead of stock market prices for a sensitivity check. The results of the analysis suggest that in the long run consumption

[33] Australia, Canada, Ireland, the Netherlands, Sweden, the UK, and the US are regarded as countries with market-based financial systems, while Belgium, Denmark, Finland, France, Germany, Italy, Japan, Norway, and Spain are considered countries with bank-based financial systems.
[34] In this respect, they follow the criteria in Borio (1996).

responds to permanent changes in stock prices more intensively in countries with market-based financial system as compared to countries with bank-based financial systems. A significant and positive role of house prices is observable only in the third specification, with estimates being higher than those for stock market capitalization (0.043 as opposed to 0.026, respectively). When splitting the sample into the two above sub-periods, results show an increased sensitivity of consumption to permanent changes in stock prices for both the two groups of countries in the 1990's. The relationship between changes in consumption and changes in house prices is always positive for the second sample period, regardless of the specification and financial system, while it is positive for the first sample period only when controlling for cross-section dependence.

Case et al. (2005) use wealth data to shed light on whether consumption may be affected differently by various forms of wealth. Their results support the conclusion that variations in housing wealth in developed countries should exert a more relevant impact on consumption than variations in stock market wealth. In particular, their analysis considers two different datasets: a panel of annual observations for 14 developed countries over the period of 1975-1999, and a panel of quarterly observations for the American states over the period 1982-1999. Their datasets for stock market wealth, housing market wealth, and consumption are obtained by imputing the aggregate value of owner-occupied housing, the value of financial assets and measures of aggregate consumption, taken from available data sources, to each of the geographic units overtime. After verifying that the series for both panels are nonstationary, various fixed effects models with variables expressed either in levels or first difference are estimated by OLS or GLS method. The estimated results show that the effect of housing market wealth is large and significant for all the specifications, while that of financial wealth is smaller and in some specifications insignificantly different from zero. More in detail, for regressions in levels, elasticity for housing wealth ranges from 0.11 to 0.17 in the international comparison, while in cross-state comparison, it ranges from 0.05 to 0.09. By contrast, when significant, elasticity for financial wealth effect is about 0.02 in the international comparison, while it ranges between about 0.03 and 0.06 in cross-state comparison.

The work by Labhard et al. (2005) differs from above papers because it focuses mainly on the financial wealth effect on consumption and the reasons why empirical estimates of wealth effects vary greatly across countries.[35] It is argued that one reason for large dispersion in the values of long-run marginal propensities to consume across countries, observed within contributions to the literature based on log-linear specifications, is due to the fact that both elasticities and wealth-consumption ratios are estimated over different periods of time. However, even within studies related to the same country, remarkable differences in the values of MPCs may be observed. This is in part because the wealth-consumption ratio is typically not constant across countries and over time.[36] Based on four structural vector autoregressions (VARs), Labhard et al. (2005) provide estimates of the elasticity of total consumption out of net financial wealth for 11 OECD countries, over the period 1970-2002, which tend to confirm the wide dispersion of wealth effects across countries. In their opinion, differences across countries in terms of the rates of return on financial assets, the length of planning horizons and the structure of asset portfolios are not so large to justify such discrepancies. It is more plausible that problems in the measurement of wealth and the incapability of partial equilibrium approaches to consider structural causes of simultaneous variations, in both consumption and wealth, are responsible for such variation in MPCs. For example, the response of consumption to shocks in earnings may not differ across countries, but if wealth is under-recorded because of the presence of a large share of unquoted equities, the resulting wealth effect will be overestimated. While it is reasonable to expect similar long-run MPCs across countries when planning horizons and rates of return are similar, the same cannot be expected for short-run wealth effects. Therefore, the authors consider estimating wealth effects by the pooled mean group estimator (PMG) of Pesaran et al. (1999) more appropriate. To this end, a ratio specification, implying a cointegration relationship between consumption-income ratio to the wealth-income ratio, is estimated providing a direct estimate of the long-run MPC out of financial wealth, at 1.7 or 6.8 in annualized terms. This value is largely consistent with estimates considered in several policy models. In addition, the null

[35] Labhard et al. (2005) also explore the housing wealth effect, but the related results are not reported in the paper because judged to be unsatisfactory. In this respect, it is underlined that, differently to the case of financial wealth, differences across countries can be identified in the short term, suggesting systematic divergent responses of consumption to shocks across countries, which in turn reflect differences in the deregulation of mortgage markets and taxation treatment. However, it is casted doubt on whether a long-run housing wealth effect across countries exists, and data deficiencies are considered such to undermine efforts to detect any such effect.

[36] In countries that feature relatively low state benefit provision, household holdings of financial wealth tend to be higher than economies that show relatively high state benefit provision. Holding wealth, as collateral to gain access to capital markets, as in the case of housing wealth, may be another reason why holdings of wealth may differ across countries.

hypothesis in the Hausman test of a common long-run financial wealth effect across the eleven examined OECD countries cannot be rejected.

Slacalek (2009) investigates housing and financial wealth effects in a panel of 16 industrialized countries estimating seemingly unrelated regressions (SUR) with homogeneity restrictions on groups of similar countries. The panel analysis refers to the following groups of countries: “complete" and “incomplete” mortgage markets, market-based and bank-based countries, Anglo-Saxon and Non-Anglo-Saxon countries, Euro area and Non-Euro area.[37] The related findings, obtained using data over the 1979-1999 period, highlight large statistically significant differences in MPCs between countries. More in detail, figures for total wealth effects range between 4-6 cents per dollar in Anglo-Saxon countries, “complete” mortgage markets, market-based economies and countries outside the Euro area, while they are smaller, ranging between 0 and 2 cents per dollar, in bank-based economies, countries with “incomplete" mortgage markets, Non-Anglo-Saxon countries, and members of the Euro area. Moreover, although the housing wealth effect seems to be smaller than the financial wealth effect in the Euro area, bank-based and Non-Anglo Saxon countries and in countries with “incomplete” mortgage markets, there is no substantial difference between these wealth component effects in other countries. In order to investigate how wealth effects change over time, the panel analysis is repeated over the 1979-1988 and 1989-1999 subsamples. The related results show evidence of an increase in wealth effects after 1988, which is more significant for Non-Anglo Saxon, bank-based and Euro area, where financial markets are less developed.

Dreger and Reimers (2012) investigate the long-run wealth effects on consumption for a panel of 15 industrialized countries, using panel cointegration techniques designed to control for cross-section dependence through a factor structure (see Bai and Ng, 2004). In particular, each panel series is meant to be the sum of common and idiosyncratic components, with the former accounting for cross-section dependence. This structure implies that a long-run equilibrium between consumption, income and wealth may exist as a result of the presence of international or national trends, or both. Using quarterly price indices to proxy wealth components, spanning from 1991q1 to 2010q2, the common factors and the idiosyncratic components are estimated as suggested by Bai and Ng

[37] The mortgage market index of Cardarelli et al. (2008) is used to distinguish between countries with “complete” and “incomplete” mortgage markets, while the aggregate structure index by Levine (2002) is used for the definition of market- and bank-based economies.

(2004),[38] and then the unit root properties of the common factors are tested by standard time series tests, while those of the independent idiosyncratic components are explored via the panel unit root test by Im et al. (2003). While all factors are found to be nonstationary, the unit root can be rejected for the idiosyncratic components of the wealth components. Results from the cointegration testing strategy proposed by Gengenbach et al. (2006) indicate a long-run relationship between the common factors of consumption, income and wealth. This implies that wealth effects in consumption equations result from the international integration, therefore decelerating consumption expenditures and increasing national saving rates should be expected if financial markets become less integrated. In models with either share or house prices, the long run relationship is unique, while in models in which both wealth components are included, two cointegration vectors seem to exist. Furthermore, Pedroni (1999, 2004) tests point to a cointegrating relationship between consumption and income at the idiosyncratic level. As for the estimation of the cointegrating vectors, the reduced rank ML estimator by Johansen (1995), and a two-step generalized least squares estimator by Brüggemann and Lütkepohl (2005) are used for common components, while a panel FMOLS estimator (see Pedroni, 1999) and a panel DOLS estimator (see the procedure in Mark et al., 2005) are applied for the idiosyncratic components.[39] The results for common factors reveal that parameter estimates of the cointegrating vector are in accordance with the permanent income hypothesis when only house prices are included in the equation. In fact, income elasticity differs substantially from unity when only equity prices are considered in the model. Moreover, if both wealth measures enter the analysis, the impact of house prices is higher than that arising from equity wealth (for example, 0.19 as opposed to 0.05, respectively, by the simple two step method). In this case, wealth effects have to be added approximately, to be in line with the evidence on the cointegration rank. A low income elasticity at about 0.5 is found for the cointegration relationship related to idiosyncratic components, perhaps reflecting measurements errors associated with the use of disposable income instead of labor income.

Differently from Dreger and Reimers (2012), De Bonis and Silvstrini (2012) highlight a larger effect of financial wealth than housing wealth on consumption by examining quarterly wealth data for a panel of 11 OECD countries over a slightly shorter

[38] The number of common factors in each variable is estimated using the BIC3 criterion (see Bai and Ng, 2002). The related results refer to a single factor estimated for all variables concerned.

[39] Heterogeneity across counties is controlled through fixed effects, time trends and short run dynamics.

period of time, running from 1997 to 2008.[40] National share price indices are also employed, as a proxy of financial wealth, in order to carry out a robustness check. In the main analysis, a ratio specification for the consumption function is used, so net financial wealth together with household consumption expenditure, and real wealth are expressed as a ratio of disposable income. All variables in this specification are found nonstationary and cointegration is assessed between consumption-income ratio and wealth-income ratios and between consumption-income ratio and the stock market index. The panel cointegration test by Westerlund (2006), which accounts for structural changes, is also applied. Evidence of a cointegrating relationship between consumption and real and financial wealth is found, as well as between consumption and the stock market index. With the exception of Austria, the Netherlands and the UK, at least one break-date is estimated for every country (shift in the level). As expected, most of the breaks are estimated between 2000 and 2003, when several financial distresses occurred. Some of the break-dates are detected in 2005, which may be the result of the upward trend of stock markets after 2003. In order to estimate the long-run marginal propensities to consume out of financial and real wealth, different estimation techniques are applied: the PMG estimation by Pesaran et al. (1999) as well as the fixed-effects and single-country level ARDL estimation. Results support the evidence of a larger financial wealth effect compared to the real wealth effect. On annual basis, estimates by the fixed-effects estimator are 2.84 and 0.32 cents per euro, while those by the PMG estimator are 3.6 and 0.4 cents per euro for financial wealth and housing wealth, respectively. In a sensitivity analysis, the PMG estimator is applied alternately to estimate the financial wealth effect with net financial wealth and the stock market index. The same point estimate at 4 cents for euro on annual basis is found in the two cases, suggesting that using the flow of funds definition of net financial wealth or the stock market index approximation does not really matter. Finally, results obtained by estimating single-country level ARDL equations would suggest that wealth effects on consumption are significant for the US and the UK, whilst they are weaker for other countries. This would support the evidence of a divide between countries with an effective mortgage equity withdrawal mechanism (typically the US and the UK) and countries that feature weak financial innovation (Euro area).

[40] The countries are: Austria, Belgium, Finland, France, Germany, Italy The Netherlands, Portugal, Spain, the US, the UK.

Jaramillo and Chailloux (2015) also find evidence of a larger financial wealth effect than housing wealth effect. These authors study not only the impact of wealth components on aggregate consumption, but also that of fiscal policy instruments, particularly over the recent period of financial crisis. Their analysis use quarterly data, spanning from 1998 to 2012, for an unbalanced panel of 14 advanced economies. To better understand the evolution of consumption, different types of income and wealth are used. Specifically, disposable income is broken down into its subcomponents: labor income, social benefits, and personal income taxes and social security contributions, with the last two variables representing fiscal variables. As for different categories of wealth, financial assets, housing assets, and household debt are included in the analysis. By analyzing changes in private consumption between 2007 and 2012, these authors highlight that patterns across countries are not similar. Some countries, such as Sweden and Australia, weathered better the storm, while other countries, such as Spain and Ireland, experienced the largest drops. Furthermore, countries with a larger decline in consumption were also those that implemented larger fiscal adjustments in the aftermath of the financial crises. However, it is argued that the fall in consumption cannot be attributed solely to the effect of fiscal policy. Wealth effects are likely to have also played an important role, since private consumption had peaked well before the beginning of fiscal consolidation in several countries, such as Ireland, Spain, the UK, and the US. After testing that all variables involved have unit roots, the PGM method is applied under alternative specifications. The results suggest that consumption is affected by wealth effects, in addition to fiscal policy. There is evidence of a statistically significant long-term relation between consumption and different components of income and wealth, with labor income having the largest positive impact. Personal income taxes and social security contributions are found to have a negative impact on consumption, while social benefits are found to have a larger positive effect. As for the role of different wealth components, while financial assets and housing assets are found to have positive coefficients, household debt is found to have negative ones. The elasticity on financial assets tends to be larger than that of housing wealth, in the majority of the cases. In terms of marginal propensity to consume, financial assets again play a major role in determining consumption at 0.03 as opposed to 0.021 for housing assets. Furthermore, the findings indicate that the variation in consumption due to a change in financial or housing assets would be more than offset if financed fully through a rise in household debt.[41]

3.3. ECONOMETRIC METHODOLOGY

This section is devoted to the description of the econometric procedure which takes cross-sectional dependence into account in order to disentangle the impact on aggregate consumption of wealth components for a panel of 14 OECD countries. The analysis aims at estimating the following long-run linear relationship between consumption, disposal income, financial wealth and housing wealth, which relies on the theoretical framework of the permanent income hypothesis or the life-cycle model (Friedman, 1957; Ando and Modigliani, 1963):

$$c_{it} = \beta_0 + \beta_y\, y_{it} + \beta_{fw} fw_{it} + \beta_{hw} hw_{it} + \varepsilon_{it}. \tag{3.1}$$

In equation (3.1), $c_{it} = lnC_{it}$ indicates the logarithm of real per capita consumption, $y_{it} = lnY_{it}$ is the logarithm of real per capita personal disposable income, $fw_{it} = lnFW_{it}$ is the logarithm of real per capita financial wealth, and hw_{it}= $lnHW_{it}$ is the logarithm of real per capita housing wealth.

The analysis is carried out in three steps. First, the presence of unit roots in each variable in equation (3.1) is tested by using the Panel Analysis of Nonstationary in Idiosyncratic and Common components (PANIC) approach by Bai and Ng (2004). Second, the existence of panel cointegration is investigated by using the procedure developed in Gengenbach et al. (2006) (see also Urbain and Westerlund, 2011). Third, the elasticities of consumption to income, financial and housing wealth are estimated by using the biased-adjusted estimator proposed by Westerlund (2007), and then they are turned into marginal propensities to consume.

The PANIC approach is based on the idea that cross-section correlation in a generic panel series, X_{it}, can be modelled with a common factor structure. This implies that the

[41] Robustness checks are also carried out and point to differences across countries in terms of accessing to credit and in terms of preferences for home ownership. In particular is found that: i) the coefficient on housing assets is higher than that of financial assets for countries with the highest household debt; ii) housing wealth effects are not significant for countries which did not experience a housing boom.

series can be thought as the sum of a set of common factors and an idiosyncratic component:

$$X_{it} = D_{it} + \lambda_i' F_t + e_{it}, \tag{3.2}$$

$$\text{(I-L)}F_t = C(L)\, u_t, \tag{3.3}$$

$$(1 - \rho_i L)e_{it} = D_i(L)\epsilon_{it}, \tag{3.4}$$

where $i = 1, ..N; t = 1, .., T, D_{it} = c_i + \beta_i t,\ C(L) = \sum_{j=0}^{\infty} C_j L^j$, and $D_i(L) = \sum_{j=0}^{\infty} D_{ij} L^j$, F_t is an $r \times 1$ vector of common factors, λ is a vector factor loadings, e_{it} denotes the idiosyncratic error. The idiosyncratic error component e_{it} is I(1) process if $\rho_i = 1$, and it is a stationary process if $|\rho_i| < 1$. As for F_t, the model allows for $\boldsymbol{r}_0$ stationary factors and $\boldsymbol{r}_1$ common trends, with $\boldsymbol{r} = \boldsymbol{r}_0 + \boldsymbol{r}_1$.[42] The series in (3.2) can be nonstationary because common factors are I(1), or the idiosyncratic component is I(1), or both.

One important aspect of the PANIC approach is to test for unit roots in common factors and idiosyncratic components separately. This is because the tests on the factors are independent of those on the idiosyncratic errors. In this way, it is possible to ascertain if the nonstationarity nature of X_{it} comes from a pervasive or an idiosyncratic source, or both of them.

Another important feature of the PANIC approach involves consistent estimation of unobserved common factors without any a priori knowledge of the stationary or nonstationary nature of idiosyncratic errors. To this end, principal components analysis is applied to first-differenced data to estimate common factors and factor loadings, in a datasets in which time and cross-section dimension are both large.

The factor analytic model in equation (3.2) can be expressed in first difference as follows:

[42] For the model with a constant only, see Bai and Ng (2004).

$$x_{it} = \lambda_i' f_t + z_{it}, \tag{3.5}$$

where $x_{it} = \Delta X_{it} - \overline{\Delta X}_i$, with $\Delta X_{it} = \beta_i + \lambda_i' \Delta F_t + \Delta e_{it}$ and $\overline{\Delta X}_i = (T-1)^{-1} \sum_{t=2}^{T} \Delta X_{it}$, $f_t = \Delta \mathrm{F}_t - \overline{\Delta F}$, with $\overline{\Delta F} = (T-1)^{-1} \sum_{t=2}^{T} \Delta \mathrm{F}_t$, and $z_{it} = \Delta e_{it} - \overline{\Delta e}_i$, with $\overline{\Delta e}_i = (T-1)^{-1} \sum_{t=2}^{T} \Delta e_{it}$. Bai and Ng (2004) apply the principal component analysis to x_{it} to obtain $\boldsymbol{r}$ estimated factors $\hat{f}_t$, the corresponding factor loadings $\hat{\lambda}_i'$, and the estimated residuals $\hat{z}_{it} = x_{it} - \hat{\lambda}_i' \hat{f}_t$.[43] For $t = 2, \ldots, T$, Bai and Ng (2004) define:

$$\hat{e}_{it} = \sum_{s=2}^{t} \hat{z}_{it}, \quad i = 1, \ldots, N,$$

$$\hat{F}_t = \sum_{s=2}^{t} \hat{f}_s, \text{ an } \boldsymbol{r} \times 1 \text{ factor.}$$

In order to test for the unit root in the common factor components, Bai and Ng (2004) distinguish two different cases:

1) If there is only one common factor in the data (r = 1), then the $ADF_{\hat{F}}^{\tau}$ statistic is applied to the following augmented regression for testing $\delta_0 = 0$:[44]

$$\Delta \hat{F}_t = c_0 + c_1 t + \delta_0 \hat{F}_{t-1} + \delta_1 \Delta \hat{F}_{t-1} + \cdots + \delta_p \Delta \hat{F}_{t-p} + error. \tag{3.6}$$

2) If the data contain more than one common factor, that is $r > 1$, let $\hat{F}_t^{\tau}$ be the residuals from a regression of $\hat{F}_t$ on a constant and a time trend. The procedure starts with $m = r$ (see Bai and Ng, 2004, pages 1113-1134), with m denoting the number of common trends in $\hat{F}_t$.

   A. Let $\hat{\beta}_{\perp}$ be the m eigenvectors associated with the m eigenvalues of $T^{-2} \sum_{t=2}^{T} \hat{F}_t^{\tau} \hat{F}_t^{\tau\prime}$. Let $\hat{Y}_t^{\tau} = \hat{\beta}_{\perp}' \hat{F}_t^{\tau}$. The following two statistics are considered:

   B.I Let $K(j) = 1 - \frac{j}{J+1}, j = 0, 1, \ldots, J$:

[43] The theory is developed by assuming r as known. In practice r is determined by applying the methodology proposed in Bai and Ng (2002). For details on the criteria to determine r in the empirical analysis, see Section 3.5 and Appendix B.

[44] For the limiting distribution of $\mathrm{ADF}_{\hat{\mathrm{F}}}^{\tau}$ test, that coincides with the DF test for the case with constant and a linear trend, see Appendix B.

(i) Let $\hat{\xi}_t^\tau$ be the residuals from estimating a first-order VAR in $\hat{Y}_t^\tau$ and let

$$\hat{\Sigma}_1^\tau = \sum_{j=1}^{J} K(j)\left(T^{-1}\sum_{t=2}^{T}\hat{\xi}_{t-j}^\tau \hat{\xi}_t^{\tau\prime}\right).$$

(ii) Let ν_c^τ (m) be the smallest eigenvalue of

$$\hat{\phi}_c^\tau(m) = 0.5\left[\sum_{t=2}^{T}\left(\hat{Y}_t^\tau \hat{Y}_{t-1}^{\tau\prime} + \hat{Y}_{t-1}^\tau \hat{Y}_t^{\tau\prime}\right) - T\left(\hat{\Sigma}_1^\tau + \hat{\Sigma}_1^{\tau\prime}\right)\right]\left(\sum_{t=2}^{T}\hat{Y}_{t-1}^\tau \hat{Y}_{t-1}^{\tau\prime}\right)^{-1}.$$

(iii) Define $MQ_c^\tau(m) = T[\hat{v}_c^\tau(m) - 1]$.

B.II For p fixed, which does not depend on N or T:

i) Estimate a VAR of order p in $\Delta\hat{Y}_t^\tau$ to get $\hat{\Pi}(L) = I_m - \hat{\Pi}_1 L - \cdots - \hat{\Pi}_p L^p$.

By filtering $\hat{Y}_t^\tau$ through $\hat{\Pi}(L)$, we have $\hat{y}_t^\tau = \hat{\Pi}(L)\hat{Y}_t^\tau$.

ii) Define $\hat{v}_f^\tau(m)$ the smallest eigenvalue of

$$\hat{\phi}_f^\tau(m) = 0.5[\sum_{t=2}^{T}(\hat{y}_t^\tau \hat{y}_{t-1}^{\tau\prime} + \hat{y}_{t-1}^\tau \hat{y}_t^{\tau\prime})](\sum_{t=2}^{T}\hat{y}_{t-1}^\tau \hat{y}_{t-1}^{\tau\prime})^{-1}.$$

iii) Define the statistics $MQ_f^\tau(m) = T\left[\hat{v}_f^\tau(m) - 1\right]$.

C: If $H_0: r_1 = m$ is rejected, set $m = m - 1$ and return to step A. Otherwise $\hat{r}_1 = m$ and stop.[45]

To test the stationarity of the idiosyncratic component, Bai and Ng (2004) propose pooling p-values from the individual $ADF_{\hat{e}}^\tau$(i) t-statistics for testing $d_{i0} = 0$ in the estimated components e_{it} in the following model:

$$\Delta\hat{e}_{it} = d_{i0}\hat{e}_{it-1} + d_{i1}\Delta\hat{e}_{it-1} + \cdots + d_{ip}\Delta\hat{e}_{it-p} + u_{it}. \quad (3.7)$$

The pooled statistic is defined as follows:

$$Z_e^c = \frac{-2\sum_{i=1}^{N} log p_{\hat{e}}^c(i) - 2N}{\sqrt{4N}} \Rightarrow N(0,1)$$

[45] For the details on the distribution of the statistics $MQ_c^\tau(m)$ and $MQ_f^\tau(m)$, see Appendix B.

where $p_{\hat{e}}^{c}(i)$ is the p-value of the ADF t-statistics for the *i*-th cross-section, $ADF_{\hat{e}}^{c}(i)$, and $\Longrightarrow$ denotes weak convergence. Choi (2001) shows that Z_e^c converge to standard normal distribution as $T_i \rightarrow \infty$ followed by $N \rightarrow \infty$.

After checking for unit root in the data, the next step consists in testing for cointegration using the procedure developed by Gengenbach et al. (2006). This procedure is as follows:

1. If I(1) common factors and I(0) idiosyncratic components are detected in the variables of interest in the preliminary PANIC analysis, then the nonstationarity in each panel series is entirely due to common stochastic trends. In this case, it is possible to investigate if the estimated common factors cointegrate with each other, and the Trace statistics by Johansen (1995) can be applied to this end.
2. If I(1) common factors and I(1) idiosyncratic components are detected in the data, then the step in 1. will be carried out in order to investigate possible cointegration among the estimated factors, while the presence of cointegration among defactored panel series will be also tested. To this end, standard panel tests for no cointegration can be used. In the empirical analysis, the panel Z_ρ and Z_t statistics by Pedroni (1999, 2004) are applied.[46]

In the third step of the analysis, equation (3.1) is estimated by using the bias-adjusted LS estimator proposed by Westerlund (2007). More in detail, Westerlund (2007) considers the following model:

$$y_{it} = \alpha_i + \beta x_{it} + e_{it}, \tag{3.8}$$

$$x_{it} = x_{it-1} + v_{it}, \tag{3.9}$$

where y_{it} is a scalar integrated variate, x_{it} is a k-dimensional vector of integrated variables, β is a k-dimensional row vector.[47]

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[46] For details on the panel Z_ρ and Z_t statistics, see Appendix B.

[47] As for the analysis in this chapter, the dependent variable is consumption (c_{it}), while the explanatory variables are disposable income (y_{it}), financial (fw_{it}) and housing wealth (hw_{it}).

The error term e_{it} is generated by the following factor model:

$$e_{it} = \lambda_i' f_t + u_{it}, \tag{3.10}$$

where f_t is a k-dimensional vector of unobservable common factors, λ_i is a vector of factor loadings and u_{it} is a scalar idiosyncratic error.[48] Define $z_{it} = (f_t', u_{it}, v_{it}')'$. Then, the long-run covariance matrix of z_{it} can be written as follows:

$$\Omega_i = \Sigma_i + \Gamma_i + \Gamma_i' = \Lambda_i + \Gamma_i',$$

where $\Sigma_i = E(z_{i0}z_{i0}')$ and $\Gamma_i = \sum_{j=1}^{\infty} E\left(z_{i0}z_{ij}'\right)$ are the contemporaneous and lagged covariances of z_{it}, respectively. The matrix Ω_i can be portioned in:

$$\Omega_i = \begin{bmatrix} \Omega_{ffi} & \Omega_{fui} & \Omega_{fvi} \\ \Omega_{ufi} & \Omega_{uui} & \Omega_{uvi} \\ \Omega_{vfi} & \Omega_{vui} & \Omega_{vvi} \end{bmatrix}.$$

This matrix is used to define the bias (see b_{NT} below). Westerlund (2007) first introduces the standard infeasible BA estimator, and then describes the feasible estimator.

The conventional estimator of β can be written as:

$$\hat{\beta} = \left(\sum_{i=1}^{N}\sum_{t=11}^{T} y_{it}\tilde{x}_{it}'\right)\left(\sum_{i=1}^{N}\sum_{t=1}^{T} \tilde{x}_{it}\tilde{x}_{it}'\right)^{-1},$$

where $\tilde{x}_{it} = x_{it} - \frac{1}{T}\sum_{s=1}^{T} x_{is}$. Then, the biased-adjusted (BA) estimator can be defined as follows:

$$B^{+} = \hat{\beta} - b_{NT},$$

where b_{NT} indicates the bias of $\hat{\beta}$ and

[48] For model assumptions, see Westerlund (2007).

$$b_{NT} = \sum_{i=1}^{N} \left(\lambda_i' U_{fvi} + U_{uvi}\right) \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{x}_{it} \tilde{x}_{it}'\right)^{-1},$$

$$U_{fvi} = \Omega_{fvi} \Omega_{vvi}^{-1} \left(\sum_{t=1}^{T} \Delta x_{it} \tilde{x}_{it}' - T\Lambda_{vvi}\right) + T\Lambda_{fvi},$$

$$U_{uvi} = \Omega_{uvi} \Omega_{vvi}^{-1} \left(\sum_{1}^{T} \Delta x_{it} \tilde{x}_{it}' - T\Lambda_{vvi}\right) + T\Lambda_{uvi}.$$

In order to implement the feasible BA estimator, Westerlund (2007) proposes a two-step procedure. In the first step, λ_i and f_t are estimated using the principal components method. Denote with λ, f, and $\hat{e}$ the $K \times N$, $T \times K$, and $T \times N$ matrices of stacked observations on λ_i, f_t, and $\hat{e}_{it}$, respectively. The principal component estimator $\hat{f}_t$ of f can be gained by calculating $\sqrt{T}$ times eigenvectors corresponding to the k largest eigenvalues of the $T \times T$ matrix $\hat{e}\hat{e}'$, and the corresponding estimated matrix of the factor loading is obtained as $\hat{\lambda} = \frac{1}{T}\hat{f}'\hat{e}$. In the second step, the estimates of λ_i and f_t, $\hat{\lambda}_i$ and $\hat{f}_t$, are used to estimate Ω_i in the following way:

$$\widehat{\Omega}_i = \hat{\Sigma}_i + \hat{\Gamma}_i + \hat{\Gamma}_i' = \widehat{\Lambda}_i + \hat{\Gamma}_i',$$

where $\hat{\Sigma}_i = \frac{1}{T}\sum_{t=1}^{T} \hat{z}_{it}\hat{z}_{it}'$ and $\hat{\Gamma}_i = \frac{1}{T}\sum_{j=1}^{M}\left(1 - \frac{j}{M+1}\right)\sum_{t=j+1}^{T} \hat{z}_{it}\hat{z}_{it-j}'$, M is a bandwidth parameter that determines the number of covariances that have to be estimated in the kernel, and $\hat{z}_{it}$ is the estimate of z_{it}, with $\hat{f}_t$ and $\hat{u}_{it} = \hat{e}_{it} - \hat{\lambda}_i'\hat{f}_t$ in place of f_t and u_{it}, respectively (see Westerlund, 2007, page 467). Using the estimates of b_{NT}, $\hat{b}_{NT}$, one can yield the feasible two-step BA estimator B^+. The empirical analysis requires estimating not only λ, f, and $\hat{e}$, but also determining K (see Westerlund, 2007). To this end, we use the BIC3 criterion by Bai and Ng (2002) (see Appendix B).

3.4. DATA

This chapter uses annual data for 14 OECD countries, over the period 1970-2012, taken from the database of the NiGEM model by the National Institute of Economic and Social Research (NIESR). The countries concerned are: Australia, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Sweden, Spain, the UK, and the US. The variables of interest for the analysis, already introduced in Section 3.3, are briefly described below.

The consumption data (C_{it}) refer to total private consumption expenditures, as a sum of durable and non-durable goods. Other studies also consider consumption which includes spending on durables. This is because durable spending represents a relatively small part of the total, and because significant resources raised by mortgage refinancing are spent on durables (see Peltonen et al., 2012). The disposable income data (Y_{it}) are defined as total market income plus transfers from government less income taxes and social contributions. The financial wealth data (FW_{it}) correspond to gross financial assets owned by households less their financial liabilities, which include both mortgages and consumer credit. The housing wealth data (HW_{it}) are all taken from data published by national statistical offices and/or central banks. In all cases the data cover the dwellings owned by the personal sector. All series are deflated by personal consumption expenditure price index and expressed in per capita terms. The population series are taken from the Organization for Economic, Co-operation and Development (OECD) Population Statistics.

3.5. EMPIRICAL RESULTS

This section is devoted to the results of the empirical analysis carried out to estimate wealth effects on consumption in a panel of 14 OECD countries. It is organized as follows: firstly, findings of a preliminary analysis on cross-sectional dependence, unit root and cointegration of the variables of interest are presented, followed by a discussion about estimated elasticities in equation (3.1), and the related MPCs.

3.5.1. CROSS-SECTIONAL DEPENDENCE, UNIT ROOT AND COINTEGRATION

As the 14 OECD countries under investigation are interconnected because of the increasing level of financial integration, it is very likely that they feature cross-sectional dependence[49], which suggests the use of appropriate unit root and cointegration tests and

[49] It should be noted that the countries under investigation may also be spatial connected. Spatial dependence may be due to the so-called *third country effect* (Metulini, 2013), that refers to the effect that a country (the third country) may exert on the trade flow between its neighbouring countries. When some structural changes happen in one country that boost its trade flow, then the trade flow of its neighbours will also be positively affected, resulting in a general increase in the volume of international trade. This in turn may foster business cycle synchronization across countries, and affect the degree of the stock market dependence (see Asgharian et al., 2013). Immigration phenomena can also boost international trade through a demand side channel, as evidenced by Metulini (2013). Bank integration is another factor that may explain spatial dependence. As

estimation method. In order to get an insight into the size of the cross-sectional dependence in the data, a cross-correlation matrix of the OLS residuals derived from estimating equation (3.1) is computed (see also Auteri and Costantini, 2010). Table 3.1 reports the results for this correlation matrix. They show that correlations range between 0.01 and 0.96, with an overall mean of 0.45. This suggests that the hypothesis of cross-sectional independence can be clearly rejected.

Table 3.1: Cross-correlation matrix. 14 OECD countries, 1970-2012.

Country	No	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Australia	1	1.00													
Canada	2	0.88	1.00												
Denmark	3	0.13	0.33	1.00											
Finland	4	0.22	0.30	0.31	1.00										
France	5	0.90	0.75	0.22	0.17	1.00									
Germany	6	0.83	0.69	0.34	0.28	0.96	1.00								
Ireland	7	0.43	0.46	0.73	0.37	0.64	0.74	1.00							
Italy	8	0.78	0.77	0.40	0.07	0.87	0.85	0.64	1.00						
Japan	9	0.06	0.05	0.48	0.33	0.32	0.35	0.60	0.39	1.00					
Netherland	10	0.19	0.19	0.64	0.34	0.44	0.57	0.90	0.42	0.63	1.00				
Spain	11	0.11	0.08	0.71	0.01	0.10	0.21	0.61	0.11	0.67	0.67	1.00			
Sweden	12	0.71	0.72	0.02	0.01	0.47	0.31	0.04	0.46	0.08	0.31	0.34	1.00		
UK	13	0.93	0.83	0.11	0.37	0.81	0.75	0.45	0.64	0.09	0.27	0.15	0.69	1.00	
US	14	0.68	0.40	0.26	0.08	0.73	0.64	0.26	0.49	0.21	0.25	0.19	0.41	0.73	1.00

Notes: This table reports cross-correlation between residuals derived from OLS estimation of equation (3.1).

Further to the correlation matrix, findings for the CD test by Pesaran (2004) are reported in Table 3.2. This test is designed to detect cross-sectional dependence in the data:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \Longrightarrow N(0,1) \text{ as N, T} \rightarrow \infty,$$

where $\hat{\rho}_{ij} = \frac{\sum_{t=1}^{T} u_{it}u_{jt}}{\left(\sum_{t=1}^{T} u_{it}^2\right)^{1/2}\left(\sum_{t=1}^{T} u_{jt}^2\right)^{1/2}}$ indicates the pairwise correlations between country i and country j, with $i \neq j$. As can been seen, results in Table 3.2 point to cross-correlation

global banks play a central role in intermediating wholesale bank funding to domestic banks, domestic credit supply may be affected through the transmission of financial conditions across borders. As a result, stronger co-movements in housing markets can be observed across countries with stronger bilateral bank flows (Milcheva and Zhu, 2016).

in each examined variable, as the null of hypothesis of cross-section independence can be rejected.

Table 3.2: Results for cross-section dependence. 14 OECD countries, 1970-2012.

Variables	$\hat{\bar{\rho}}$	CD	p-value
c_{it}	0.758	47.39	0.000
y_{it}	0.702	43.90	0.000
hw_{it}	0.615	38.48	0.000
fw_{it}	0.741	46.38	0.000

Notes: The table reports the results of the CD test by Pesaran (2004). Variables are expressed in log real per capita term. The average cross-correlation coefficient $\hat{\bar{\rho}} = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}$ is the average of the country-by-country cross-correlation coefficients $\hat{\rho}_{ij}$.

As already mentioned in Section 3.3, the testing procedure by Gengenbach et al. (2006) is used to check for unit root and cointegration in the data. Accordingly, the panel unit root results based on the PANIC approach by Bai and Ng (2004) are reported in Table 3.3. In theory, the number of factors r in each variable is unknown. In order to determine the number of factors, information criteria as in Bai and Ng (2002) are used. In particular, this study uses the BIC3 method (see notes in Table 3.3 and Appendix B). The findings for unit root show clear-cut evidence of nonstationarity in both the two type of components in all examined variables. As a consequence, the existence of cointegration in the common factor and idiosyncratic components is tested separately (see Section 3.3).

Table 3.3: Unit root test results. 14 OECD countries, 1970-2012.

Variables	$BN_{ADF_{\hat{F}}^c}$	$BN_{Z_{\hat{e}}^c}$
c_{it}	-1.972	-1.339
	(0.298)	(0.181)
y_{it}	-1.953	-0.905
	(0.305)	(0.365)
fw_{it}	-1.711	-0.589
	(0.418)	(0.556)
hw_{it}	-1.491	-0.932
	(0.527)	(0.351)

Notes: The number of common factors (r) selected using the BIC 3 criterion is equal to 1 (see Appendix B for the details on BIC3 criterion). The maximum number of factors is set to 4 (see, Bai and Ng, 2002). $\mathrm{BN}_{\mathrm{ADF}_{\hat{\mathrm{F}}}}$ and $\mathrm{BN}_{\mathrm{P}_{\hat{\mathrm{e}}}^{\mathrm{c}}}$ denote the Bai and Ng's (2004) unit root tests on common factor and idiosyncratic component, respectively. The ADF test regression includes a constant and trend. p-values are reported in parenthesis.

Findings in Table 3.4 show that cointegration is present in both components. More specifically, the results by Johansen's (1995) test point to the existence of one cointegrating vector (the null of no cointegrating vectors can be rejected, while the null of one cointegrating vector cannot be rejected), and tests by Pedroni (1999, 2004) also show the existence of cointegration among the idiosyncratic components of the variables in the panel, since the null of no cointegration can be rejected.

Table 3.4: Cointegration test results. 14 OECD countries, 1970-2012.

Factor cointegration (Johansen, 1995)		Idiosyncratic cointegration (Pedroni, 1999, 2004)	
H_0: r	Trace statistics	Z_ρ	Z_t
0	54.348**	-6.181***	-12.755***
	(0.047)	(0.000)	(0.000)
1	26.320		
	(0.324)		
2	6.754		
	(0.912)		
3	2.163		
	(0.745)		

Notes: A VAR(2) is used in the analysis for cointegration. Mackinnon et al. (1999) p-values for Johansen's (1995) trace statistics. The model for the Johnsen test includes a constant. *** and ** indicate significance at the 1% and 5% level, respectively; p-values are in parenthesis; $\mathbf{Z}_\rho$ and $\mathbf{Z}_t$ denote the panel statistics for the null of no cointegration (Pedroni, 1999, 2004). For technical details on the panel $\mathbf{Z}_\rho$ and $\mathbf{Z}_t$ statistics, see Appendix B.

3.5.2. ESTIMATING WEALTH EFFECTS ON CONSUMPTION

Evidence of cointegration is a necessary prerequisite to estimate elasticities in equation (3.1) by the estimator introduced in Westerlund (2007). As can be seen in Table 3.5, the estimated elasticities are significant at 1% level.[50] Moreover, the estimated effect out of housing wealth is about twofold than that out of financial wealth.

Comparing these results with those in previous works, it can be noted that Case et al. (2005) and Dreger and Reimers (2012) find even far larger housing wealth effects than financial ones, the former using wealth data and the latter using asset prices. However, Case et al. (2005) do not account for cross-sectional dependence, while Dreger and Reimers (2012) do, though the latter find cointegration only among the common factors.

[50] As the focus of this work is the study of wealth effects, results related to disposable income are not discussed.

Table 3.5: Estimated elasticities and implied MPCs. 14 OECD countries, 1970-2012.

Variables	Elasticity	MPC
y_{it}	0.927***	0.843***
	(0.015)	
fw_{it}	0.029***	0.019***
	(0.006)	
hw_{it}	0.060***	0.027***
	(0.010)	

Notes: The table reports elasticities in equation (3.1) estimated using the least square biased-adjusted estimator by Westerlund (2007). Numbers in parenthesis are the standard errors. *** denote significance at the 1% level. The table also reports the related MPCs, computed by multiplying the elasticity of each variable for the average sample ratio of consumption to the same variable.

The estimated elasticities in Table 3.5 are turned into MPCs out of income, financial and housing wealth by multiplying the related elasticity for the average sample ratio of consumption to the respective variable of interest (see Catte et al., 2004; Donihue and Avramenko, 2007).[51] The results are reported in the same table.

It turns out that MPCs for financial and housing wealth are 1.9 cents and 2.7 cents per dollar, respectively.[52] These findings contrast with those in Slacalek (2009) and De Bonis and Silvestrini (2012), who report larger values of MPCs for financial wealth than housing wealth. Perhaps, different econometric techniques and different sample periods may account for these contrasting results. In particular, unlike Slacalek (2009), the analysis in this chapter also covers the 2000-2012 period, which saw large variations in both financial and housing wealth, with the latter representing a far large share of household portfolio in most of the examined countries. Further, while cross-sectional dependence is taken into account, this feature is ruled out in the econometric approach used in De Bonis and Silvestrini (2012).

It should be noted that Slacalek (2009) also conducts an analysis at country level. The results show large cross-country variability in the estimated wealth effects, confirming some uncertainty about wealth effects at country level (Labhard et al., 2005). Moreover, in some cases wealth effects (especially the housing wealth effect) are even negative and

[51] Wealth effects are estimated in terms of percentage increase in wealth when using elasticities or in terms of cents per dollar change in wealth when using MPCs.
[52] Labhard et al. (2005) estimate a consumption function using only financial wealth and find a result similar to the one found in this work for the financial wealth effect.

insignificant. As argued by Labhard et al. (2005) and Altissimo et al. (2005), large variation in estimated wealth effects across countries may reflect imprecise point estimates due to differences in how wealth is measured across countries. However, more reliable and plausible estimates of the financial and housing wealth effects can be obtained at panel level by exploiting the cross-sectional dimension in the analysis. In fact, Slacalek (2009) finds positive and significant wealth effects when considering panel data under the hypothesis of cross-sectional correlation, as it is also the case in this chapter. Such results likely reflect the fact that when a panel analysis is carried out and cross-sectional correlation is also taken into account, the additional variation in the cross-section dimension allows for far more precise estimates of wealth effects.

In order to evaluate how the kind of financial system affects consumption responses to changes in wealth, the sample of countries is split into two diverse groups (see Bayoumi and Edison, 2003; Ludwig and Sløk, 2004; Slacalek, 2009), namely bank-based and market-based countries. In this respect, the approach in Bayoumi and Edison (2003) and Ludwig and Sløk (2004) is followed. More in detail, Denmark, Finland, France, Germany, Italy, Japan, and Spain are included in the group of countries with bank-based financial systems, while Australia, Canada, Ireland, the Netherlands, Sweden, the United Kingdom and the United States are regarded as countries with market-based financial systems.[53] The estimated elasticities of equation (3.1) for the two groups of countries are reported in Table 3.6.

Table 3.6: Estimated elasticities. Bank- and market-based countries, 1970-2012.

Variable	Elasticity	
	BB	MB
y_{it}	0.959***	0.889***
	(0.020)	(0.021)
fw_{it}	0.016**	0.043***
	(0.007)	(0.010)
hw_{it}	0.062***	0.057***
	(0.016)	(0.012)

Notes: BB and MB denotes countries with bank- and market-based financial systems, respectively. Elasticities are estimated using the least square biased-adjusted estimator by Westerlund (2007). Numbers in parenthesis denote standard errors. *** and ** denote significance at the 1% and 5% level, respectively.

[53] In Slacalek (2009), the two groups of bank-based and market-based countries are slightly different from those considered in this work.

It emerges that wealth effects are significant in both groups, with the effect on consumption of housing wealth being higher than that of financial wealth, especially for the bank-based group. Interestingly, the size of the housing wealth effect does not change substantially when splitting the sample of countries, remaining at a value of about 0.06 in both groups. By contrast, there is a significant difference in the size of financial wealth effect in the two groups. Precisely, it is at 0.016 for the bank-based group as opposed to 0.043 for the market-based group. Ludwig and Sløk (2004) find similar results using stock market capitalization and house prices for the 1960-2000 period, while controlling for the common factor problem.

Table 3.7 reports the MPCs out of income, financial and housing wealth for the two groups of countries, as derived from elasticities in Table 3.6. According to these findings, wealth effects are larger for market-based than bank-based economies, a result also found in Slacalek (2009).[54] More specifically, the financial wealth effect in market-based economies is almost twice as large as that in bank-based countries (0.023 and 0.013, respectively). This result likely reflects the more widespread ownership of financial assets among households and deeper and more liquid financial markets in market-based countries (e.g. Guichard et al., 2009).[55] On the other hand, a less marked difference is notable for housing wealth effects in the two groups, with a larger figure for the market-based group at 3 cents per dollar as opposed to 2.4 cents per dollar for the bank-based countries. These results suggest the role of a stronger collateral channel in market-based countries (see Tsatsaronis and Zhu, 2004, Catte et al., 2004, Guichard et al., 2009, among others).

Table 3.7: Marginal propensities to consume. Bank- and market-based countries, 1970-2012.

Variables	MPCs	
	BB	MB
Y_{it}	0.860***	0.816***
FW_{it}	0.013**	0.023***
HW_{it}	0.024***	0.030***

Notes: *** and ** represent significance at the 1% and 5% level, respectively.

[54] Differently, Slacalek (2009) find that the MPCs for housing wealth is insignificant for bank-based countries.
[55] Bayoumi and Edison (2003) also find a larger financial wealth effect in market-based economies.

Results in Table 3.7 also allow one to stress that the housing wealth effect is larger than the financial wealth effect in both groups. Figures for the bank-based group are in line with those found in Bayoumi and Edison (2003) and Skudelny (2009) for a similar panel of countries. More specifically, Bayoumi and Edison (2003) estimate a marginal propensity to consume out of financial and housing wealth at about 1% and 4%, respectively, while in Skudelny (2009) these figures are 0.7% and 2.5%, respectively. On the contrary, Slacalek (2009) finds for the bank-based economies a larger financial wealth effect than housing wealth effect, with the latter being significant only in the 1990s.[56] Again, this may reflect the fact that the sample period in Slacalek (2009) does not consider years characterized by very large increases in house prices in the run-up to the recent financial crisis in many bank-based economies, especially in France and Spain, with growth rates being larger than 10% (see ECB, 2015). Indeed, despite the financial crisis and the debt sovereign crisis in the Euro area, house prices increased by 1.3% per year over the period 2000-2012 in bank-based economies.[57] Further, unlike Slacalek (2009), estimates for financial wealth effect in my work possibly reflect the large drops in the stock prices in the early 2000s, and in particular during the recent financial crisis, when the stock prices fell by 6% in the Euro area and by 5% in Japan (see Bayoumi and Edison, 2003; Guichard et al., 2009).

Also the findings found for the market-based group are line with those in Bayoumi and Edison (2003)[58], but contrast with those in Slacalek (2009) who finds larger wealth effects with no difference in values for the two wealth components.

3.6. CONCLUSIONS

Increasingly international financial integration has made asset prices largely correlated across countries. As a result, studying wealth effects in an international setting should requires econometric techniques which take into account cross-sectional dependence. This chapter investigates the long-run financial and housing wealth effects on consumption in a panel of 14 OECD countries over the period 1970-2012, using annual wealth data and recently developed nonstationary panel methodologies based on common factor models. The analysis is carried out for the full sample of countries and for the bank-

[56] Slacalek (2009) split the full sample of period, 1979q1-1999q4, into two sub-sample periods, 1979q1-1988q4 and 1989q1-1999q4.

[57] Bayoumi and Edison (2003) argue that wealth effects in bank-based countries are dominated by movements in house prices.

[58] Bayoumi and Edison (2003) also show a substantial increase in the housing wealth effect over time.

based and market-based groups in order to assess how the financial system influences consumption responses to wealth changes.

The contribution of this work is twofold. First, a newly updated dataset of wealth data is used covering recent developments in housing and financial markets. This allows one to compute marginal propensities to consume out of housing and financial wealth, which represent more appropriate measures of wealth effects than elasticities computed by using asset prices.

Second, the long-run financial and housing wealth effects are estimated by using a recently developed estimator by Westerlund (2007) that takes into account cross-sectional dependence through a common factor structure, avoiding potential distortions induced by commonly used econometric techniques based on the unrealistic assumption of cross-sectional independence.

The empirical analysis delivers three main results. First, both housing and financial wealth have a positive and significant impact on aggregate consumption. Second, the housing wealth effect is larger than the financial wealth effect for the sample of all countries as well as for the two groups of countries. Third, wealth effects are larger in market-base economies than bank-based ones.

This analysis shows that housing wealth plays a major role on consumption. This is because it represents the most important part of net worth of the private sector in most of the industrialized countries, and periods of prolonged rising house prices, since the 1980s, had been likely perceived as permanent increases in wealth, leading to stronger consumption. Further, because rising house prices increase the value of the collateral against which households can borrow, their borrowing capacity had also increased in many countries and, in turn, their spending.

However, sharp corrections in property prices have proven to be able to threaten the financial positions of households and financial institutions, especially when rising house prices are accompanied by rising mortgage liabilities and low personal saving ratio. The recent financial crisis represents a significant example of how the housing collateral channel may be instrumental in triggering boom-bust cycle in the housing markets with highly disruptive impact on output growth as well as on financial system soundness.

Monetary and fiscal policies have a crucial role in minimizing boom and bust cycles in housing markets and their negative effects on the economy, even when well-regulated and supervised financial systems are in place.

As for the monetary policy, it has been stressed that it should act before such imbalances occur to be really helpful, and it should be symmetric (IMF, 2000). The latter implies that police stance should be looser at any time a severe fall in asset prices can threaten the solvency of the financial system and cause a severe recession, while it should be tighter when asset prices increase at apparently unsustainable levels. However, monetary policy may be ineffective when the economy falls into a liquidity trap after a collapse in asset prices, and in the case of monetary unions or large currency areas in which house price bubbles are not generalized (IMF, 2000). In such circumstances, fiscal and regulatory policies may play an important role. As for fiscal reforms, for example, those aimed at reducing the tax deductibility on mortgage interest payments may help to reduce pressures on the mortgage market.

A better supervision and regulation of financial sectors is also very important in order to avoid booms and busts. In this respect, it could be useful to enhance the monitoring of lending standards as well as to incorporate more reliable assessment of credit risk into credit decisions. In this respect, macroprudential policies designed to impose higher capital requirements for real estate loans have been recently implemented by some national authorities in the Euro area in order to increase resilience of banks to potential excesses in the housing market (ESRB 2014). Collateral values should also be better monitored by bank. In particular, larger down payments for real estate loans should be required in period of booming property prices.

Appendix B

B1. BIC3 criterion

The BIC3 criterion is used to determine the optimal number of factors (r) in the model described by equation (3.3). Bai and Ng (2002) first suppose that one could observe the factors, but not the factor loadings. This implies that k factors should be chosen to best describe the variations of X_{it} (see equation (3.3)), and then estimate the corresponding factor loadings by using the standard ordinary least square estimator. Be F^k a matrix of k factors, then:

$$V(k, F^k) = \min_{\Lambda} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(X_{it} - \lambda_i^{k\prime} F_t^k\right)^2,$$

denotes the sum of square residuals from the regressions of X_i on k factors for all i. Then r is detected by minimizing a loss function, $V(k, F^k) + kg(N, T)$, with $g(N, T)$ being the penalty for overfitting, $r \leq$ kmax, where kmax is a bounded integer. As for the BIC3 criterion, the loss function is the following:

$$BIC_3(k) = V\left(k, \hat{F}^k\right) + k\hat{\sigma}^2 \left(\frac{(N+T-k)\ln(NT)}{NT}\right),$$

where $V\left(k, \hat{F}^k\right) = \min_{\Lambda} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \left(X_{it} - \lambda_i^{k\prime} \hat{F}_t^k\right)^2$, $\hat{\sigma}^2$ is a consistent estimates of $(NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} E(e_{it})^2$.

B2. Limiting distribution of the $\mathrm{ADF}_{\hat{\mathrm{F}}}^{\boldsymbol{\tau}}$ statistics and $\boldsymbol{\Phi}_*^{\boldsymbol{\tau}}$

Suppose that the data is generated by (3.1)-(3.3), and the assumptions in Theorem 1 in Bai and Ng (2004) holds. Let W_u i=1,..N, be standard Brownian motions. Then, as $N, T \to \infty$, the following holds (see Theorem 3 in Bai and Ng, 2004):

1. When $r = 1$, under the null hypothesis that F_t has a unit root, and p (the order of autoregression) is chosen in such a way that $p \to \infty$ and $p^3/\min[N, T] \to 0$:

$$\mathrm{ADF}_{\hat{\mathrm{F}}}^{\tau} \Rightarrow \frac{\int_0^1 W_u^{\tau}(s) dW_u(s)}{\left(\int_0^1 W_u^{\tau}(s) dW_u(s)\right)^{1/2}},$$

where $W_u^\tau(t) = W_u(t) - \int_0^1 (4-7s)\, W_u(s)ds - t\int_0^1 (12-6s)\, W_u(s)ds.$

2. r>1. Let W_m^τ be a vector of m-dimensional detrended Brownian motions. Let v_*^τ(m) be the smallest eigenvalue of

$$\Phi_*^\tau = \frac{1}{2}[W_m^\tau(1)W_m^\tau(1)' - I_m]\left[\int_0^1 W_m^\tau(s)W_m^\tau(s)'\,ds\right]W_u.$$

   i. J is the truncation point of the Bartlett kernel such that $\frac{\mathrm{J}}{\min[\sqrt{N},\sqrt{T}]} \rightarrow 0$, as J, N, T $\rightarrow \infty$. Then, under the null hypothesis that F_t has m stochastic trend, $MQ_c^\tau(m) \xrightarrow{d} v_*^\tau$(m);

   ii. F_t has m stochastic trends under the null hypothesis and can be represented by a finite $VAR(\bar{p})$. If a $VAR(p)$, with $p \geq \bar{p}$, is estimated, then $MQ_f^\tau(m)$ $\xrightarrow{d} v_*^\tau$(m).

B3. Panel cointegration tests Z_ρ and Z_t (Pedroni, 1999, 2004)

Consider the following panel regression:

$$y_{it} = a_i + \beta_{1i}X_{1it} + \beta_{2i}X_{2it} + \ldots + \beta_{Mi}X_{Mit} + e_{it}, \tag{B.1}$$

where $i = 1, \ldots, N; t = 1, \ldots, T; m = 1, \ldots M$. The variables in (B.1) are assumed to be integrated of order one. For each i, the null hypothesis of no cointegration implies that the residual e_{it} are also integrated of order 1. As for the alternative hypothesis, the analysis in this chapter considers the case where all the individuals are cointegrated. Therefore, the null hypothesis of no cointegration is tested using a residual-based test of the null that $H_0: \gamma_i = 1$ for all i against the alternative $H_0: \gamma_i = \gamma < 1$ in the following regressions:

$$\widehat{e}_{it} = \hat{\gamma}_i \hat{e}_{it-1} + \hat{\mu}_{it}, \tag{B.2}$$

and

$$\widehat{e}_{it} = \hat{\gamma}_i \hat{e}_{it-1} + \sum_{k=1}^{K_i} \hat{\gamma}_{i,k} \Delta\hat{e}_{it-k} + \hat{\mu}_{it.}^{*} \tag{B.3}$$

The panel Z_ρ and Z_t statistics for the null of no cointegration are given by:

$$Z_\rho \equiv \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}_{11i}^{-2}\hat{e}_{it-1}^{2}\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}_{11i}^{-2}(\hat{e}_{it-1}\Delta\hat{e}_{it}-\hat{\lambda}_i),$$

and

$$Z_t \equiv \left(\tilde{s}^2\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}_{11i}^{-2}\hat{e}_{it-1}^{2}\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\hat{L}_{11i}^{-2}\hat{e}_{it-1}\Delta\hat{e}_{it},$$

where $\hat{\lambda}_i = \frac{1}{T}\sum_{s=1}^{k_i}\left(1-\frac{s}{k_i+1}\right)\sum_{t=s+1}^{T}\hat{\mu}_{it}\hat{\mu}_{it-s}$, $\tilde{s}^2 \equiv \frac{1}{N}\sum_{i=1}^{N}\hat{s}_i^2$, $\hat{s}_i^2 \equiv \frac{1}{T}\sum_{t=1}^{T}\hat{\mu}_{it}^{*2}$, $\hat{L}_{11i}^2 = \frac{1}{T}\sum_{t=1}^{T}\hat{\eta}_{it}^2 + \frac{2}{T}\sum_{s=1}^{k_i}\left(1-\frac{s}{k_i+1}\right)\sum_{t=s+1}^{T}\hat{\eta}_{it}\hat{\eta}_{it-s}$, $\Delta y_{it} = \sum_{m=1}^{M}\hat{b}_{mi}\Delta x_{mit} + \hat{\eta}_{it}$.

CHAPTER FOUR

CONSUMPTION-WEALTH RATIO AND STOCK RETURN PREDICTABILITY: EVIDENCE FROM A PANEL OF 9 EURO COUNTRIES

4.1. INTRODUCTION

The empirical asset pricing literature has found evidence of stock return predictability over longer horizons, in the last three decades.[59] This is in sharp contrast with the early prominent foundation in financial economics whereby stock markets were efficient with stock prices following a random walk, implying unpredictability of stock returns. What is more, stock return predictability does not seem to be incompatible with efficiency in the stock markets. Theoretical works have shown that forecastable stock returns can be the result of time-varying attitude of rational, utility maximizing investors towards risk (see Constantinides and Duffie, 1996; Campbell and Cochrane, 1999).

The bulk of empirical literature on stock return predictability has focused on US economy and has largely studied the predictive power of financial indicators. The ratios of price to dividends or earnings, the dividend yield, the dividend-earnings ratio, the relative bill rate, and the term spread are among the most popular ones. Lettau and Ludvigson (2001), by contrast, use a macroeconomic indicator to assess predictability of stock returns over business cycle horizons. This is on the grounds that expected stock returns vary countercyclically, implying that they are higher during recessions and lower during expansions (see Fama and French, 1989; Ferson and Harvey, 1991). More in detail, Lettau and Ludvigson (2001) use a proxy for the log consumption-wealth ratio, called "cay_t". This indicator represents the cointegrating residual from an estimated long-run relationship between three macroeconomic aggregates: consumption, asset wealth and labor income. The economic explanation behind cay_t relies on the desire of investors to maintain a smooth consumption path. As a result, when they expect higher excess stock returns in the

[59] The breakthrough in this literature came from seminal works by LeRoy and Porter (1981), Shiller (1981), Fama and French (1988), and Campbell and Shiller (1988a, 1988b).

future, they will increase consumption compared their asset wealth and income, while the opposite will be true when they expect lower excess returns, suggesting a positive relationship between cay_t and excess stock returns.

In terms of econometric technique, previous studies have mostly used cointegration time series approaches to investigating whether or not stock returns are forecastable on single countries, with the exception given by de Castro and Issler (2015), who use a panel cointegration approach to assess the predictive power of cay_t for a panel of G7 countries. In this way, the authors take a broader international perspective in examining the predictive power of cay_t.

The study in this chapter follows a similar approach and looks at the predictive power of cay_{it} for a panel of 9 Euro countries over the period 1988q1-2014q4.[60] To the best of my knowledge, this is the first study to carry out an exercise on forecasting stock returns in the Euro area using panel cointegration analysis. Further, and this is the second contribution of the chapter, the analysis is conducted using an approach that takes cross-sectional dependence into account, through a common factor structure. The hypothesis of cross-sectional dependence can be realistically applied to the set of Euro countries under investigation, because these countries not only share the same currency, but also some economic characteristics.

The analysis proceeds as follows. First, the procedure developed in Gengenbach et al. (2006) is used to test for unit root and cointegration, and then the least square biased-adjusted estimator by Westerlund (2007) is applied so to estimate the long-run relationship between consumption, asset wealth and income, by which cay_{it} is derived for the panel of countries. Lastly, the predictions of excess returns are obtained using the panel "estimable" generalize least square (EGLS) estimator, which corrects for potential heteroscedasticity and autocorrelation, and cross-sectional dependence (see Reed and Ye, 2011). The forecasting exercise is conducted in-sample and out-of-sample. As for the in-sample exercise, cay_{it} enters the forecasting exercise both as sole predictor and along with two financial variables, namely the dividend-yield and the relative bill rate.

The empirical results in this study point to predictability of future excess stock returns in the panel data examined both in-sample and out-of-sample. More in detail, in-

[60] The notation for "cay_{it}" is consistent with the panel estimation performed in this chapter.

sample results reveal that: i) cay_{it} affects positively and significantly future excess returns over each horizon ranging from 1 to 8 quarters; ii) its forecasting power increases over horizons, up to explain 15% of variation in excess returns; and iii) when combined with the dividend-yield and the relative bill rate, cay_{it} maintains its forecasting power up to one year, and at 8 quarters ahead all regressors together are able to explain up to 28% of variation in excess returns.

As for the out-of-sample forecasting predictions, results highlight that a model with cay_{it} performs better than two benchmark models: the constant expected returns benchmark and the autoregressive benchmark. Moreover, consistent with in-sample results, cay_{it}-augmented model improves over horizons compared to the two benchmarks.

The rest of the chapter is organized as follows. Section 4.2 discusses the related literature. Section 4.3 describes the theoretical framework that accounts for the use of cay_t as a predictor for excess stock returns. In Section 4.4, the econometric methodology and data are described. Section 4.5 presents the results of the empirical analysis. Section 4.6 concludes.

4.2. RELATED LITERATURE

In this section, the literature related to excess return predictability using cay_t as a predictor is reviewed. This literature uses time series approaches, with the exception of de Castro and Issler (2015), who carry out a panel data analysis.

The work by Lettau and Ludvigson (2001) marks the beginning of the literature investigating the predictive power of cay_t for future stock returns. The authors are the first to define cay_t, an empirical proxy for fluctuations in the aggregate consumption-wealth ratio, and provide evidence of its strong forecasting power for both real stock returns and excess returns at business cycle frequencies. They explain that this feature of the data stems from an implication of forward looking models of consumption behaviour. In particular, employing a log-linear approximation of the intertemporal budget constraint, they show that optimal models of consumption behaviour imply that the log consumption-aggregate wealth ratio should predict asset returns because the former is a function of expected future returns on the market portfolio as well as of consumption growth, a theoretical result already obtained by Campbell and Mankiw (1989). Moreover, once aggregate wealth is approximated with a linear combination of labour income and asset holdings, the same models imply that consumption, labor income and asset holdings are cointegrated and that temporary deviations from their shared trend produce variations in the consumption-aggregate wealth ratio. This framework would suggest that agents will allow consumption to increase above its common trend with aggregate wealth and labour income when future stock returns are expected to increase in the future. This is done in order to insulate future consumption from variations in stock returns, while the opposite should be true when agents expect lower future stock returns.

Using US quarterly stock market data (1952q4-1998q3), Lettau and Ludvigson (2001) estimate the series of trend deviations, cay_t, and investigate its predictive power for real stock returns and excess returns in several in-sample and out-of-sample forecasting regressions. The in-sample one-quarter ahead forecasting results show that cay_t is significant with large positive estimated coefficients, explaining 9% of both real returns and excess returns. When cay_t is added to the log dividend-yield and the log dividend-payout ratio in the forecasting regression, it is the only predictor to be strongly significant, with an adjusted R^2 of about 9%. When the detrended short-term interest rate *($RREL_t$)*, the lagged term spread, and the lagged default spread are also considered, not only cay_t but also $RREL_t$ is found highly significant, with a slight increase in the adjusted R^2. As cay_t should have better forecasting power at longer rather than shorter horizons, horizons from 1 to 24 quarters are considered. The results show that cay_t, as a sole predictor, is stronger for excess returns than financial indicators at short to intermediate horizons, while dividend-yield is a stronger predictor than cay_t only at horizon of 6 years, and $RREL_t$ is statistically significant at horizons up to one year. When all variables enter in the long-run forecasting regression, cay_t continues to be the best predictor at short to intermediate horizons.

As for the out-of-sample exercise, the forecasting performance of cay_t is compared to that of two different benchmarks: an autoregressive model and the constant expected returns. Not only is this exercise performed by using cay_t estimated over the entire sample (fixed cay_t), but also by using cay_t re-estimated recursively every period with only data available at the time of the forecast (re-estimated cay_t). This is because fixed cay_t is likely to induce "look-ahead" bias in the forecasts. The related findings point to a lower mean-squared forecast error when using the cay_t-augmented model. However, using fixed cay_t

results in better performances.[61] Results from non-nested forecast comparisons are also provided. The results indicate that the model with cay_t is better than competitor models in which each other forecasting variable is the sole predictor.

In re-examining the evidence in Lettau and Ludvigson (2001), Brennan and Xia (2005) call into question the in-sample predictive power of cay_t for future US stock returns using data over the period 1952q4-2000q4. The results show that within-sample estimates of cay_t have no predictive power for labor income growth and consumption growth, but have weakly predictive power for wealth, which implies that cay_t has weakly predictive power for stock returns, given that wealth and stock returns are highly correlated. According to Brennan and Xia (2005), the strong predictive power of cay_t found in Lettau and Ludvigson (2001) reflects "look ahead bias" induced by estimating the cointegrating parameters using the full sample data. In order to assess whether or not the strong forecasting power of cay_t in Lettau and Ludvigson (2001) is genuine, a variable called tay_t, representing the deviations from a cointegrating relation between a calendar time trend (in months), income and wealth, is calculated.[62] This variable is then used as predictor in in-sample predictive regressions for the S&P quarterly real return and excess return, respectively. The results show that tay_t outperforms cay_t in all the cases. In addition, when both predictors enter the regression, cay_t is no longer found significant.

To corroborate in-sample results, Brennan and Xia (2005) compare the out-of-sample performance of cay_t with that of tay_t. This is done because if the in-sample predictive relation is spurious or unstable, one should expect no out-of-sample forecasting power. This exercise is carried out with the two predictors estimated over the entire sample and re-estimated in each time using only data available when the forecast is performed. The results show that both variables lose their predicting power when estimating recursively out-of-sample. The same results are found even when a smaller forecasting period of the recursive exercise is considered. Taken together, these findings suggest that cay_t has no out-of-sample predictive power for stock returns, and confirm that its strong in-sample predictive power is very likely due to the "look-ahead" bias.

[61] This is because re-estimating the parameters of the cointegrating relationship generates greater sampling error into the estimated coefficients, especially during the early estimation recursions.
[62] The residual tay_t has a correlation of 0.75 with cay_t.

Lettau and Ludvigson (2005a) argue that the criticism by Brennan and Xia (2005) are not well-founded. First of all, it is pointed out that cay_t cannot be considered spurious for forecasting future returns simply because all available data is used to estimate the cointegrating coefficients. It is shown that there is no need to estimate the cointegrating parameters to assess the forecasting power of cay_t, as alternative approaches can be applied.[63] What is more, when estimating the cointegrating coefficients, biased results would arise if some information available in the sample was ignored to this end, because when a set of variables are cointegrated over a sample period, all the data of this sample, and not a subsample of it, should be used to uncover the true parameters.[64]

Secondly, it is argued that replacing cay_t with tay_t does not imply that the forecasting power of cay_t is spurious, because tay_t is actually a proxy of cay_t, given that a large part of aggregate consumption variability is governed by a deterministic time trend. This would explain the forecasting power of tay_t. Thirdly, Lettau and Ludvigson (2005a) question the claim in Brennan and Xia (2005) that out-of-sample tests would address the issue of whether the good in-sample performance is due to look-ahead bias. Their argument is based on results in Inoue and Kilian (2004), who show that, while in-sample tests do not show larger size distortions than out-of-sample tests, the former are more powerful. This implies that in-sample tests are more reliable than out-of-sample tests for assessing forecasting power. Moreover, given a higher degree of persistence in tay_t than cay_t, it is tay_t that likely has a spurious forecasting power (see also Ferson et al., 2003).

Rudd and Whelan (2006) and Hahn and Lee (2006) also call into question results in Lettau and Ludvigson (2001). As for the former, it is argued that the measure of real consumption in Lettau and Ludvigson (2001) is inconsistent with a budget constraint, where measures of real income and wealth (which includes the value of the stock of consumer durables) are obtained by deflating the related nominal series by a price index for total consumption expenditures.[65] It would be consistent if the ratio of the log of total

[63] Lettau and Ludvigson (2005b) estimate a multivariate regression equation of h-period excess stock returns on log consumption, log asset wealth, and log labor income, and find that the related empirical results are similar to those in Lettau and Ludvigson (2001). Therefore, it is argued that the predictive power of cay_t cannot be due to look-ahead bias.

[64] In this respect, it is also pointed out that results from their Monte Carlo simulations analysis suggest that just over 40 years of data would be enough to estimate cointegrating coefficients superconsistently, so that they can be used as known in out-of-sample forecasts.

[65] Real consumption in Lettau and Ludvigson (2001) consists of real outlays on nondurables and services, excluding shoes and clothing.

real consumption expenditures to the log of real nondurables and services consumption was stable overtime, but US data show that this ratio has displayed a distinct upward trend over the postwar period. Rudd and Whelan (2006) propose an alternative methodology to overcome this inconsistency, which considers a budget constraint defined with the log of total real consumption expenditures and the log of nominal income and assets defined relative to the deflator for total consumption outlays.[66] In this case, however, the value of stocks of consumer durables should not be part of the asset measure. This approach does not require those assumptions regarding the relationship between observable and unobservable measures of consumption that are made in Lettau and Ludvigson (2001). However, when their preferred real measures of consumption, assets, and labor income are used over the period 1952q4-2001q1, no robust evidence of cointegration is found. This result suggests that an estimated linear relationship between consumption, income, and assets may not provide an adequate empirical proxy to the aggregate consumption-wealth ratio, and the absence of cointegration suggests that this proxy is unlikely to be a good predictor of asset returns.

The subsequent in-sample forecasting analysis, conducted over horizons from 1 to 24, confirms these concerns. In fact, higher adjusted R^2 values are found when using Lettau and Ludvigson's definition of cay_t than Rudd and Whelan's variant of cay_t over horizons from 1 to 4 quarters. The situation is instead reversed over longer horizons, likely reflecting spurious results due to the higher persistence of Rudd and Whelan's variant of cay_t. As for the out-of-sample exercises, the two versions of cay_t are re-estimated in each period, and are related to the constant expected returns benchmark. The results show that cay_t by Lettau and Ludvigson outperforms the benchmark at horizons longer than two years, while cay_t by Rudd and Whelan never improves upon the benchmark, and the performance gets worse with the forecast horizons.

Hahn and Lee (2006) show that omitting the existence of a deterministic trend in the cointegrating relationship between consumption, asset wealth, and labor income gives rise to bias estimates affecting the forecasting power of cay_t.[67] In order to assess whether a

[66] In this case, the value of stocks of consumer durables should not be part of the asset measure.

[67] In their opinion, the existence of a deterministic trend in the equilibrium relationship also has an economic justification. They argue that consumption, asset wealth, and labour income are data aggregated over heterogeneous consumers, whose degree of heterogeneity can change slowly over time, generating in this way a deterministic time trend in the aggregate variables. Consumer heterogeneity depends on changes in demography, income distribution, wealth distribution, and stock market participation.

deterministic time trend should be included in the specification of the cointegrating regression (see equation (13) in Hahn and Lee, 2006), a Wald test should be carried out to test if the null hypothesis that the coefficient for the trend is zero. It is shown that if the null is rejected, but the estimated model is the restricted one (see equation (14) in Hahn and Lee, 2006), than the estimates of the cointegrating coefficients are biased, with the result that the bias is incorporated in the regression error. As a result, the error is equal to the sum of two components: tay_t, multiplied by the coefficient of time trend, and the true cointegrating error from the unrestricted model. The former component represents the distortion and is expressed as a function of the bias in the estimated coefficients. Using data over the period 1952q4-2002q4, Hahn and Lee (2006) estimate both the unrestricted and the restricted models using OLS, DLS, CCR, and FME estimators. All related estimates are found statistically significant, with coefficients being quite similar across different estimation procedures, but different across the two models concerned. In particular, the OLS estimates of the restricted model are in line with those in Lettau and Ludvigson (2001), while those for the unrestricted model are lower, with the coefficient of the time trend being highly significant. Moreover, the results of the Wald test point to a rejection of the deterministic cointegration restriction, implying that the unrestricted model is the appropriate specification.

More importantly, Hahn and Lee (2006) provide evidence that the bias affects excess stock return or real stock return forecasting. In fact, as for the one-period ahead forecasting regression, cay_t from the restricted model is found to explain more than 9% of next period's variation of excess returns, but most of its predictive power comes from its biased component As for the true cointegrating residual, it only explains 1.6% or 3.5% of the remaining variation, with the OLS and DOLS estimators, respectively.[68] Moreover, the bias component of cay_t from the restricted model is highly persistent because it mostly reflects fluctuations of asset wealth, which is nonstationary. Therefore, its predictive power is likely to be spurious. Similar results are found for the long-horizon excess return forecasts with the Hodrick (1992) standard error.[69]

Guo (2006) provides evidence that, in out-of-sample exercises, cay_t forecasts US stock returns better when is augmented by a measure of aggregate stock market volatility

[68] Similar results are found in the case of real stock returns.
[69] In this case statistical inference problems also arise from the use of overlapping returns to forecast long horizon returns.

(σ^2). This result is likely due to the omitted-variable problem. In fact, these two variables are negatively correlated, but are both positively correlated with future stock returns in the forecasting regression. Results from in-sample regressions for the entire period (1952q3-2002q4) show that the consumption-wealth ratio well predicts stock market returns. Stock market variance alone is insignificant, but it is significant if added to the consumption-wealth ratio in the same regression, with a resulting much higher adjusted R^2 (14.7%) and point estimates. It is also found that the stochastically detrended risk-free rate ($RREL_t$) further contributes to explain stock returns beyond the previous variables (R^2 is about 16%). Similar results occur repeating the analysis in two sub-periods, 1952q3-1977q4 and 1978q1-2002q4, though predictability is weaker in the second one.

The out-of-sample exercise is first performed estimating cay_t over the full sample, and then recursively. In the latter scenario, cay_t is lagged twice because consumption and labor income data are released with a one-quarter delay. In both cases, four forecast models are estimated for the periods 1968q2-2002q4 and 1976q1-2002q4: a benchmark model of constant excess returns, the model using only cay_t, the model of cay_t augmented by stock market volatility, denoted by *augmented* $\widehat{cay_t}$, and lastly the model of cay_t augmented by σ^2 and $RREL_t$. In the first scenario, although cay_t alone shows some out-of-sample predictive power, it is *augmented* $\widehat{cay_t}$ to have the best out-of-sample performance when different measures of forecast accuracy are used. When it comes to re-estimated cay_t, a weaker performance of the models can be observed. Specifically, for the period 1968q2-2002q4, the augmented model of cay_t outperforms the benchmark model and the model of cay_t by itself, but the best model is the one that also includes $RREL_t$. For the period 1976q1-2002q4 the performance weakens, with the benchmark model showing the smallest RMSE.[70] Formal tests for nested forecast models are also carried out showing that, in both scenarios, *augmented* $\widehat{cay_t}$ significantly outperforms the benchmark and the model with cay_t alone.

Welch and Goyal (2008) re-examine the in-sample (IS) and out-of-sample (OOS) performance of several variables, including cay_t, which have been shown to be good

[70] The poor out-of-sample performance of recursively estimated cay_t is primarily due to the large estimation errors in the cointegration parameters.

predictors for the US equity premium in the empirical literature.[71] The analysis carries out predictions of equity premia on annual, five years, and monthly horizons, respectively, using different time period specifications.[72] Looking specifically at the performance of cay_t, when estimated over the full-sample ($caypt_t$), the evidence from annual data confirms the findings in Lettau and Ludvigson (2001), with cay_t outperforming the benchmark in out-of-sample (in-sample and out-of-sample performances are similar). However, when cay_t is estimated recursively ($cayat_t$) in an out-of-sample experiment, it exhibits no superior out-of-sample performance. This is true over both the entire sample period and the latest years. As for five-yearly predictions, $caya_t$ shows a good out-of-sample performance. However, Welch and Goyal (2008) underline that result are considered with caution because of the small number of observations used for inference, and statistical issues related to overlapping returns. Finally, the analysis for monthly predictions examines the so-called $cay3_t$. In this case, the analysis does not involve the cointegrating residual related to consumption, income and wealth, but each of these variables is entered as a regressor up to date directly into the forecasting regression. When restrictions proposed in Campbell and Thompson (2008) are applied, $cay3_t$ shows good performance IS, but it has only marginal performance OOS. $cay3_t$ does not perform well even in-sample over the last 30 years of the period.

Campbell and Thompson (2008) examine the out-of-sample performance of a large range of forecasting predictors for aggregate US stock returns.[73] Taking into account the perspective of a real-world investor, they propose the following restrictions in order to improve the out-of-sample performance of examined predictors: i) the regression coefficient yields the expected sign, otherwise it is set to zero; ii) the fitted value of the equity premium is positive, otherwise it is set equal to zero. In particular, simple rather than log monthly or annual stock returns on the S&P 500 Index are predicted. The out-of-sample forecast evaluation is set at the 1927 year, when accurate data on total monthly

[71] The variables explored in this article are: the dividend price ratio, dividend-yield, the earnings price ratio, dividend-earning (payout) ratio, various interest rates and spreads, the inflation rates, the book-to-market ratio, volatility, the investment-capital ratio, and aggregate net or equity issuing activity.
[72] Specifically, three time periods are considered: in the first one, out-of-sample forecasts begin 20 years after the beginning of the sample; in the second one, out-of-sample forecasts begin in 1965, while in the third one, only data after 1927 are used in the estimation.
[73] The examined forecasting variables are: the dividend price ratio, earnings price ratio, smoothed earnings price ratio, book-to-market ratio (each of these ratios is measured in levels, rather than logs), ROE , T-Bill rate, long-term yield, term spread, default spread, inflation, net equity issuance, and consumption-wealth ratio (cay_t).

stock returns are available from CRSP, or 20 years after the beginning of the sample period in the remaining cases.

Looking at the specific performance of the consumption-wealth ratio (cay_t), it emerges that this predictor stands out among the successful variables.[74] In terms of unrestricted out-of-sample performance, the consumption-wealth ratio does not deliver positive out-of-sample R^2 statistics, perhaps as a consequence of estimating three coefficients over a relatively short sample period, compared to other predictors. However, when the previous mentioned restrictions are imposed on the out-of-sample forecasting exercises, the related performances almost always improve. Among others variables, this is particularly true for the consumption-wealth ratio. As for annual predictions, these perform reasonable well out-of-sample, despite weak in-sample predictive power. Again, the theoretical restrictions help improve this outcome, though not enough in the case of the consumption-wealth ratio that is not able to beat the historical mean return.

Considering the perspective of real-world investor, Guo (2009) examines how the out-of-sample predictive power of cay_t for aggregate US stock returns varies when estimated with real-time data instead of revised data, as usually applied in the previous literature. This is because the ingredients for cay_t's construction, especially consumption and labor income, undergone substantial periodic revisions over time. In order to achieve the main purpose of the paper, out-of-sample forecasts of stock returns are carried out with recursively estimated cay_t from both the current vintage data and real-time data. The first approach confirms the early results in Guo (2006): in revised data cay_t outperforms the benchmark model of constant stock returns only when realized market variance is added in the regression. By contrast, when real-time data are used, cay_t exhibits negligible out-of-sample forecasting power even when combined with realized market variance.

Della Corte et al. (2010) re-examine the forecasting power of cay_t on the future equity premium across four countries, France, Japan, the UK, the US, using annual data spanning over the 1900-2006 period. In the preliminary analysis devoted to verifying the

[74] cay_t is not estimated in a separate cointegrating regression, but consumption, income, and wealth are included directly as regressors in the forecasting equation for stock returns.

existence of a long-run relationship between consumption, income and wealth in the examined countries, a structural break is detected between 1944 and 1946.[75]

The findings obtained from the in-sample predictive regressions for equity premium suggest that, during the first subsample (1900-1944), cay_t does not predict the equity premium in any of the four countries examined, while cay_t is found significant for all countries, except Japan, during the postwar period (1946-2006). As a robustness check, two additional conditioning variables (the term spread and the stock market variance) are entered into the predictive regression over the postwar period. The estimation results confirm the strong performance of cay_t for all countries except Japan, with the related parameter estimates being substantially unchanged compared to those obtained with cay_t as the sole predictor variable.

An out-of-sample forecast exercise for one step-ahead is also carried out to compare the performance of cay_t with that of the historical average. The analysis is carried out for both the prewar and postwar periods, and with cay_t estimated over the full sample period (fixed cay_t) and recursively (re-estimated cay_t). While cay_t performs worse than the historical average over the pre-war period, mixed results are found over the post-war period: fixed cay_t outperforms the benchmark in the US, France, and the UK. However, this is no longer true when the re-estimated cay_t is used, with the US the only marginal case. These results improve when restrictions proposed by Campbell and Thompson (2008) are imposed, but again statistically significance is observed only for the US during post-war period.

Differently from previous studies, Sousa (2010a) points out the importance of taking wealth composition into account in order to predict stock market fluctuations. Sousa (2010a) derives an equilibrium relation between an empirical proxy, $cday_t$, and expected future asset returns, with $cday_t$ representing the transitory deviation from the common trend in consumption, housing wealth, financial wealth and labor income. Then the long-run predictive power of $cday_t$ is compared to that of cay_t from Lettau and Ludvigson (2001), for both the US and the UK, using quarterly data for the period 1975q1-2008q4.[76] The related findings display a better performance of $cday_t$ that not only explains a larger

[75] This feature is attributed to measurement problems and limited stock market participation affecting the prewar period.
[76] Long-run regressions are estimated over horizons from 1 to 4.

variation of excess returns over the next 4 quarters, but also shows a larger estimated coefficient, with its relative predictive power greater at longer horizons. These results are due to the ability of $cday_t$ to track risks associated with different compositions of wealth such as different taxation, transaction costs or degrees of liquidity.

The predictive powers of $cday_t$ and cay_t are also assessed in an out-of-sample forecasting exercise over horizons of 1, 2 and 4 quarters with different starting dates, using fixed cointegrating vectors.[77] The related findings suggest that $cday_t$ performs better than cay_t, and this is true especially for the US. Its predictive power increases as the horizon increases, a result which corroborates in-sample results.

To the best of my knowledge, de Castro and Issler (2015) is the only previous work investigating the role of the consumption-wealth ratio on predicting future stock returns through a panel unit root and cointegration approach. To this end, an error correction term (cay_{f_t}) of a single vector error correction model (VECM) for the entire panel is estimated by the FMOLS estimator by Phillips and Hansen (1990), with consumption, asset wealth and labor income as endogenous variables, using an unbalanced panel of quarterly aggregate data for G7 countries over the period 1981q1-2014q1. A VECM for each country is also estimated, and the related cointegrating vector is used to compute a variable with heterogeneous parameters, labeled $cay_{fh_{i,t}}$. In order to assess the forecasting power of cay_{f_t} and $cay_{fh_{i,t}}$, one-quarter-ahead panel regressions for real returns and excess returns are performed, including fixed effects with White cross-section corrections to standard errors. The related results show that cay_{f_t} is significant for real stock returns and excess returns. The same is not true for $cay_{fh_{i,t}}$, and financial variables included in the regression. When long-run forecasting regressions from 1 to 24 quarters are performed, the results point to cay_{f_t} as a better predictor than $cay_{fh_{i,t}}$. Compared with financial variables as sole predictors, cay_{f_t} is also better than the dividend-yield and the payout ratio, especially up to six years horizon, while the $RREL_t$ displays a better performance up to three quarters ahead. When cay_{f_t} and all financial variables are included in the same regression, cay_{f_t} and $RREL_t$ are found to be stronger predictors for intermediate horizons, while for longer horizons the dividend-yield and the payout ratio are also recognized to be good forecasters.

[77] The stating dates are: 1990q4, 1995q4, 2000q4, and 2005q4.

As for out-of-sample forecast analysis, nested and non-nested panel forecasts are evaluated using the mean square error (MSE), with cay_{f_t} estimated over the full-sample and re-estimated for each period of time (*reest* cay_{f_t}). While the performance of *reest* cay_{f_t} is disappointing at one-quarter ahead horizon, both cay_{f_t} and *reest* cay_{f_t} improve the forecasts compared to either a benchmark consisting in constant or lagged excess returns, in the case of two years accumulated excess returns.

4.3. THEORETICAL FRAMEWORK

In this section, the theoretical framework that relates cay_t to expected stock returns is reviewed. The section relies on the contributions of Campbell and Mankiw (1989), Campbell (1996), and Lettau and Ludvigson (2001).

Consider the following standard budget constraint faced by a representative consumer in an economy where all wealth is tradable:

$$W_{t+1} = \left(1 + R_{w,t+1}\right)(W_t - C_t), \tag{4.1}$$

where W_t represents aggregate wealth (sum of asset holdings and human capital), C_t denotes private consumption, and $R_{w,t+1}$ indicates the net return on aggregate wealth between period *t* and *t+1*.

Conditional on a stationary consumption-aggregate wealth ratio, Campbell and Mankiw (1989) show that the budget constraint can be approximated by taking the first-order Taylor expansion of equation (4.1), resulting in:

$$\Delta w_t \approx k + r_{w,t+1} + (1 - 1/\rho_w)(c_t - w_t), \tag{4.2}$$

where lower-case letters denote the logs of corresponding upper-case letters, with $r \equiv \log(1 + R)$, ρ_w indicating the steady-state ratio of new investment to total wealth, $(W - C)/W$, and k being a constant.[78] Solving the differential equation (4.2) and

[78] It should be noted that from now on linearization constants in the equation are omitted (see Lettau and Ludvigson, 2001).

imposing the condition that $\lim_{i\to\infty} \rho_w^i (c_{t+i} - w_{t+i}) = 0$, the log consumption-wealth ratio can be written as:

$$c_t - w_t = \sum_{i=1}^{\infty} \rho_w^i (r_{w,t+i} - \Delta c_{t+i}). \qquad (4.3)$$

By taking the conditional expectations of both side of equation (4.3),[79] one obtains the following:

$$c_t - w_t = E_t \sum_{i=1}^{\infty} \rho_w^i (r_{w,t+i} - \Delta c_{t+i}). \qquad (4.4)$$

Equation (4.4) states that the log of the consumption-wealth ratio is a function of the expected future returns on aggregate wealth and future consumption growth. This equation also implies that if the log of the consumption-wealth ratio varies over time, it is expected to predict stock returns, consumption growth or both of them.

Since the human capital component of aggregate wealth is not observable, the framework illustrated so far is not suitable to predict returns. For this reason, Lettau and Ludvigson (2001) propose to use aggregate labour income as a proxy of the nonstationary component of human capital.[80] The predictive components of the consumption-wealth ratio can be now expressed as observable variables. To this aim, let A_t and $1 + R_{a,t}$ be the asset holdings and its gross return, respectively (see Lettau and Ludvigson, 2001). Then, aggregate wealth is:

$$W_t = A_t + H_t,$$

and log aggregate wealth can be approximated as:

[79] Equation (4.3) holds ex post and ex ante because of the agent's intertemporal budget constraint (see Lettau and Ludvigson, 2001). Yet, the constant is ignored.

[80] This implies that $h_t = k + y_t + z_t$, where k denotes a constant and z_t indicates a mean zero stationary random variable. The assumption made by Lettau and Ludvigson (2001) relies on the following argument. Labour income can be expressed as annuity value of human wealth, $Y_t = R_{h,t+1} H_t$, where H_t represents the net return to human capital. Then, it can be shown that $r_{h,t}$ = log $(1 + R_{h,t+1}) \approx 1/{+}\rho_y(y_t - h_t)$, where $\rho_y \equiv (1 + Y/H)/(Y/H)$, and, as a result, z_t= - $\rho_y r_{h,t}$.

$$w_t \approx \omega a_t + (1-\omega)h_t, \tag{4.5}$$

where ω is equal to the average share of asset holdings in total wealth $\mathrm{A/W}$. The return to aggregate wealth can be defined as:

$$1 + R_{w,t} = \omega_t\left(1 + R_{a,t}\right) + (1-\omega_t)(1 + R_{h,t}). \tag{4.6}$$

Equation (4.6) can be approximated in terms of log returns as follows (see Campbell, 1996):

$$r_{w,t} \approx \omega r_{a,t} + (1-\omega)r_{h,t}. \tag{4.7}$$

Substituting equation (4.7) into equation (4.4),[81] one obtains the following:

$$c_t - \omega a_t - (1-\omega)h_t = E_t \textstyle\sum_{i=1}^{\infty} \rho_\omega^i \left\{\left[\omega r_{a,t+i} + (1-\omega)r_{h,t+i}\right] - \Delta c_{t+i}\right\}. \tag{4.8}$$

In order to replace an unobservable variable, h_t, in (4.8), one can use $h_t = k + y_t + z_t$, so to obtain the following expression for the log consumption-aggregate wealth ratio equation with only observable variables on the left-hand side:

$$c_t - \omega a_t - (1-\omega)y_t =$$

$$E_t \textstyle\sum_{i=1}^{\infty} \rho_\omega^i \left\{\left[\omega r_{a,t+i} + (1-\omega)r_{h,t+i}\right] - \Delta c_{t+i}\right\} + (1-\omega)z_t. \tag{4.9}$$

Given the fact that all the variables on right-hand side are presumably stationary, c_t, a_t, and y_t must be cointegrated, and the left-hand side of equation (4.9) represents the deviation in the common trend of c_t, a_t, and y_t. The trend deviation term $c_t - \omega a_t - (1-\omega)y_t$ is denoted as cay_t. Equation (4.9) also states that cay_t is good proxy for market

[81] The constant is ignored (see Lettau and Ludvigson, 2001).

expectations of future asset returns if $r_{h,t+i}$ and Δc_{t+i} are not too variable or if they are highly correlated with expected returns on assets (see Lettau and Ludvigson, 2001).

The theory behind equation (4.9) underlines that cay_t, as a proxy of the consumption-wealth ratio, should track longer-term tendencies of asset returns rather than offering accurate forecasts of booms or crashes in asset markets in the short-run (see Lettau and Ludvigson, 2001; Lettau and Ludvigson, 2010). This is because the consumption-wealth ratio is a function of expected returns on the market portfolio into the distant future. In particular, equation (4.9) implies that the increasing power of cay_t at forecasting returns over longer time horizons may depend on how large the discount rates (ρ_{ω}^{i}) applied to expected returns are (Lettau and Ludvigson, 2001). Equation (4.9) is in line with a large range of forward-looking models of investors' behavior where consumption is a function of both human and asset wealth. These models suggest that consumption behavior reveals investors' expectations of future returns as well as consumption growth. Investors who desire to maintain a flat pattern of their consumption tend to "smooth out" transitory changes in their asset wealth which are driven by variations in expected returns over time. If excess returns are expected to be higher (lower) in the future, forward-looking investors will increase (decrease) consumption out of asset wealth and income, so that consumption will rise (fall) above (below) its shared trend with those variables (Lettau and Ludvigson, 2001). In such a way, investors may preserve future consumption from variations in expected returns, and stationary deviations from the common trend among consumption, asset wealth and income will probably be a good predictor of excess stock returns over longer horizons, because they capture market expectations of asset returns into the distant future.

4.4. ECONOMETRIC METHODOLOGY AND DATA

This section is devoted to the econometric methodology and the description of the data.

4.4.1. ECONOMETRIC METHODOLOGY

The empirical analysis in this chapter proceeds in two steps. In the first one, the transitory deviation from the cointegrating regression between consumption, disposable income and asset wealth is estimated using a panel approach that takes cross-sectional dependence into account, through a common factor structure. Applying this approach in panel data for 9 Euro area countries is more appropriate than applying a panel approach based on the hypothesis of independence between units. In fact, this assumption is unlikely to hold in practice in a context where examined countries share the same currency beside other economic features. In the second step of the analysis, the resulting panel series of trend deviations, denoted cay_{it}, enters in a series of panel forecasting regressions as a predictor of excess returns.[82]

The estimation of cay_{it} is based on the same methodology applied in Chapter 3. Notably, this methodology requires a preliminary inspection concerning the presence of cross-section dependence in consumption (c_{it}), disposable income (y_{it}) and net wealth (w_{it}), with all these variables expressed in log, real per capita terms (see section 4.4.2). To this end, the CD test by Pesaran (2004), that assumes the null hypothesis of cross-sectional independence, is performed. Once the presence of cross-section dependence in the data is verified, the panel unit root test by Bai and Ng (2004), which is based on a factor model structure, is applied to assess the nonstationarity of each of above series. The presence of a unit root in the series permits to test if they are cointegrated by using the procedure by Genegnbach et al. (2006). If cointegration cannot be rejected in the data, then it is possible to derive cay_{it}, and estimate the panel version relation in the left-hand side of equation (4.9) by using the estimator by Westerlund (2007).[83]

As for the predictions of the excess returns and log excess returns, the following panel regressions are considered:

$$R^e_{it+H,H} = \gamma' X_{it} + \nu_{it+H,H}, \tag{4.10}$$

and

$$r^e_{it+H,H} = \beta' X_{it} + \varepsilon_{it+H,H}, \tag{4.11}$$

[82] The notation for "cay_{it}" is consistent with the panel estimation of this series, with *i* ranging from 1 to 9, referring to the examined countries, and *t*, ranging from 1988q1 to 2014q4.

[83] Using a different symbol for asset wealth, the panel version of relation in the left-hand side of equation (4.9) is the following: $c_{it} - \omega w_{it} - (1-\omega) y_{it}$, where c_{it} is consumption, w_{it} is asset wealth and y_{it} is disposable income. All these variables are expressed in log, real per capita terms.

with the dependent variables constructed as follows: [84]

$$R^e_{it+H,H} = R^e_{it+1} + \cdots + R^e_{it+H} \quad \text{and} \quad r^e_{it+H,H} = r^e_{it+1} + \cdots + r^e_{it+H}, \qquad (4.12)$$

where $R^e_{it+1} = R^s_{it+1} - R^f_{it+1}$ and $r^e_{it+1} = r^s_{it+1} - r^f_{it+1}$, are the level of excess returns and the log of excess returns, with R^s_{it} and r^s_{it} denoting real returns of share prices for the country *i* at time *t*, and its log counterpart, respectively; and R^f_{it} and r^f_{it} are real returns on a 3-month interest rate (the risk-free rate) for country *i* at time *t* and its log counterpart, respectively. Therefore, the dependent variables in equations (4.10) and (4.11) are the sum of the level of excess returns and the log of excess returns, respectively, for horizons from 1 to H.

As for the right-hand side of equations (4.10) and (4.11), X_{it} may denote cay_{it}, as a sole predictor, or a set of predictors, that apart from cay_{it}, may include the dividend-yield ($Divyld_{it}$) and the stochastically detrended risk-free rate or the relative bill rate ($RREL_{it}$). The last variable is computed as difference between the nominal risk-free rate and its last four-quarter average.

Equations (4.10) and (4.11) are estimated using the "estimable GLS" estimator.[85] Consider the following fixed effect model (see Reed and Ye, 2011):

$$\begin{bmatrix} \boldsymbol{y}_1 \\ \boldsymbol{y}_2 \\ \vdots \\ \boldsymbol{y}_N \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_N \end{bmatrix} + \begin{bmatrix} \boldsymbol{X}_1 \\ \boldsymbol{X}_2 \\ \vdots \\ \boldsymbol{X}_N \end{bmatrix} \beta_x + \begin{bmatrix} \boldsymbol{\varepsilon}_1 \\ \boldsymbol{\varepsilon}_2 \\ \vdots \\ \boldsymbol{\varepsilon}_N \end{bmatrix},$$

or

$$\boldsymbol{y} = \beta_0 + \boldsymbol{X}\beta_x + \boldsymbol{\varepsilon},$$

where N and T indicate the number of cross-sectional units and the time dimension, respectively. $\boldsymbol{y}_i$ is a $T \times 1$ vector of observations of the dependent variable for the i-th cross-sectional unit; $\boldsymbol{X}_i$ is a $T \times 1$ vector of explanatory variable; β_i, $i = 1,2, \dots, N$, and β_x

[84] Dependent variables are defined as in Lettau and Ludvigson (2010) and adapted to panel data.
[85] In the analysis, "GLS Weights" along with White cross-sectional covariance method are used (see Reed and Ye, 2011).

are scalars; and $\boldsymbol{\varepsilon}_i$ is a $T \times 1$ vector of error terms, with $\boldsymbol{\varepsilon} \sim \boldsymbol{N}(\mathbf{0}, \boldsymbol{\Omega}_{NT})$.[86] The “estimable GLS” estimator gives the following formula for $\widehat{\boldsymbol{\beta}}$ and Var($\widehat{\boldsymbol{\beta}}$):

$$\widehat{\boldsymbol{\beta}} = \left(\boldsymbol{X}'\widehat{\boldsymbol{\Omega}}^{-1}\boldsymbol{X}\right)^{-\mathbf{1}}\boldsymbol{X}'\widehat{\boldsymbol{\Omega}}^{-1}\boldsymbol{Y},$$

and

$$\mathrm{Var}\,\widehat{(\boldsymbol{\beta})} = \left(\boldsymbol{X}'\widehat{\boldsymbol{\Omega}}^{-1}\boldsymbol{X}\right)^{-\mathbf{1}}.$$

4.4.2. DATA

In this study, data for 9 Euro area countries over the period 1988q1-2014q4 are used. The countries are Austria, Belgium, Finland, France, Germany, Ireland, Italy, Netherlands, and Spain.[87] Data are mainly taken from Datastream and OECD main economic indicators, with the exception of population series which is collected from World Bank.[88]

Total private consumption expenditures (c_{it}), personal disposable income (y_{it}), net wealth (w_{it}), deflated by consumption deflator and expressed in log per capital terms, are used to derive cay_{it}. These data are taken from Datastream.[89] Share prices and the 3-month interest rate, both taken from OECD main economic indicators, enter to compute excess stock returns, the dependent variable of forecasting regressions.[90] Dividend-yield series, taken from Datastream, are used as an additional predictor for excess returns.

4.5. EMPIRICAL RESULTS

In this section, the results of the analysis are presented. In particular, the results of the panel procedure necessary to estimate cay_{it} are firstly illustrated, followed by the results obtained from panel forecasting exercises for excess returns and log excess returns, both in-sample and out-of-sample, using cay_{it} as a predictor.

[86] For the analysis in this chapter, $\boldsymbol{y}$ represents the level of excess returns or the log of excess returns, while $\boldsymbol{X}$ represents cay_{it}, or a vector with cay_{it}, $Divyld_{it}$, and $RREL_{it}$, as components. For details on the covariance matrix, see Reed and Ye (2011).

[87] The countries are selected on the basis of the availability of data.

[88] The population series are interpolated from annual data.

[89] As for the net wealth data, back series for Finland (1988-1994), France (1988-1993), Ireland (1988-2002) and Italy (1988-1994) were constructed using NiGEM data.

[90] The 3-month interest rate is the free-risk rate.

4.5.1. ESTIMATING cay_{it}

As already mentioned in the section of econometric methodology, the procedure to estimate cay_{it} requires verifying the presence of cross-sectional dependence between countries in each panel series of interest, before testing for unit root and cointegration. In order to detect this feature in the data, the CD test by Pesaran (2004), that assumes the null hypothesis of cross-sectional independence, is applied (see Chapter 3 for details), and the related results in Table 4.1 strongly point to cross-sectional correlation in consumption, disposable income, and asset wealth.

Table 4.1: Results for cross-section dependence. 9 Euro countries, 1988q1- 2014q4.

Levels			
Variables	$\hat{\rho}$	CD statistics	p-value
c_{it}	0.464	18.24	0.000
y_{it}	0.392	10.00	0.000
w_{it}	0.546	2.25	0.024

Notes: Variables are expressed in log real per capita terms. The average cross-correlation coefficient $\hat{\bar{\rho}} = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}$ is the average of the country-by-country cross-correlation coefficients $\hat{\rho}_{ij}$. CD indicates the statistics by Pesaran (2004) to test for cross-sectional dependence in the data.

Previous results justify the implementation of PANIC procedure by Bai and Ng (2004), which is based on the hypothesis that data feature cross-sectional dependence through a common factor structure. This procedure requires preliminary determination of the number of common factors in each panel series. The Bai and Ng (2002) procedure is applied for this goal, and the related results give evidence of one common factor for each variable. As a result, the ADF test and panel unit root test by Choy (2001) are applied to assess the nonstationary nature of the common factor and the idiosyncratic component, respectively, in each series.

Results in Table 4.2 provide evidence of unit roots in all the variables, as the null hypothesis of nonstationary cannot be rejected for both factors and idiosyncratic components.

Table 4.2: Unit root test results. 9 Euro countries, 1988q1-2014q4.

Variables	$BN_{ADF_{\hat{F}}^c}$	$BN_{Z_{\hat{e}}^c}$
c_{it}	-1.480	-1.705
	(0.540)	(0.088)
y_{it}	-0.706	0.975
	(0.840)	(0.329)
w_{it}	-2.017	0.422
	(0.280)	(0.673)

Notes: Variables are expressed in log, real per capita terms. The number of common factors (*r)* is equal to 1 for each series, as selected by using the BIC 3 criterion. The maximum number of factors is set equal to 3 (see Bai and Ng, 2002). $BN_{ADF_{\hat{F}}^c}$ and $BN_{Z_{\hat{e}}^c}$ denote the unit root tests by Bai and Ng (2004) on common factors and idiosyncratic components, respectively. The ADF test regression includes constant and trend. p-values are in parenthesis.

At this stage, the procedure by Gegenbach et al. (2006) is applied to test for cointegration in both components. The results for the factor component show the existence of one cointegrating vector, when the Trace test by Johansen (1995) is used (see Table 4.3), while results related to the panel cointegration test by Pedroni (1999, 2004) point to cointegration among the idiosyncratic components.

Table 4.3: Cointegration test results. 9 Euro countries, 1988q1-2014q4.

	Factor cointegration	Idiosyncratic cointegration	
	(Johansen, 1995)	(Pedroni, 1999, 2004**)**	
H_0: r	Trace test	Z_ρ	Z_t
0	48.644^{***} (0.000)	-3.214^{***} (0.000)	-3.049^{***} (0.000)
1	18.445 (0.087)		
2	5.029 (0.280)		

Notes: A VAR(2) is used in the analysis for cointegration. The model for the Johnsen test includes a constant. *** and ** indicate significance at the 1% and 5% level, respectively; Z_ρ and Z_t denote the ADF statistics for the panel cointegration test by Pedroni (1999, 2004); p-values are in parenthesis.

The existence of cointegration in the data is the necessary condition to estimate cay_{it} (see Lettau and Ludvigson, 2001; Rudd and Whelan, 2006; Della Corte et al., 2010). To this end, the panel data version of relation in the left-hand side of equation (4.9) is estimated by using the adjusted-OLS estimator proposed in Westerlund (2007), making it possible to compute cay_{it} as follows:

$$\widehat{cay}_{it} = c_{it} - 0.9239y_{it} - 0.0744w_{it}, \quad (4.13)$$

with $i = 1, \dots, 9$ and $t = 1988q1, \dots, 2014q4$.

4.5.2. FORECASTING STOCK RETURNS

In this section, cay_{it} is used as a predictor for excess returns and log excess returns in both in-sample and out-of-sample forecasting exercises. A robustness check for prediction in-sample is also carried out, consisting in including two additional repressors, the dividend-yield ($Divyld_{it}$) and the relative bill rate ($RREL_{it}$), to the forecasting equation.

Figures 4.1 and 4.2 provide a visual evidence of how cay_{it}, as derived in (4.13), is able to anticipate excess returns and log excess returns in-sample, respectively. These figures display individual graphs for each of the countries under investigation where estimates of cay_{it} over time are reported along with excess returns and log excess returns, respectively. Based on forward-looking behaviour, variations of cay_{it} should precede variations in stock returns over time, because investors tend to increase or decrease their current consumption with respect to their wealth in accordance with their expectations about future stock returns (see Lettau and Ludvigson, 2001).

Both figures seem to confirm such a tendency of cay_{it}: for each country it is possible to observe several cases where increases in cay_{it} are followed by increases in excess returns (log excess returns) and decreases in cay_{it} are followed by drops in excess returns (log excess returns). It is of interest to note the sharp and persistent increase in cay_{it} in the mid-1990s preceding large increases in excess returns in the late 1990s, likely reflecting the Internet bubble in many countries, and the subsequent sharp decline in cay_{it} in the late 1990s preceding the burst of the Internet bubble in the early 2000s. Moreover, cay_{it} drops sharply in 2006 before the recent financial crisis, and then recovers partially afterwards, before the subsequent rebound of stock prices during 2009.

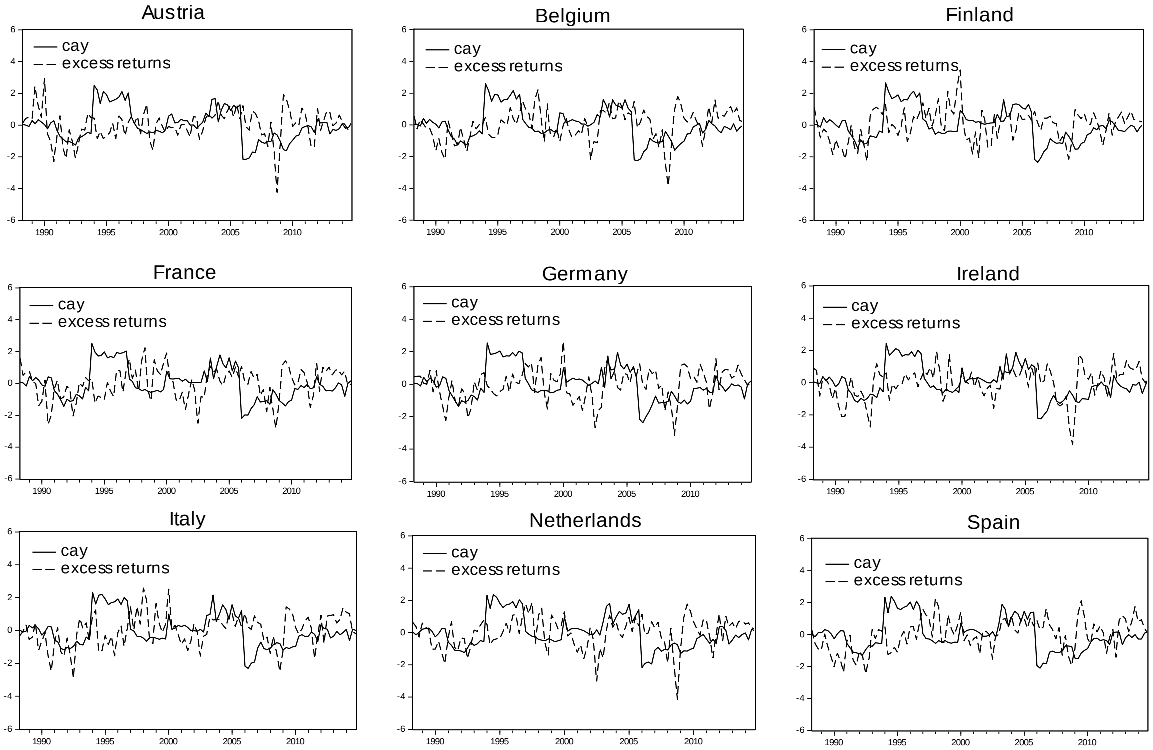

Figure 4.1: Trend deviations and excess returns for 9 Euro countries, 1988q1-2014q4.

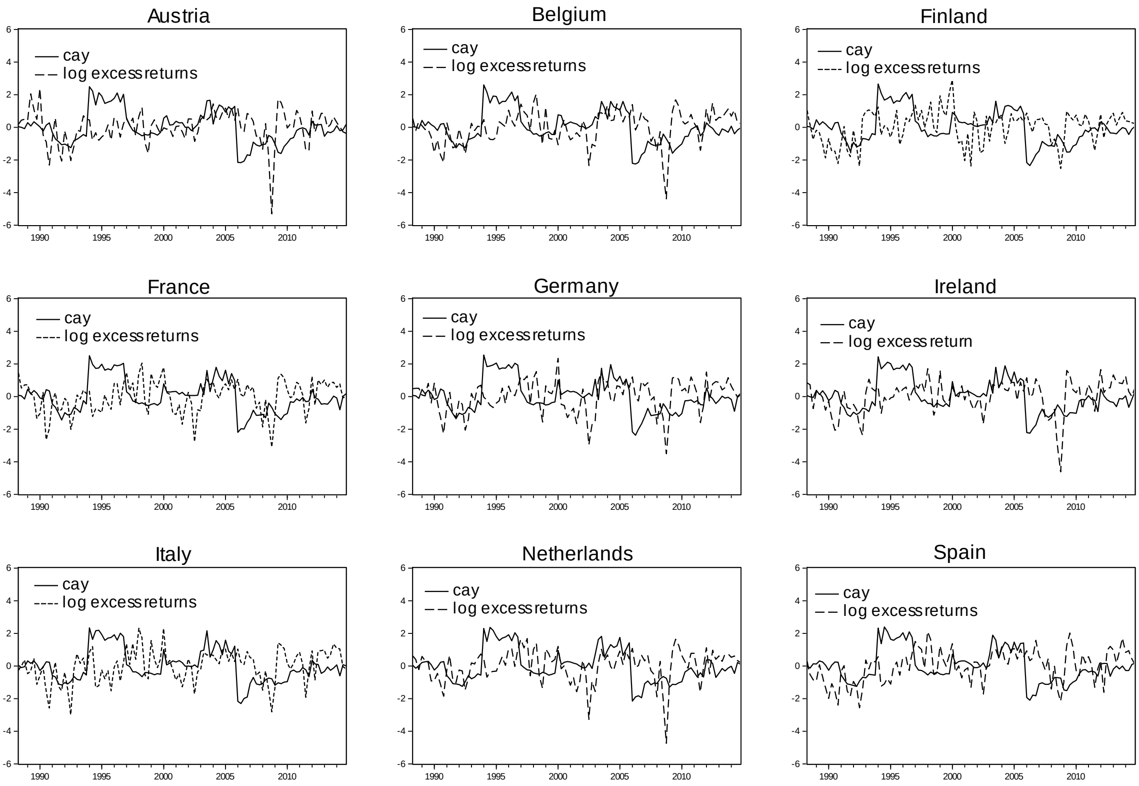

Figure 4.2: Trend deviations and log excess returns for 9 Euro countries, 1988q1-2014q4.

4.5.2.1. IN-SAMPLE FORECASTING

Table 4.4 reports the results of the in-sample forecasting analysis of level excess returns and log excess returns, using lagged cay_{it} as predictor over horizons spanning 1 to 8 quarters.[91] The forecasting regressions are estimated by using EGLS estimator with standard errors corrected for cross-section correlation (see Section 4.4).

As it can be seen, the findings are consistent with the theoretical framework illustrated in previous section. In fact, cay_{it} is found positively and significantly related to both excess returns and log excess returns over all the horizons considered, though coefficient in cay_{it} is significant only at 10% level at one-quarter ahead. What is more, its forecasting power increases over horizons, since the adjusted R^2 as well as the magnitude of related slope coefficients increase across one to eight quarters ahead. In particular, the figures for R^2 show that, while cay_{it} is able to predict only about 1% at one-quarter ahead, its forecasting ability increases notably from the two-step-ahead horizon, reaching 15% and 7% at eight quarters ahead for excess returns and log excess returns, respectively.

[91] The dependent variables in Panel A and Panel B are defined in equation (4.12) in the section of econometric methodology

Furthermore, at this horizon, one-standard-deviation increase in cay_{it} yields 217 and 210 basis points rise in excess returns and log excess returns, respectively. This implies roughly a 9% and 8% increase at an annual rate, respectively.[92] These results corroborate the theoretical background for cay_{it} according to which this variable should be a better forecaster at longer rather than shorter horizons.

Table 4.4: In- sample long-horizon forecasting regressions for excess returns and log excess returns. 9 Euro countries, 1988q1-2014q4.

			Panel A		
			Excess returns		
Regressor	Forecast horizon H				
	1	2	3	4	8
cay_{it}	0.048*	0.122**	0.132**	0.198***	0.254***
(t-stat)	(1.776)	(2.424)	(2.497)	(2.729)	(2.643)
$\bar{R}^2$	[0.009]	[0.025]	[0.041]	[0.053]	[0.153]
			Panel B		
			Log excess returns		
Regressor	Forecast horizon H				
	1	2	3	4	8
cay_{it}	0.047*	0.121**	0.127**	0.188***	0.245***
(t-stat)	(1.805)	(2.396)	(2.437)	(2.578)	(2.908)
$\bar{R}^2$	[0.008]	[0.022]	[0.032]	[0.047]	[0.069]

Notes: This table reports the estimates of long-horizon regressions of excess returns and log excess returns on one-period lagged cay_{it} using the "estimable GLS" estimator (see Section 4.4). The dependent variable is the H-period excess return and log excess return (see equation (4.12)). The forecast horizon length is in quarters. t-statistics are displayed in parenthesis. Figures for $\bar{R}^2$ (adjusted R-square) are reported in squared brackets. Symbols ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Boudoukh et al. (2008) point out that a monotonous rise in the long-horizon R^2 statistics and coefficients may also be observed as long as the predictor concerned is persistent. Overlapping data for the construction of long-horizon returns and small sample bias due to the persistence of the predictors, whose innovations are correlated with those in the returns, may account for this phenomenon (see Stambaugh, 1999; Valkanov, 2003). Boudoukh et al. (2008), however, observe that for credible data-generating processes this feature is not the result of small sample biases but rather the result of overlapping return data interacting with the persistence of predictor variable.

[92] The standard deviation of cay_{it} is 0.08.

Comparing results for excess returns in Table 4.4 with those reported in de Castro and Issler (2015), the only previous study where a panel cointegration approach is applied, it is worth noting that parameter estimates are lower in terms of magnitude, particularly from the three-step-ahead horizon.[93] By contrast, when looking at the figures for the adjusted R^2, there is no significant difference between the two studies a part from the figure at the longest horizon, where 15% variation of excess returns is explained as opposed to 9.8% in de Castro and Issler (2015).[94]

In order to evaluate how robust the previous results are, Table 4.5 reports forecasts obtained by adding to cay_{it} additional variables that in previous works have been found to display predictive power for excess returns. As control variables, standard regressors are considered, such as the dividend yield ratio ($Divyld_{it}$) (see Afonso and Sousa, 2011) and the relative bill rate ($RREL_{it}$), which is constructed as the difference between the nominal risk-free rate and its last four-quarter average (see Lettau and Ludvigson, 2010).

It emerges that cay_{it} continues to be a significant predictor at all horizons when the dividend yield and $RREL_{it}$ enter the forecasting regression, with again a weaker significance level at 10% at one-quarter-ahead horizon. This is true for both future excess returns and log excess returns. For both dependent variables, the predictive power of cay_{it} remains unaffected over all horizons, because the related coefficients do not change significantly across horizons, while the figures for the adjusted R^2 are always larger than those in Table 4.4, especially over three- and four-quarters ahead horizons.

The dividend-yield helps to improve the predictability of returns at all horizons, especially at the longest one, where, in the case of the level of excess returns, it is the only significant regressor together with cay_{it} (both at 1% significance level), contributing to explaining a significant 28% variation. In the case of log excess returns, it contributes to explaining 23% of variation eight quarters ahead, with $RREL_{it}$ also significant at 5% level. These results are consistent with those in previous works where the performance of the dividend-yield is found particularly strong at longer horizons.

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93 Comparisons with findings in de Castro and Issler (2015) refer to the analysis in section 7, Table n.10, of their paper, where forecasting regressions are run using FMOLS estimation of cay_{it}. The analysis refers to G7 countries and is carried out using a panel technique that does not take into account for cross-sectional dependence through a common factor structure. These are two main aspects that may account for differences in the results between the two studies.

94 Long-horizon regressions in de Castro and Issler (2015) are performed over horizons from 1 to 24 quarters.

Table 4.5: In- sample long-horizon forecasting regressions for excess returns and log excess returns. 9 Euro countries, 1988q1-2014q4.

Regressor	Panel A: Excess returns — Forecast horizon H				
	1	2	3	4	8
cay_{it}	0.049*	0.124**	0.128**	0.192***	0.245**
(t-stat)	(1.872)	(2.479)	(2.344)	(2.683)	(2.033)
$Divyld_{it}$	0.010**	0.017**	0.037***	0.114***	0.417***
(t-stat)	(2.017)	(2.123)	(2.928)	(8.318)	(23.804)
$RREL_{it}$	0.004	-0.010	-0.020***	-0.018***	-0.008
(t-stat)	(1.004)	(-1.336)	(-2.967)	(-2.425)	(-1.327)
$\bar{R}^2$	[0.016]	[0.032]	[0.061]	[0.139]	[0.276]

Regressor	Panel B: Log excess returns — Forecast horizon H				
	1	2	3	4	8
cay_{it}	0.048*	0.124**	0.124**	0.186**	0.223***
(t-stat)	(1.692)	(2.468)	(2.322)	(2.555)	(2.651)
$Divyld_{it}$	0.012**	0.020**	0.033***	0.112***	0.187***
(t-stat)	(2.308)	(2.502)	(2.846)	(8.119)	(12.996)
$RREL_{it}$	0.004	-0.009	-0.019***	-0.016**	-0.014**
(t-stat)	(1.089)	(-1.290)	(-2.837)	(-2.152)	(-1.906)
$\bar{R}^2$	[0.016]	[0.032]	[0.047]	[0.125]	[0.227]

Notes: This table reports estimates of long-horizon regressions of excess returns and log excess returns on one-period lagged variables using the "estimable GLS" estimator. The forecast horizon length is in quarters. The dependent variable is the H-period excess return and log excess return (see equation (4.12)). The regressors are cay_{it}, the log dividend-yield, $Divyld_{it}$, and the detrended risk-free rate, $RREL_{it}$.*t*-statistics are displayed in parenthesis. Figures for $\bar{R}^2$ are in squared brackets. Symbols ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

As for the relative bill rate, when significant, this variable is found of the expected negative sign, and it seems to be able to improve the forecasting performance only at three and four quarters ahead for the case of excess returns, while for the log excess returns this is true starting from the two-step-ahead horizon.

de Castro and Issler (2015) also run long-horizon regressions for excess returns with cay_{it} and other financial variables all together. In particular, they also consider the payout ratio as regressor, in addition to the variables listed in Table 4.5. Similarly to results in this chapter, cay_{it} is found a strong predictor at shorter and longer horizons. By contrast, the dividend yield does not seem to be a good predictor at shorter horizons, and the same seems to be true for the bill rate because, though significant at two and three steps ahead, it displays a positive sign.

4.5.2.2. OUT-OF-SAMPLE FORECASTING

This section is devoted to the results of out-of-sample nested forecasts. In particular, the performance of an unrestricted model, which includes cay_{it}, is compared to those of two restricted benchmark models: a model with a constant as predictor for excess returns (the constant expected returns benchmark); and a model with one-period lagged dependent variable as a predictor (the autoregressive benchmark, AR).

An out-of-sample forecasting analysis is crucial for two main reasons. First, it is useful from the point of view of the real world investor. In fact, this analysis allows investors to test whether it is plausible to exploit the predictability of stock returns observed in in-sample regressions on real time data, in order to time the market and manage to obtain higher returns for bearing a same risk. Second, as s argued by Goyal and Wealch (2008), entertaining an out-of-sample test is useful in order to assess if the model under investigation is stable and well-specified. Diagnostic tests, however, should not be thought as a substitute of in-sample performance to test the quality of the model, but as a necessary complement to be applied only conditional to significant in-sample results.

It is quite common that in-sample performance could differ from out-of-sample one. Notably, one should expect to detect no out-of-sample forecasting power if in-sample predictive relations are spurious or unstable. One case for spurious in-sample results is underscored by Ferson et al. (2003), who argue that this is likely the case when both expected returns and the predictor are very persistent. These authors also find that regressors with autocorrelation coefficients at around 0.85 generally display relatively good results for the t-statistics and R^2 statistics.

Tables 4.6 and 4.7 report nested out-of-sample comparisons of forecasts for excess returns made by referring to the constant expected returns benchmark, and the autoregressive benchmark, respectively. Following the approach in de Castro and Issler (2015), comparisons are made at one quarter and eight quarters ahead. More in detail, in both horizons, the ratio of the mean forecast error resulting from the model augmented by cay_{it} to the mean forecast error of the benchmark model is computed. A value of the ratio less than 1 indicates a better forecasting performance of the model including cay_{it}. Since changing the starting point of the out-of-sample forecasting period may affect the performance of the forecasting model, as shown by Brennan and Xia (2005), three different forecasting periods are considered, starting from 1999q1, 2005q1, and 2009q1, respectively (see also Sousa, 2010a). The recursive scheme is applied for the predictive regression, which is initially estimated in-sample using data from the outset of the sample to the quarter immediately preceding the starting date of the forecast period concerned. By contrast, cay_{it} enters the predictive regression as *fixed* cay_{it}, which is estimated over the full sample period, instead of being re-estimated recursively. As underscored in Lettau and Ludvigson (2001), using *fixed* cay_{it} is theoretically motivated, because the parameters of the cointegrating relationship can be considered as known when sufficient data is available to yield superconsistent estimates. In fact, as pointed out also by Lettau and Ludvigson (2005a), in response to the criticism of Brennan and Xia (2005), a bias would arise if some information was ignored to estimate cay_{it}, since the ability of this variable to forecast requires the identification of the true cointegrating parameters. Therefore, if the cointegrating parameters can be consistently estimated, they can be considered as known in subsequent estimation, such as forecasting regressions.

Findings in Tables 4.6 and 4.7 show that the ratio of mean squared errors is below 1 for forecast horizons 1 and 8, and for both the level of excess return and the log counterpart, indicating that the performance of the cay_{it} forecasting model is superior in terms of mean squared error compared to those of the two benchmark models, a result also found in de Castro and Issler (2015). These finding are also consistent with in-sample predictions, in the sense that, as the forecast horizon moves from short to long-run period, the performance of the models augmented with cay_{it} tends to improve compared to the related benchmark, as documented by the decreasing values of the relevant MSE ratios. It is important to notice that this occurs regardless of the starting point of the out-of-sample forecast (see also Sousa, 2010a).

It is also worth noting that, in general, for the same horizon, the performance of the model including cay_{it} tends to improve upon the autoregressive benchmark, as the forecasting period becomes shorter, while this tendency is not apparent in the case of the constant benchmark model.

Table 4.6: Nested out-of-sample forecasts of excess returns and log excess returns. 9 Euro countries, 1988q1-2014q4. Benchmark model: constant.

	Benchmark model: constant			
	Excess returns		Log excess returns	
	$MSE_{cay_{it}}$ $/MSE_{constant}$		$MSE_{cay_{it}}$ $/MSE_{constant}$	
	Forecast Horizon		Forecast Horizon	
Starting period	h=1	h=8	h=1	h=8
1999q1	0.938	0.842	0.948	0.835
2004q1	0.965	0.835	0.949	0.850
2009q1	0.969	0.861	0.930	0.890

Notes: The table reports the results of nested forecast comparisons for one-quarter- and eight-quarter-ahead of excess returns and log excess returns, respectively. The MSE ratios from the unrestricted model including one-period lagged cay_{it} over the restricted model of constant excess returns and constant log excess returns are displayed, respectively. Three different out-of-sample forecast periods are considered, whose starting period is displayed in the left hand-side of the table. Coefficients used to compute cay_{it} refer to a fixed cointegrated vector. The EGLS estimator is used to estimate recursively forecast regressions using data from the beginning of the sample to the quarter immediately preceeding the forecast period.

Table 4.7: Nested out-of-sample forecasts of excess returns and log excess returns. 9 Euro countries, 1988q1-2014q4. Benchmark model: AR.

	Benchmark model: Autoregressive (AR)			
	Excess returns		Log excess returns	
	$MSE_{cay_{it}}$ $/MSE_{AR}$		$MSE_{cay_{it}}$ $/MSE_{AR}$	
	Forecast Horizon		Forecast Horizon	
Starting period	h=1	h=8	h=1	h=8
1999q1	0.949	0.859	0.960	0.859
2004q1	0.948	0.829	0.939	0.839
2009q1	0.946	0.831	0.929	0.835

Notes: The table reports the results of nested forecast comparisons for one-quarter- and eight-quarter-ahead of excess returns and log excess returns, respectively. The MSE ratios from the unrestricted model including one-period lagged cay_{it} over the benchmarks of one-period lagged value of excess returns and log excess returns are displayed, respectively. Three different out-of-sample forecast periods are considered, whose starting period is displayed in the left hand-side of the table. Coefficients used to compute cay_{it} refer to a fixed cointegrated vector. The EGLS estimator is used to estimate recursively forecast regressions using data from the beginning of the sample to the quarter immediately preceding the forecast period.

4.6. CONCLUSIONS

An intense debate about stock return predictability has featured the empirical asset pricing literature over the last three decades. With few exceptions, such as Goyal and Wealch (2008), many works have found evidence of stock return predictability over longer horizons, especially through financial indicators predictors. The work by Lettau and Ludvigson (2001) introduces a novelty in this literature, because they use a macroeconomic indicator as a predictor, which shows a strong performance. This indicator, denoted "cay_t", represents an empirical proxy for the aggregate consumption-wealth ratio, and is derived as the temporary deviation of aggregate consumption from its shared trend with asset wealth and labor income.

To the best of my knowledge, the analysis in this chapter is the first which focuses on the predictive power of cay_{it} for future excess stock returns for 9 Euro countries over the period 1988q1-2014q4. For this purpose, unlike previous works, a panel unit-root and cointegration approach, which takes cross-sectional dependence into account, is applied to estimate cay_{it}. In this context, in fact, where examined countries share the same monetary system and some economic characteristics, it is unlikely that units in the panel are independent to each other. Notably, the procedure developed in Gengenbach et al. (2006) is used to test for unit root and cointegration, and the least square biased-adjusted estimator by Westerlund (2007) is applied in order to estimate cay_{it}.

As for the predictions of excess returns in- and out-of-sample, they are obtained using the panel EGLS estimator, which corrects for potential heteroscedasticity and autocorrelation, and cross-sectional dependence.

The related results point to predictability of future excess stock returns in the panel data examined both in-sample and out-of-sample. More in detail, in-sample results reveal that: i) cay_{it} is positively and significantly related to future excess returns over each horizon ranging from 1 to 8 quarters; ii) its forecasting power increases over horizons, up to explain 15% of variation in excess returns; and iii) when combined with the dividend-yield and the relative bill rate, cay_{it} maintains its forecasting power up to one year, and at 8 quarters ahead all regressors together are able to explain up to 28% of variation in excess returns.

As for the out-of-sample forecasting predictions, results highlight that a model with cay_{it} performs better than two benchmark models: the constant expected returns benchmark and the autoregressive benchmark. Moreover, consistent with in-sample results, cay_{it}-augmented model improves over horizons compared to the two benchmarks.

CHAPTER FIVE

CONCLUDING REMARKS

This thesis contains three essays. The first two essays contribute to the literature on wealth effects on consumption, while the third one is a contribution to the literature investigating stock returns predictability.

The first two essays are centred on the estimation of long-run effects on consumption of the two main components of aggregate wealth, that is financial and housing wealth.

In particular, the first essay aims to re-examine and compare log-run financial and housing wealth effects on consumption in Italy and the UK, taking into account the recent period of financial crisis. This is motivated by the considerations that these countries feature different financial systems, which may account for significant differences in the magnitude of estimated wealth effects, and that the financial crisis has exerted a different impact on the economics of the two countries due to their diverse financial systems.

This essay also attempts to investigate how wealth effects evolved over the sample period under investigation in the two countries via exercises of rolling regressions.

The whole empirical analysis is carried out using both a cointegration estimation method, involving the DOLS estimator by Stock and Watson (1993), and the estimation procedure proposed by Carroll et al. (2011a), which relies on the sluggishness of consumption growth. These procedures provide quite similar results for estimates of wealth effects. By and large, similar trends for the dynamics of wealth effects are also noticeable as results of rolling exercises.

Estimation results over the entire sample point to a significant difference between the two countries in terms of housing wealth effect. In spite of the huge amount of this form of wealth in Italy, a negligible and insignificant effect is detectable, while the reverse seems to be true for the UK. The result for Italy is consistent with an underdeveloped mortgage market, while that for the UK is in line with findings found for Anglo-Saxon countries featuring market-based financial systems with highly deregulated mortgage markets.

The financial wealth effect is significant in both countries, with no substantial difference in terms of magnitude, though this form of wealth dominates in the UK. Probably, these findings may be accounted for the larger proportion of wealth hold in the form of insurance and pension products in the UK than Italy.

As far as the dynamics of wealth effects are concerned, the results for Italy confirm that the housing wealth effect is negligible over time. On the other hand, the two methods of estimation show slightly increasing trends for the financial wealth effect, since the late 1990s. Probably, these trends reflect the effects of measures that have encouraged the development of the financial market in Italy.

As for the UK, both methods estimate descending trends for the financial wealth effect since the late 1990s. This pattern might be the result of a shift in preferences of consumers towards real assets over a period which saw remarkable increases in house prices. In fact, both methods estimate a larger housing wealth effect along the same period, with trends being increasing during large part of the 2000s.

It is worth noting that in the UK during the financial crisis MPCs out of both financial and housing wealth display increasing trends, especially when MPCs are estimated by the method of Carroll et al. (2011a). By contrast, in Italy a somewhat similar trend is noticeable only for the financial wealth effect, and only in MPCs derived by the procedure by Carroll et al. (2011a). Perhaps, stronger persistence in consumption habits may be an explanation for increasing dynamics in this period, which in the case of the UK are more pronounced probably because of more incisive drops in wealth components and a more negative impact of credit constrains.

The second essay of this thesis addresses the task of investigating long-run effects of financial and housing wealth on consumption in an international setting, using wealth data for a panel of 14 OECD countries. In order to achieve this goal, a recently developed nonstationary panel methodologies that controls for cross-section dependence via a common structure is used. Such a choice draws motivation from the consideration that assumption of independence between examined countries is unreasonable. This is because international financial integration, since the 1970s, has led asset prices to be increasingly correlated across countries (see IMF, 2007; Vansteenkiste and Hiebert, 2011; Hoesli and Reka, 2015). As a result, investigating wealth effects in this context without controlling for cross-sectional dependence would likely result in biased and inconsistent estimates (see Andrews, 2005; Bai and Kao, 2006) In addition, unit root and cointegration tests which do not account for cross-dependence suffer from large size distortions (see Banerjee et al., 2004, 2005).

In particular, the procedure developed in Gengenbach et al. (2006) (see also Urbain and Westerlund, 2011) is used to test for unit root and cointegration. In addition, long-run wealth effects on consumption are estimated by least square biased-adjusted estimator proposed in Westerlund (2007), which is also based on a factor model. Availability of a newly updated data set on wealth components, in turn, makes it possible to compute common long-run MPCs out of financial and housing wealth. The same analysis is also applied to the two groups of bank-based and market-based economies. This is because differences in terms of financial system affect how wealth shocks are turned into consumer spending.

The empirical analysis gives evidence of significant impacts of two forms of wealth under scrutiny on aggregate consumption, with the MPC out of housing wealth larger in magnitude than that out of financial wealth. This result contrasts with those in previous works (e.g. Slacaleck, 2009; De Bonis and Silvestrini, 2012), which highlight a larger financial wealth effect. It is likely that the implementation of a panel cointegration technique controlling for cross-sectional dependence over a sample period, which saw increasingly economic integration and large increases in the values of housing wealth in many industrialized countries, may account for such a difference.

Empirical results also point to larger wealth effects in market-based economies than bank-based ones. More specifically, the financial wealth effect in market-based economies is almost twice as large as that in bank-based countries. This result likely reflects the more widespread ownership of financial assets among households and deeper and more liquid financial markets in market-based countries. On the other hand, a less marked difference is notable for housing wealth effects in the two groups, with results suggesting the role of a stronger collateral channel in market-based countries. Again in both groups the MPC out of housing wealth effect is larger than the financial wealth effect. These results are in line with those found in same previous works which consider similar groups of bank- and market-based groups (e.g. Bayoumi and Edison, 2003; Skudelny, 2009).

The third essay of the thesis uses a proxy of the log consumption-wealth ratio, denoted "cay_{it}", to predict future stock excess returns using panel data of 9 Euro area countries. cay_{it} is defined as the cointegrating residual between consumption, disposable income and asset wealth. The time-series version of this macroeconomic indicator was first used by Lettau and Ludvigson (2001) to investigate the predictability of US real stock and excess returns, on the grounds that investors desire to maintain smooth their consumption path. Therefore, expectations of higher (lower) excess returns in the future should be associated with increases (decreases) in consumption relative to asset wealth and income.

Previous works on this topic have mainly used time-series approaches, with the exception of de Castro and Issler (2015), who take a broader international perspective using a panel cointegration approach for a panel of G7 countries. The analysis in this essay differs from that in de Castro and Issler (2015) because it takes cross-sectional dependence into account when deriving cay_{it}. For this purpose, the procedure developed in Gengenbach et al. (2006) is used to test for unit root and cointegration, while the least square biased-adjusted estimator by Westerlund (2007) is applied in the estimation of the long-run relationship between consumption, asset wealth and disposable income. Such an approach is far reasonable in a context like this where countries share the same currency and other economic features.

Predictions of excess returns are obtained by using the "estimable" generalize least square (EGLS) estimator, which corrects for potential heteroscedasticity and autocorrelation, and cross-sectional dependence (see Reed and Ye, 2011). Estimation results point to predictability of future excess stock returns in the panel data examined both in-sample and out-of-sample. Notably, the results of the in-sample forecasting experiment reveal that: i) cay_{it} affects positively and significantly future excess returns over each horizon ranging from 1 to 8 quarters; ii) its forecasting power increases over horizons; and iii) when combined with the dividend-yield and the relative bill rate, cay_{it} maintains its forecasting power up to one year, and at 8 quarters ahead all regressors together are able to explain a substantial variation in excess returns.

Results of the out-of-sample exercise suggest that the model with cay_{it} as a sole predictor performs better than two benchmark models: the constant expected returns benchmark and the autoregressive benchmark. Moreover, these results are consistent with those in-sample, since the augmented cay_{it} model improves its performance at eight quarters ahead compared to that at one quarter ahead.

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