Universidade de São Paulo
Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto
Departamento de Economia
Programa de Pós-Graduação em Economia — Área: Economia Aplicada

Marcos Hitoshi Endo

Essays on Consumption Predictability

Ensaios em Previsibilidade do Consumo

Supervisor: Prof. Dr. Fábio Augusto Reis Gomes

Ribeirão Preto

2020

MARCOS HITOSHI ENDO

Essays on Consumption Predictability

Ensaios em Previsibilidade do Consumo

Tese apresentada ao Programa de Pós-Graduação em Economia — Área: Economia Aplicada da Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto da Universidade de São Paulo, para obtenção do título de Doutor em Ciências. Versão Corrigida. A original encontra-se disponível na FEA-RP/USP.

Supervisor: Prof. Dr. Fábio Augusto Reis Gomes

Ribeirão Preto

2020

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

Endo, Marcos Hitoshi
Essays on Consumption Predictability/ Universidade de São Paulo – USP
Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto
Departamento de Economia
Programa de Pós-Graduação em Economia - Área: Economia Aplicada; Supervisor: Prof. Dr. Fábio Augusto Reis Gomes
Ribeirão Preto, 2020- 129 p. : il. 30cm

Tese de Doutorado – Universidade de São Paulo, 2020.

1. Consumption. 2. Instrumental Variables. 3. Permanent Income Hypothesis. 4. Weak Instruments. 5. Structural Breaks. I. Orientador: prof. Dr. Fabio Augusto Reis Gomes. II. Universidade de São Paulo. III. Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto.

Acknowledgements

Em primeiro lugar, agradeço aos meus pais, Sérgio e Sônia, que sempre me incentivaram a estudar e criaram as possibilidades para que eu percorresse todo esse caminho até aqui.

Aos amigos que fiz ao longo dessa jornada e que tornaram as muitas horas de estudo bem mais prazerosas.

Ao meu orientador, Fabio Augusto Reis Gomes, por sua excepcional orientação e motivação nos momentos mais importantes do doutorado.

À Janaina, minha companheira de doutorado e de vida.

Abstract

ENDO, M. H. (2020) **Essays on Consumption Predictability**. Doctoral Dissertation - Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto, Universidade de São Paulo, Ribeirão Preto, 2020.

This doctoral dissertation is composed of three self-contained essays that study the relationship between the aggregate consumption growth and the main macroeconomic variables investigated by the consumption literature. The first essay examines the predictability of the Brazilian aggregate consumption growth taking into account four factors: intertemporal substitution, rule-of-thumb behavior, liquidity constraints and habit formation. The results suggest that estimations are plagued by weak instruments, thus we use valid (robust) confidence intervals that suggest that income growth rate and/or credit growth rate are the relevant predictors. The second essay studies whether consumption responds symmetrically or asymmetrically to predictable income. Instead of finding evidence for myopia or liquidity constraints, the findings support the "perverse asymmetry" hypothesis raised by Shea (1995a). The third essay studies the consumption predictability in the US. Using structural break tests and robust confidence intervals to deal with the parameter stability and weak instruments, respectively, the results show evidence that the relevant predictability factors have changed over time.

Keywords: Consumption predictability; Consumption smoothing; Myopia; Credit conditions; Liquidity constraints; Euler equation; Instrumental variables, Weak instruments; Structural breaks; Hypothesis tests; Brazil; US.

Resumo

ENDO, M. H. (2020) **Ensaios em Previsibilidade do Consumo**. Tese (Doutorado) - Faculdade de Economia, Administração e Contabilidade de Ribeirão Preto, Universidade de São Paulo, Ribeirão Preto, 2020.

Esta tese é composta por três ensaios independentes que estudam a relação entre o crescimento do consumo agregado e as pricipais variáveis macroeconomicas estudadas pela literatura de consumo. O primeiro ensaio examina a previsibilidade do crescimento do consumo agregado brasileiro levando em consideração quatro fatores: substituição intertemporal, comportamento "rule-of-thumb", restrições a liquidez e formação de hábito. Os resultados sugerem que as estimações eão afetadas por instrumentos fracos, portanto usamos intervalos de conficança robustos que sugerem que o crescimento da renda e/ou do crédito são preditores relevantes. O segundo ensaio estuda se o consumo responde simetricamente ou assimetricamente à renda previsível. Ao invés de encontrar evidência de miopia ou restrição à liquidez, os resultados suportam a hipótese de "assimetria perversa" levantada por Shea (1995a). O terceiro ensaio estuda a previsibilidade do consumo nos EUA. Usando testes de quebras estruturais e intervalos de confiança robustos para lidar com a estabilidade dos parametros e instrumentos fracos, os resultados sugerem que os fatores relevantes para a previsibilidade do consumo mudaram ao longo do tempo.

Palavras-chaves: Previsibilidade do consumo; Suavização do consumo; Miopia; Condições de crédito; Restrições à liquidez; equação de Euler; Variáveis Instrumentais; Instrumentos fracos; Quebras estruturais; Testes de hipótese; Brasil; EUA.

List of Figures

List of Tables

Contents

1 General Introduction

This doctoral dissertation is composed of three self-contained essays that study the relationship between the aggregate consumption growth and the main macroeconomic variables investigated by the consumption literature.

The first essay examines the predictability of the Brazilian aggregate consumption growth, taking in account four factors: expected returns on assets (intertemporal substitution); anticipated growth rates in both income and credit (rule-of-thumb behavior and liquidity constraints); lagged consumption growth rate (habit formation). To accomplish such task, we investigate the presence of weak instruments, and apply the suitable econometric tools to handle it. The findings suggest that estimations are plagued by weak instruments, and the point estimates suggest that growth rates in income and credit are relevant predictability factors. Finally, valid (robust) confidence intervals suggest that income growth rate and/or credit growth rate have significant predictive power for the Brazilian growth rate in consumption.

The second essay studies whether consumption responds symmetrically or asymmetrically to predictable income. To accomplish such test, an adaptation of Shea (1995a) testing equation is proposed. This change makes the testing of whether consumption is more sensible to predictable income increases than decreases become more straightforward and allows us to employ usual instrumental variable estimators and econometric tools developed to deal with the weak instruments problem. This new approach yields the following results: *i)* there is overwhelming evidence that instruments are weak; *ii)* the point estimates for negative income growth are higher than those for positive income growth; *iii)* hypothesis testings indicate the same findings; *iv)* confidence sets robust to weak instruments show support for previous point estimates and hypothesis tests results. Therefore, instead of finding evidence for myopia or liquidity constraints, the findings support the “perverse asymmetry” hypothesis raised by Shea (1995a).

The third essay studies the US case. Because the aggregate consumer behavior is frequently summarized by Euler equations, when testing them, we jointly evaluate a model and its auxiliary assumptions. We build a model that takes into account four factors: intertemporal substitution (returns on assets), habit formation (lagged consumption), rule-of-thumb behavior (current income) and credit conditions (credit level). In general, the literature estimates such models assuming the following auxiliary assumptions: log-normality of consumption and assets returns, parameters constancy over time and that valid instruments are available. We adopt a strategy that evaluates those assumptions. More specifically, we use structural break tests to deal with the parameter stability and use robust confidence intervals given the evidence that instruments are weak. After incorporating the break dates, the results show that income growth and habit persistence were important to predict consumption growth in the past. From Jun-50 to Dec-83, these variables and debt growth were relevant. From Jan-84 to Dec-06, we do not find evidence of rule-of-thumb behavior anymore and habit persistence was the only relevant factor. In the last sub-sample, after Jan-07, habit was not relevant anymore and we do not have enough information to estimate the coefficient for income and debt growth.

2 Predictability of the Brazilian consumption growth: the relevance of anticipated growth rates in income and credit

Abstract

This paper examines the predictability of the Brazilian aggregate consumption growth, taking into account four factors: expected returns on assets (intertemporal substitution); anticipated growth rates in both income and credit (rule-of-thumb behavior and liquidity constraints); lagged consumption growth rate (habit formation). To accomplish such task, we investigate the presence of weak instruments, and apply the suitable econometric tools to handle it. The findings suggest that estimations are plagued by weak instruments, and the point estimates suggest that growth rates in income and credit are relevant predictability factors. Finally, valid (robust) confidence intervals suggest that income growth rate and/or credit growth rate have significant predictive power for the Brazilian growth rate in consumption.

Keywords: Consumption predictability; Credit conditions; Weak instruments; Brazil.

2.1 Introduction

In a seminal paper, Hall (1978) assumes a frictionless economy inhabited by an infinitely lived representative agent, whose preferences are represented by quadratic utility, concluding that optimal consumption follows a random walk process.[1] This result means that consumption revisions are unpredictable and, unless an innovation take place, consumption is perfectly stable (smooth) in accordance with the Permanent Income Hypothesis (PIH). Not by chance, consumption predictability, apart from last period consumption, is viewed as a basic violation of the PIH (Kiley (2010)). Indeed, assuming explicitly the PIH, Flavin (1981) also concludes that consumption follows a random walk process. However, Hall (1978) himself finds evidence that stock prices are valuable in predicting consumption, whereas Flavin (1981) finds evidence that consumption is excessively sensitive to current income.

These sources of consumption predictability are at odds with the PIH; however, other consumption models could capture such features.[2] Indeed, the failure of the PIH combined with the well-known drawbacks behind the quadratic utility led researchers to: *i)* adopt more appealing utility functions;[3] *ii)* introduce time-varying assets returns; *iii*) take into account the excessive sensitivity of consumption to (anticipated) income.

Replacing the quadratic utility by the constant-relative-risk-aversion (CRRA) one, Mankiw (1981), Hansen and Singleton (1983) and Hall (1988) – among others – have shown that consumption growth rate depends on the expected (time-varying) returns of the assets held by the consumer, which is in accordance with Hall (1978) empirical findings.[4] However, even after controlling for the intertemporal substitution induced by

---

[1] To be precise, Hall (1978) assumes yet that the interest rate is constant, R, and equal to the reciprocal of the intertemporal discount factor, β, i.e. $\beta R = 1$.

[2] Browning and Crossley (2001) argue convincingly that the life-cycle framework is the standard way that economists think about the intertemporal allocation of consumption, and it should be viewed as a source of models that can be taken to the data.

[3] The quadratic utility has a bliss point, and above it the marginal utility becomes negative. Besides, such utility implies globally increasing absolute risk aversion, which means that wealthier people invest less in risky assets, which contradicts both intuition and empirical evidence (Blanchard and Mankiw (1988))

[4] Recursive preferences also entail the conclusion that consumption growth rate depends on the expected returns of the assets held by the consumer (Epstein and Zin (1989), Weil (1989) and Epstein and Zin (1991)).

expected returns on assets, consumption growth remains predictable by anticipated income growth rate (Mankiw (1981)).

Not coincidentally, Campbell and Mankiw (1989) have argued that the time series data on consumption are best viewed as generated not by a single consumer, but by two types of consumers. The first one smooths the consumption path, which means that its consumption growth rate respond to expected asset returns. The second type follows the rule of thumb of consuming her/his current income. As a result, Campbell and Mankiw (1989) put forward a testing equation in which the consumption growth rate depends on the expected returns on assets and the anticipated income growth rate. Using G7 data, Campbell and Mankiw (1989) and Campbell and Mankiw (1990) conclude that rule-of-thumb behavior is widespread. For the U.S. economy, about 50% of consumers follow the rule-of-thumb behavior.[5]

The rule-of-thumb behavior is generally associated with liquidity constraints (see, for instance, Vaidyanathan (1993), Evans and Karras (1996) and Sarantis and Stewart (2003)). In turn, Sarantis and Stewart (2003) examine empirically the relative influence of liquidity constraints and precautionary saving on the cross-country variation in the proportion of current income consumers for 20 OECD countries. Their finding suggest that the presence of such consumers is primarily due to liquidity constraints.[6] In this vein, consumers would like to smooth consumption, but the lack of credit leads consumption to track the current income instead of the permanent income.

Unfortunately, Campbell and Mankiw (1989) approach does not deliver a theoretical connection between rule-of-thumb behavior and credit conditions. In other words, the cause of rule-of-thumb behavior is not addressed by the authors. This gap was filled by Ludvigson (1999), who develops a model in which consumers face borrowing constraints that varies stochastically with their income. Such model correctly predicts the statistically significant correlation between consumption growth rate and anticipated income growth

[5] For the quadratic utility, the model is linear in the income level, and we could say that 50% of the total income belongs to rule-of-thumb consumers. However, for CRRA utility we follow Sarantis and Stewart (2003) and interpret such a result as the proportion of consumers who follows the rule-of-thumb behavior, or simply, the proportion of current income consumers.

[6] The findings of these studies help us to discuss the Brazilian case in Section 3.3.

rate. The model proposed by Ludvigson (1999) also explains the correlation between consumption growth rate and the anticipated credit growth rate, documented by herself for US aggregate data. Prior to Ludvigson (1999), Bacchetta and Gerlach (1997) analyze empirically five countries, including the US, and their findings suggests that credit growth is a relevant predictor for the consumption growth rate in all cases. More recently, Brady (2008) re-estimate the Ludvigson (1999) model, in which the consumption growth rate depends on expected assets returns and anticipated income and credit growth rates. His results are in line with the view that the relevance of anticipated income and credit are related to liquidity constraints.

Weber (2002) and Sommer (2007) argue that neglecting habit formation may lead researches to overestimate the severity of the rule-of-thumb behavior. After allowing for habit formation, their estimates of the proportion of current income consumers become quantitatively small. Despite this, Kiley (2010) findings show support for both habit formation and rule-of-thumb behavior. Finally, Everaert and Pozzi (2014) investigate a panel of 15 OECD, and their findings support income growth rate as the only variable with significant predictive power for aggregate consumption growth, even taking into account habit formation and intertemporal substitution (expected returns on assets).

Regarding the Brazilian case, many studies have been investigated the severity of the rule-of-thumb behavior (see, for instance, Cavalcanti (1993), Vaidyanathan (1993), Evans and Karras (1996), Júnior, Delalibera and Neto (2018)). In general, the findings support that rule-of-thumb consumers are quantitatively important, which has been viewed as an evidence of credit constraints (Júnior, Delalibera and Neto (2018)). In spite of that, to the best of our knowledge, no one has investigate the predictive content of the credit conditions for consumption growth rate for the Brazilian case, which is the main purpose of our work.

To accomplish such a task we estimate the testing equation proposed by Ludvigson (1999), and an extended version of it by adding habit formation. Hence, we take into account the concerning of Weber (2002) and Sommer (2007). Following Yogo (2004), we investigate the presence of the weak instruments problem, and apply suitable econometric tools to handle it. In particular, we present valid (robust) confidence intervals for the coefficients of the growth rates in both credit and income.

Using Brazilian quarterly data from 1996 to 2019, the econometric methodology yields the following results. First, the econometric specifications are plagued by weak instruments. Second, the point estimates show strong support for income growth rate relevance. Furthermore, in most specifications the credit growth rate is relevant at 10% significance level. The credit growth rate losses relevance when habit formation is taken into account, but habit itself is not relevant, even at 10% significance level. Third, the confidence intervals that are robust to weak instruments suggest that income growth rate and/or credit growth rate are relevant predictability factors. Therefore, at least one of these two factors is able to predict the Brazilian aggregate consumption growth rate. In this perspective, the evidence suggest that Brazilian consumers face credit constraints.

The paper proceeds as follows. Section 3.2 briefly review the consumption models of interest. Section 3.3 review the Brazilian literature, by focusing on previous estimates of the proportion of current income consumers. Section 3.4 presents the econometric methodology. Section 3.5 presents the results. Finally, Section 3.6 summarizes the main conclusions.

2.2 Consumption Models

As discussed by Gomes and Issler (2017), the standard approach in macroeconomics consists of a single-good economy of identical consumers, whose instantaneous utility function is the constant-relative-risk-aversion (CRRA), given by:

$$u(C_t) = \begin{cases} \frac{C_t^{1-\gamma}-1}{1-\gamma} & \text{if} \quad \gamma \neq 1 \quad \text{and} \quad \gamma > 0 \\ \ln C_t & \text{if} \quad \gamma = 1 \end{cases} \tag{2.1}$$

where C_t is consumption in period t, and $\gamma > 0$ is the constant relative risk aversion coefficient. Thus, subject to the budget constraint, the consumer chooses consumption and portfolio in order to maximize the expected lifetime utility, given by $\mathbb{E}_t\left[\sum_{i=0}^{\infty} \beta^i u(C_{t+i})\right]$, where $\beta \in (0,1)$ is the intertemporal discount; $\mathbb{E}_t(\cdot)$ is the mathematical expectation operator, which is formed conditional on information available to the consumer up to period t, $\mathcal{I}_t$.

The representative consumer can transfer wealth from one period to the next by buying assets indexed by i, whose (gross) returns are $R_{i,t}$, for $i = 1, ..., N$. In this framework, the well-known consumer Euler equation is given by:[7]

$$\mathbb{E}_t \left\{ \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} R_{i,t+1} \right\} = 1, \qquad i = 1, ..., N \tag{2.2}$$

Since Hansen and Singleton (1983) and Hall (1988), the log-normality hypothesis is commonly adopted in Macroeconomic and Finance literature in order to obtain a log-linear version of the Euler equation (2.2). Joint conditional log-normality and homoskedasticity of $\left(\frac{C_{t+1}}{C_t}, R_{1,t}, ..., R_{N,t}\right)$ yields the usual representation for the consumption growth rate:

$$\Delta c_{t+1} = \mu + \psi r_{i,t+1} + \varepsilon_{i,t+1}, i = 1, ..., N \tag{2.3}$$

where ψ is the elasticity of intertemporal substitution (EIS), being the reciprocal of the relative risk aversion coefficient ($\psi = 1/\gamma$); $\mu = \psi(\ln \beta + 0.5\sigma_i^2)$, and $\sigma_i^2 = \mathbb{V}(\Delta C_{t+1} - \psi r_{i,t})$; $r_{i,t+1} = \ln R_{i,t+1}$; $\varepsilon_{i,t+1}$ is the error term, which is an innovation regarding the optimizing agent's information set $\mathcal{I}_t$, i.e. $\mathbb{E}_t[\varepsilon_{i,t+1}] = 0$.

In a influential work Campbell and Mankiw (1989) extended the basic optimizing model incorporating what they have labeled rule-of-thumb behavior. They proposed a hybrid model in which there are two types of consumers. The first type smooths consumption according to the Euler equation – in our case, the equation (2.3) –, but the second type follows a simple rule of thumb: consumes only his/her current income. For this reason, they are called current income consumers, or simply rule-of-thumb consumers. Obviously, if consumption tracks per period income flows, the consumption growth rate responds solely to anticipated income growth rate. For this reason, Campbell and Mankiw (1989) put forward the following testing equation:

$$\Delta \ln C_{t+1} = \lambda \Delta \ln Y_{t+1} + \tilde{\mu} + \tilde{\psi} r_{i,t+1} + \tilde{\varepsilon}_{i,t+1}, \qquad i = 1, ..., N \tag{2.4}$$

where Y_t is the income level in period t, and λ is the fraction of current income consumers. The model (2.4) can be viewed as a testing equation for non-nested models: λ times the

[7] See Hansen and Singleton (1982) and Hansen and Singleton (1983).

growth rate of aggregate income plus $(1-\lambda)$ times the high-hand side of the Euler equation (2.3). In this vein, $\tilde{\mu} \equiv (1-\lambda)\mu$, $\tilde{\psi} \equiv (1-\lambda)\psi$, and $\tilde{\varepsilon}_{i,t+1} \equiv (1-\lambda)\varepsilon_{i,t+1}$. Note that the error term remains unpredictable, i.e. $\mathbb{E}_t[\tilde{\varepsilon}_{i,t+1}] = 0$, and the severer the rule-of-thumb behavior, the lower the impact of the asset returns on the growth rate of consumption.

Much earlier, Jappelli and Pagano (1989) and Campbell and Mankiw (1991) note that the proportion of current income consumers seems to be lower in countries with more developed financial markets. Vaidyanathan (1993), Evans and Karras (1996) and Sarantis and Stewart (2003) investigate formally the factors behind cross-country variability in $\hat{\lambda}$ by regressing it against several economic indicators. Vaidyanathan (1993) estimates λ for 54 countries, including industrialized and the developing economies. After that, she finds an inverse relationship between $\hat{\lambda}$ and the degree of both economic development and financial deepening. For instance, the lower the GDP, the larger $\hat{\lambda}$; and the higher the M2-GDP ratio, the lower the $\hat{\lambda}$.

In turn, Evans and Karras (1996) estimate λ for 54 countries, finding strong evidence of excess sensitivity of consumption to changes in current income. After that, they find evidence that $\hat{\lambda}$'s are affected positively by output variability and negatively by the savings rate, concluding that the structural interpretation of λ as a measure of liquidity constraint is reasonable. Finally, Sarantis and Stewart (2003) estimate the proportion of current income consumers for 20 OECD countries. The estimates are significant and varies considerably across countries. Sarantis and Stewart (2003) findings support that the proportion of current income consumers are related to credit, level and change in unemployment, income growth, population growth and the rate of interest. Although some variables are related to the precautionary motive, the authors conclude that variables related to liquidity constraints appear to be the dominant.

Ludvigson (1999) address the connection between rule-of-thumb consumers and credit conditions theoretically. She proposes a model of intertemporal choice in which the consumers maximize life-time utility subject to an upper borrowing limit given by:

$$D_{t+1} \leq \bar{D}_{t+1} \equiv \frac{1}{\omega} Y_t \exp\left(\xi_t\right) \tag{2.5}$$

where D_t and Y_t are the consumers' debt and income in period t, respectively. The parameter ω is fixed and known, and ξ is an aggregate shock to the credit ceiling, being independent of individual income.[8] The constraint (2.5) leads to the following Euler equation:[9]

$$u'(C_t) = \max\{u'(X_t), \beta R E_t[u'(C_{t+1})]\} \tag{2.6}$$

where X_t is the consumer's upper spending limit at time t. The intuition behind the equation (2.6) is straightforward: since X_t is the most that can be consumed, marginal utility cannot be less than $u'(X_t)$, and without any restriction over borrowing limit the Euler equation (2.6) collapses to the usual one, in which current marginal utility of consumption is equal to the discounted expected marginal utility of consumption next period. Assuming the CRRA utility, Ludvigson (1999) calibrates and simulates the model concluding that when consumer's resources are sufficiently low, she/he spends all resources because the marginal value today is higher than the marginal value of consumption tomorrow. As a result, spending over this region is directly determined by the time-varying credit ceiling. Based on effective and simulated data for US economy, Ludvigson (1999) concludes that anticipated income and credit growth rates have predictive content for consumption growth rate. Brady (2008) re-estimate the Ludvigson (1999) model using US aggregate data, and the findings are aligned with the view that the relevance of growth rates in income and credit is related to liquidity constraints.

As mentioned, Weber (2002) and Sommer (2007) argue that neglecting habit formation may lead researches to overestimate the severity of the rule-of-thumb behavior. In this sense, large estimates of the proportion of current income consumers, λ, would be due to a misspecification of the econometric model, rather than severe liquidity restrictions. For US case, Weber (2002) and Sommer (2007) find quantitatively small estimates of λ, after take into account habit formation. In attention to their concern, we follow Kiley (2010) and Everaert and Pozzi (2014) by extending the CRRA utility to introduce habit,

[8] As mentioned by Ludvigson (1999), the model proposed by Deaton (1991) correspond to the case in which ω approaches infinity, and consumers cannot borrow.

[9] To be precise, Ludvigson (1999) theoretical model has a constant interest rate, R.

as follows:

$$u(C_t, \bar{C}_{t-1}) = \frac{1}{1-\gamma} \left(\frac{C_t}{\bar{C}_{t-1}^{\alpha}} \right)^{1-\gamma} \tag{2.7}$$

where $\bar{C}_t$ is the aggregate consumption per capita in period t, and $\alpha \geq$ measures the strength of habit formation. Thus, habit is external – as in Abel (1990) "catching up with the Joneses" formulation –, and the habit level depends on the aggregate consumption, instead of the consumer's own consumption.[10] Under log-normality and homoskedasticity, the instantaneous utility (4.5) leads to a log-linear Euler equation in which the consumption growth rate depends on expected returns on assets and the lagged consumption growth rate. In other words, habit adds persistence to Euler equation (2.3).

Finally, it is worth mentioning that the investigation of the consumption predictability depends on auxiliary hypotheses – log-normality and homoskedasticity – made to derive a time series representation for the consumption growth rate. Such hypotheses imply that the testing equations have normally distributed and homoskedastic error terms. Thus, following Gomes and Issler (2017) we evaluate these implications by means of residual-based tests.

2.3 Brazilian literature

In Section 2.3.1 we discuss the credit conditions in Brazil and in Section 2.3.2 we review the previous estimates of current income consumers. As will be seen, many studies applied the Campbell and Mankiw (1989) approach; however, no one takes in account direct measures of credit conditions.

2.3.1 Credit conditions

Historically, the Brazilian household debt to GDP ratio has been relatively low compared to the advanced economies. While in the end of the 1990's and beginning of the 2000's the Brazilian ratio has fluctuated around 10% (see Garber et al. (2019)), the

[10] When $\gamma = 1$, the CRRA utility (4.1) becomes $u(C_t) = \ln C_t$. The logarithm of the fraction $C_t/\bar{C}_{t-1}^{\alpha}$ is separable in present private consumption and past aggregate consumption, being incapable to elicit habit formation because today marginal utility of private consumption is not affected by past aggregate consumption.

median ratio for advanced economies was already 45% in December of 2000.[11] During the 2000's, however, a series factors allowed the expansion of credit in the Brazilian economy. Garber et al. (2019) enumerate potencial causes for this boom: *i)* favorable macroeconomic context led by a stabilization after the adoption of the Real plan in 1994 and the implementation of the inflation targeting in 1999; *ii)* institutional reforms and domestic programs such as a new law on payroll lending in 2003, a new Fiduciary law in 2004, the *Bolsa Familia*, a social program in which low income families receives cash transfers if their children attend school and *Minha Casa Minha Vida*, a program aiming to subsidize low and middle income households buying houses; *iii)* a favorable international financial environment that allowed Brazil experience a net inflow of capital, especially after 2008.

All these changes contributed to a household debt boom in Brazil between 2004 and 2014. Of course, Brazil was not the only country to observe a credit expansion. Müller (2017) finds that, from 1980 to 2014, emerging countries household credit as fraction of GDP increase by 15 percentage points. The Brazilian credit expansion, however, happened during a period in which many programs aiming at improving living standards and income have taken place, especially for poorer people, which may have loosen the credit restriction for the households.

Garber et al. (2019) analyzed the Brazilian case using individual level credit data, which allowed them to draw a precise picture of the changes that occurred during the period. According to them, from 2003 to 2011, the boom was widespread across types of debt, including mortgages, auto, payroll and nonpayroll loans and credit card debt loans and after 2011 it is was driven primarily by government banks lending via mortgages and payroll loans. They also find out that the expansion rate was higher for the lower income population, which is associated with increase in access to lending for this share of population. This breakdown shows that the credit expansion has loosen the restriction to both durable and nondurable goods expenditures. It also mitigated the credit constraints to people with higher probability of limited access to lending: the lower income class.

[11] https://www.imf.org/en/Publications/GFSR/Issues/2017/09/27/global-financial-stability-report-october-2017

After all these developments and expansion of the consumer credit volume, in 2014 the household debt to GDP ratio more than doubled, reaching the 25% mark. However, even after this increment, the ratio is still relatively lower compared to that of the advanced economies, where IMF data show the median was around 62% in December 2014. In this vein, we still expect sizable estimates of the proportion of current income consumers for Brazil.

2.3.2 Rule-of-thumb behavior: previous estimates

Regarding the Brazilian literature, most studies have focus on Campbell and Mankiw (1989) approach, and their conclusions are (qualitatively) similar, namely, the income growth rate is relevant, while the returns on assets are irrelevant, at the usual levels of significance (see, for instance, Reis et al. (1998), Issler and Rocha (2000), Gomes (2004), Júnior, Delalibera and Neto (2018)). Table 1 summarizes the estimates of λ of these and other previous studies. In most cases the average $\hat{\lambda}$ is larger than 0.7, which implies that rule-of-thumb behavior is quantitatively important.

As detailed in Table 2.1, in most testing equations there is no other regressors or only the returns on assets. Gomes (2004) and Júnior, Delalibera and Neto (2018) take into account habit formation; however, in both cases, the findings do not support consumption persistence. Gomes (2013) finds no support for non-separability between private consumption and government consumption.[12] It is worth mentioning that Júnior, Delalibera and Neto (2018) find no support for non-separability between consumption and leisure (hours worked).

Finally, except by Júnior, Delalibera and Neto (2018), the studies listed in Table 2.1 do not take into account the weak instruments problem. Júnior, Delalibera and Neto (2018) apply robust statistics to test whether the predictors of consumption growth rate are jointly relevant. We employ confidence intervals that are robust to weak instruments to evaluate the relevance of the predictors of the consumption growth rate, specially the credit conditions.

[12] Out of eight estimates of the non-separability parameter, only one is significant at 10%.

Authors	Other Regressors[b]	Rule-of-thumb behavior[a] Average $\hat{\lambda}$	Minimum $\hat{\lambda}$	Maximum $\hat{\lambda}$
Cavalcanti (1993)[c],[d]	R_t	0.32	0.32	0.32
Vaidyanathan (1993)[c]	None	0.70	0.70	0.702
Evans and Karras (1996)[c]	$\Delta \ln G_t$	0.64	0.64	0.64
Reis et al. (1998)	None	0.81	0.63	0.93
	$\ln R_t$	0.84	0.61	1.14
Issler and Rocha (2000)[e]	None	0.74	0.74	0.74
Gomes and Paz (2004)	None	0.61	0.58	0.63
Gomes (2004)	None	0.97	0.97	0.98
	$\Delta \ln C_{t-\tau}$	1.14	1.11	1.16
	$\Delta \ln C_{t-\tau}$, MA(1)	0.85	0.82	0.88
Gomes, Issler and Salvato (2005)[f]	None	0.19	0.13	0.25
	$\ln R_t$	0.25	0.19	0.37
Gomes and Paz (2010)	MA(2), $\ln R_t$	0.86	0.73	1.06
Gomes (2010)	None	0.95	0.86	1.00
	$\ln R_t$	0.93	0.66	1.29
Gomes (2013)	None	0.67	0.64	0.69
	$\Delta \ln G_t$	0.78	0.68	0.92
Júnior, Delalibera and Neto (2018)	$\Delta \ln C_{t-\tau}$, $\ln R_t$, $\Delta \ln H_t$	0.82	0.71	1.03

Notes:
[a] We analyze the estimates of λ that are significant at 10%.
[b] $\Delta \ln C_{t-\tau}$, R_t, $\Delta \ln G_t$, $\Delta \ln H_t$ and $MA(q)$ are, lagged consumption growth rate, returns on assets, government expenditure growth rate, hours worked growth rate, moving average process of order q.
[c] There is just one estimate of λ. For this reason, the average, minimum and maximum $\hat{\lambda}$ are equal.
[d] The author uses a non-linear equation that depends on asset returns to recover λ.
[e] There are two estimates of λ, but only on is significant at 10%. For this reason, the average, minimum and maximum $\hat{\lambda}$ are equal.
[f] Differently from the other studies, this one employs the expenditures on durable goods, which explains why the estimates of λ are relatively low.

Table 2.1 – Analysis of the estimates of λ for the Brazilian case

2.4 Econometric Methodology

In this section we outline our econometric methodology to investigate the consumption growth rate predictability. In Section 3.4.1 we describe the data set. Given the endogeneity problem, we present in Section 3.4.2 the instrumental variable approach used to recover the parameters of interest. In Section 2.4.3 we put forward the diagnostic tests used. As become usual, we investigate the weak instruments problem and whether the instruments are exogenous. Furthermore, we investigate the assumptions behind the log-linear Euler equations – log-normality and homoskedasticity –, as done by Gomes and

Issler (2017).

2.4.1 Data

The data set span the period from 1996:Q1 to 2019:Q4 (95 observations). Time-series on consumption and income comes from the *Instituto Brasileiro de Geografia e Estatistica* (IBGE), being, respectively, the Final Consumption of Households and the Gross Domestic Product (GDP). Regarding the credit conditions, we use the Credit Operations Balance from the Brazilian Central Bank (BCB).[13] The asset returns are measured by the Selic interest rate from the BCB, which is the short-term interest rate of the Brazilian government bond. To calculate real series we employ the National Consumer Price Index – *Índice Nacional de Preços ao Consumidor Amplo* – from IBGE, and its inflation rate is used as an instrumental variable. Furthermore, we use the population series from IBGE to calculate (real) per capita series on consumption, income and credit.[14] Finally, we remove the seasonality of real per capita consumption, income and credit by means of the X-13 methodology.

From now on, consumption (C_t), income (Y_t) and credit (D_t) refer to seasonally adjusted quarterly real per capita consumption, GDP and credit, respectively. Interest rate (r_t) refers to quarterly real interest rate, and the inflation rate (π_t) comes from the National Consumer Price Index. Figure 2.1 display the evolution of such series over the sample period.

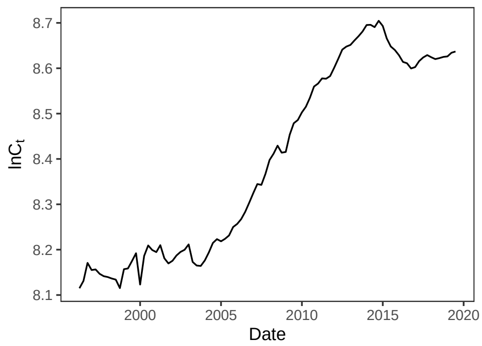
We apply the Augmented Dickey-Fuller (ADF), Dickey-Fuller-GLS (DF-GLS), Phillips-Perron (PP) and Zivot-Andrews (ZA) unit root test to investigate the integration order of these variables.[15] Additionally, we employ the KPSS stationarity test. Table 2.2 display the results. The unit root tests strongly support that (log) consumption and income are I(1). For (log) credit the Phillips-Perron and Zivot-Andrews tests imply that

[13] Unfortunately, the time series on the credit operations balance of Brazilian households starts in 2007, which implies a short period. To increase the number of observations we employ the total credit operations balance.

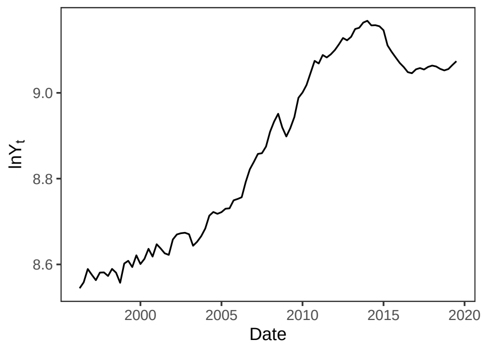
[14] The IBGE releases the population number in annual frequency and, for this reason, we interpolate it to obtain a quarterly measure.

[15] Zivot-Andrews unit root test allows a break at an unknown point in either the intercept, the linear trend or in both.

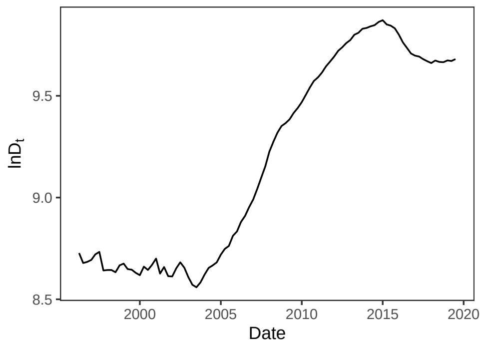
Figure 2.1 – Time series on consumption, income, credit, interest rate and inflation rate



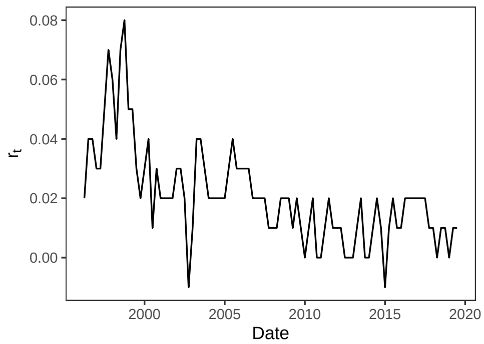
(a) Consumption



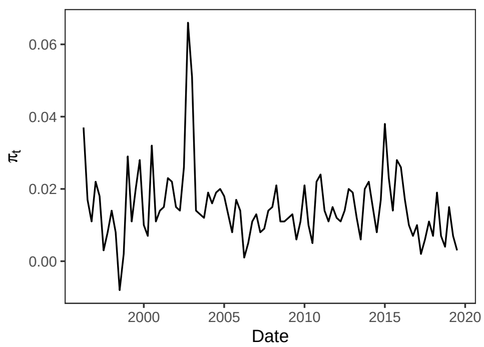
(b) Income



(c) Credit



(d) Interest rate



(e) Inflation rate

it is I(1). For interest rate and inflation rate the evidence is mixed, but such series are commonly viewed as I(0).

Table 4.1 shows the descriptive statistics of the interest rate, the inflation rate, and the growth rates in consumption, income and credit, which are the variables used in the estimation procedures. While the growth rates in consumption and income are similar, the credit has a larger growth rate, which is in line with visual inspection of the Figure 2.1. In line with the analysis of Garber et al. (2019), we note a huge increase in the credit from 2005 until 2014.

Table 2.2 – Unit Root Test Statistics

	$\ln C_t$	$\ln Y_t$	$\ln D_t$	$\Delta \ln C_t$	$\Delta \ln Y_t$	$\Delta \ln D_t$	r_t	π_t
ADF	-0.9372	-0.5572	-2.2858	-6.2479***	-5.7768***	-1.3740	-3.7846**	-3.1888*
DF-GLS	-1.2918	-0.9853	-1.3514	-2.8868*	-3.3682**	-1.6409	-2.4118	-2.3655
PP	-1.0549	-0.5766	-1.2202	-9.1905***	-8.0894***	-6.0531***	-6.3227***	-5.1679***
KPSS	0.2787***	0.3192***	0.2978***	0.2016**	0.1970**	0.4106***	0.0720	0.1669**
ZA	-2.4427	-3.4167	-2.8093	-10.5109***	-9.2483***	-8.4347***	-7.6569***	-7.2594***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Reported results are the test statistic for the Augmented Dickey-Fuller (ADF), Dickey-Fuller-GLS (DF-GLS), the Phillips-Perron (PP), KPSS and Zivot-Andrews (ZA) tests. The null hypothesis for the ADF, DF-GLS, PP and ZA are the presence of unit root and for the KPSS the null hypothesis is that the series is stationary.

Table 2.3 – Descriptive Statistics

	$\Delta \ln C_t$	$\Delta \ln Y_t$	$\Delta \ln D_t$	r_t	π_t
Minimum	-0.0690	-0.0353	-0.0913	-0.0080	-0.0100
Maximum	0.0631	0.0450	0.0726	0.0660	0.0800
Mean	0.0058	0.0058	0.0098	0.0151	0.0206
Standard Deviation	0.0173	0.0165	0.0291	0.0101	0.0164
Median	0.0067	0.0051	0.0142	0.0140	0.0200

Notes: $\Delta \ln C_t$, $\Delta \ln Y_t$ and $\Delta \ln D_t$ are, respectively, the quarterly growth rate of quarterly real per capita consumption, income and credit; r_t and π_t are the quarterly real interest rate and inflation, respectively.

2.4.2 Econometric Model

To examine the consumption growth rate predictability we employ four testing equations. The first one has the interest rate, in accordance with the log-linear Euler equation (2.3). Then, we add the income growth rate, in accordance with the Campbell and Mankiw (1989) approach. Following Ludvigson (1999), we add the credit growth rate. Last, we add a lagged growth rate in consumption to capture consumption persistence. Hence we estimate the following testing equations:

$$\Delta \ln C_t = \pi_0 + \pi_1 r_{i,t} + \varepsilon_{i,t} \tag{2.8}$$

$$\Delta \ln C_t = \pi_0 + \pi_1 r_{i,t} + \pi_2 \Delta \ln Y_t + \varepsilon_{i,t} \tag{2.9}$$

$$\Delta \ln C_t = \pi_0 + \pi_1 r_{i,t} + \pi_2 \Delta \ln Y_t + \pi_3 \Delta \ln D_t + \varepsilon_{i,t} \tag{2.10}$$

$$\Delta \ln C_t = \pi_0 + \pi_1 r_{i,t} + \pi_2 \Delta \ln Y_t + \pi_3 \Delta \ln D_t + \pi_4 \Delta \ln C_{t-1} + \varepsilon_{i,t} \tag{2.11}$$

where π_2 recover the parameter λ. The parameter π_3 was not estimated by previous studies, constituting a contribution of the present study.

As Campbell (2003) note, weak instruments are a problem in estimating linearized consumer Euler equations because both asset returns and consumption growth are notoriously difficult to predict. Indeed, Yogo (2004) estimates the log-linear Euler equation (2.3) for eleven developed countries, finding evidence that instruments are weak, especially for returns on stocks. Some instrumental variables (IV) estimators, such as the limited information maximum likelihood (LIML) and Fuller-k, provide more reliable point estimates and inferences under weak instruments than does the two-stage least squares (TSLS). Indeed, as discussed by Stock, Wright and Yogo (2002), LIML and Fuller-k estimators are partially robust to the weak instrument problem. Thus, following Yogo (2004), we employ these estimators. In addition, to handle with heteroscedastic and serial correlated errors, we employ the continuously updated GMM (CUE-GMM) estimator.

We use two instrument sets for the endogenous regressors. Instrument Set 1 includes the second and third lags of consumption growth, interest rate, income growth, credit growth, habit persistence and a constant term. Instrument set 2 adds to Set 1 the second and third lags of the inflation rate. Because habit is constructed as lagged consumption growth, the third lag of the consumption growth and the second lag of habit are the same, so we keep just one of them. Therefore, Set 1 consists of $\Delta \ln C_{t-2}$, $\Delta \ln Y_{t-2}$, $\Delta \ln D_{t-2}$, r_{t-2}, $\Delta \ln C_{t-3}$, $\Delta \ln Y_{t-3}$, $\Delta \ln D_{t-3}$, r_{t-3}, $\Delta \ln C_{t-4}$, and a constant. Set 2 consists of Set 1, π_{t-2} and π_{t-3}.

Set	Instruments
1	Constant, $\Delta \ln C_{t-2}$, $\Delta \ln Y_{t-2}$, $\Delta \ln D_{t-2}$, r_{t-2}, $\Delta \ln C_{t-3}$, $\Delta \ln Y_{t-3}$, $\Delta \ln D_{t-3}$, r_{t-3}, $\Delta \ln C_{t-4}$
2	Constant, $\Delta \ln C_{t-2}$, $\Delta \ln Y_{t-2}$, $\Delta \ln D_{t-2}$, r_{t-2}, π_{t-2}, $\Delta \ln C_{t-3}$, $\Delta \ln Y_{t-3}$, $\Delta \ln D_{t-3}$, r_{t-3}, π_{t-3}, $\Delta \ln C_{t-4}$

Table 2.4 – Instrument Sets

Finally, we also employ confidence intervals that are (fully) robust to weak instruments. Such confidence intervals are based on similar tests as the Anderson-Rubin (AR) one (Anderson, Rubin et al. (1949)). Guggenberger et al. (2012) developed a test based on the AR statistic, which is suitable for many endogenous variables case. Basically, the test uses the LIML estimates for the strongly identified parameters, allowing us to construct robust confidence interval to a subset of endogenous variables. The author shows that this subset AR test has correct asymptotic size, while subset tests based on the Lagranger Multiplier statistic are distorted asymptotically and, because the LM statistic appears in the subset Conditional Likelihood (CLR) subset test, Guggenberger et al. (2012) conjecture that the latter test is also distorted.[16]

2.4.3 Diagnostic Tests and Robust Inference

To estimate the models of interest, we need instrument variables that are not only exogenous, but correlated with the endogenous variables. In order to test the instruments validity, we rely on the Sargan test of overidentifying restrictions, where the null hypothesis is that instruments are exogenous. Of course, we are aware that weak instruments problem make the Sargan test unreliable.

Regarding the presence of weak instruments, we inspect the F-statistic of the first-stage regression of the TSLS estimator, and we employ the tests developed by Cragg and Donald (1993) and Kleibergen and Paap (2006) statistic. The Cragg-Donald statistic is based on the eigenvalue of the matrix version of the F-statistic from the first-stage TSLS regression. This test assumes that error term is i.i.d and its critical values were tabulated by Yogo and Stock (2005). When the i.i.d. assumption is no longer valid, the reported statistic is the Kleibergen-Paap statistic, which allows the use of heteroscedasticity and autocorrelation consistent (HAC) estimators for the covariance matrix. Thus, we employ such test along with GMM-CUE estimator. In this case, the critical values are the ones tabulated by Yogo and Stock (2005) for the LIML case.

[16] Inference on a subset of parameters can be done by projection methods (see, for instance, Dufour and Taamouti (2005)). However, Guggenberger et al. (2012) also shows that the subset AR has non-worse power than projection-type methods.

The log-linear representation of the consumer's Euler equations comes from log-normality and homocedasticity assumptions. These auxiliary assumptions imply that the error term is conditionally Gaussian, homoscedastic and uncorrelated with elements of the conditioning set $\mathcal{I}_{t-1}$. Furthermore, the error term must be independent of any function of the variables in $\mathcal{I}_{t-1}$. Following Gomes and Issler (2017), we investigate these restrictions by means of residual-based tests of normality, conditional homoskedasticity and serial correlation, and the Ramsey Regression Equation Specification Error Test (RESET). It is worth mentioning that we apply versions of these diagnostic tests suitable for instrumental variable setting.

We investigate whether residuals are normally distributed using the test developed by D'agostino, Belanger and Jr (1990), whose null hypothesis is that the series has normal distribution. We investigate heteroscedasticity using a test for instrumental variables developed by Pagan and Hall (1983) whose null hypothesis is that residuals are homoskedastic. To do so, we use the full set of instruments as indicator variables hypothesized to be related to the heteroscedasticity in the log-linear Euler equations. For serial correlation, we use a test proposed by Cumby and Huizinga (1992). The null hypothesis is that the residuals of the regression is a moving average up to order q against the alternative that the autocorrelations are nonzero at lags greater than q. We use $q = 0$, which means that we test whether the residual series is uncorrelated against the alternative that there is serial correlation of first order. The test is robust to conditional heteroscedasticity and an autocorrelation-robust covariance matrix is computed using the Bartlett kernel. Finally, for testing the omission of higher order variables, we use Pesaran and Taylor (1999) version of the RESET test. Under the null that there are no neglected nonlinearities, and the residuals should be uncorrelated with low-order polynomials in the forecast values of the dependent variable. We employ a polynomial of third degree.

2.5 Results

First, tables 2.5 to 2.8 present the result of the testing equations (2.8) to (2.11) for each combination of the estimators – TSLS, LIML, Fuller-k and CUE-GMM – and the instrument sets – set 1 and set 2–, reaching 32 specifications. These tables presents in columns (1) and (5) specifications that match the basic log-linear Euler equation (2.3). Columns (2) and (6) correspond to the Campbell and Mankiw (1989) rule-of-thumb behavior approach. Columns (3) and (7) include a credit measure to the equation as in Ludvigson (1999). Finally, columns (4) and (8) add the lagged consumption in order to take into account habit persistence. Besides the point estimates and their standard errors, each table presents an extensive list of diagnostic tests, such as the Sargan overidentification test, and the Cragg-Donald or Kleigenbergen-Paap weak instrument tests.

Table 2.5 reports the results based on the TSLS estimator. The interest rate is not relevant in any specification, hence is no evidence of intertemporal substitution. Regarding the income growth rate, its coefficient is significant at the 1% level in all specifications. Therefore, there is strong evidence in favour of the rule-of-thumb behavior. The estimates of λ ranges from 0.72 to 0.98, which is a very large upper bound. However, when credit growth rate is take into account, $\hat{\lambda}$ is no longer close to 1. Indeed, the credit growth rate is relevant at 5% in specifications (3) and (7), and at 10% in specification (8). Its coefficient is very stable, around 0.20. Notice that credit growth rate looses relevance in specifications that add consumption persistence. Despite this pattern, the lagged growth rate is not relevant, even at 10% level. The TSLS point estimates shows strong support for rule-of-thumb behavior and support for liquidity constraints. However, given the results of the diagnostic tests, these results must be viewed with caution. Regarding the Sargan overidentification test, we do not reject the instruments exogeneity null hypothesis, except for testing equation (2.8). However, such test is not reliable when instruments are weak, which seems to be the case. According to the Cragg-Donald test, the instruments are weak as the statistics are bellow the tabulated thresholds calculated by Yogo and Stock (2005).[17] Regarding the log-normality analysis, there is strong evidence in favour of het-

[17] We use the critical values for the TSLS bias. The number of excluded instruments are 9 and 11 for the instrument sets 1 and 2, respectively. The number of endogenous varies from one to four across columns (1) to (8) in Table 2.5. However, the critical values were tabulated for the maximum number of three endogenous and, consequently, we do not have available the critical values for the specifications in columns (4) and (8), which contains four endogenous. For instance, at a significance level of 5%, when there is 9 excluded instruments, the critical values are 11.46, 10.42 and 9.37 for one, two and three endogenous, respectively. For eleven excluded instruments, the critical values change marginally to 11.51, 10.69 and 9.85 for one, two and three endogenous, respectively. Given the low values of the

eroscedasticity, but against serial correlation. In two (three) cases, the RESET test shows evidence of non-linearities in the residuals, at 5% (10%) level of significance. Finally, there is overwhelming evidence in favour of non-Gaussian error term. Without log-normality and homoskedasticity, the testing equations should be viewed as approximations of the Euler equations, instead of equivalent versions of the non-linear Euler equations.

Table 2.5 – TSLS estimation of testing equations (2.8) to (2.11)

	Instrument Set 1				Instrument Set 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
r_t	-0.1563	-0.1200	-0.0037	-0.0187	-0.2172	-0.0962	0.0065	0.0055
	(0.1634)	(0.1352)	(0.1456)	(0.1490)	(0.1452)	(0.1209)	(0.1306)	(0.1314)
$\Delta \ln Y_t$		0.9888***	0.7794***	0.7584***		0.9592***	0.7589***	0.7284***
		(0.2209)	(0.2410)	(0.2458)		(0.2052)	(0.2257)	(0.2327)
$\Delta \ln D_t$			0.2315**	0.1929			0.2316**	0.2012*
			(0.1010)	(0.1176)			(0.0995)	(0.1124)
$\Delta \ln C_{t-1}$				0.1245				0.1046
				(0.1875)				(0.1760)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]								
Sargan	0.0083	0.1807	0.5825	0.5271	0.0180	0.3025	0.7725	0.7267
Instrument Relevance [statistic]								
Cragg-Donald	6.8187	1.7240	1.6689	1.5671	8.7158	1.5955	1.5654	1.2921
Log-Normality Tests [p-value]								
Ser. Correl	0.8494	0.2490	0.2994	0.1792	0.8279	0.2515	0.2935	0.1795
Heterosk.	0.0556	0.0012	0.0022	0.1022	0.1289	0.0020	0.0036	0.1212
RESET	0.8398	0.2368	0.0063	0.0009	0.6291	0.4443	0.0763	0.1357
Normality	0.0007	0.0046	0.0231	0.0025	0.0009	0.0032	0.0196	0.0030

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Instrument set 1: $\Delta \ln C_{t-2}$, $\Delta \ln Y_{t-2}$, $\Delta \ln D_{t-2}$, r_{t-2}, $\Delta \ln C_{t-3}$, $\Delta \ln Y_{t-3}$, $\Delta \ln D_{t-3}$, r_{t-3}, $\Delta \ln C_{t-4}$, and a constant. Instrument Set 2: adds π_{t-2} and π_{t-3} to the Set 1. A constant was also added to the regressions.

Table 2.6 presents the results based on LIML estimator. Qualitatively, the results are very similar to those in Table 2.5. However, some details are worth mentioning. First of all, the point estimates of the income growth rate coefficients are the higher than the TSLS estimates. In particular, in specifications (2) and (6), it is above one. The interpretation of λ as the proportion of current income consumer implies that it should lie in the $[0, 1]$ interval. However, when credit conditions are taken into account, $\hat{\lambda}$ is lower than one. As before, there is no evidence in favour of habit persistence, and out of four specifications,

Cragg-Donald statistics specially in columns (4) and (8), the conclusion that instruments are weak seems to be reliable.

the coefficient of the credit growth rate is relevant three times, at 10% significance level. Regarding the diagnostic tests, the results are also similar. There is strong evidence that instruments are weak. There is evidence against the log-normality and homoscedasticity assumptions, especially due to heteroscedasticity and non-normally distributed residuals.

Table 2.6 – LIML estimations of testing equations (2.8) to (2.11)

	Instrument Set 1				Instrument Set 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
r_t	-0.1470	-0.1241	0.0163	-0.0131	-0.2571	-0.0521	0.0358	0.0264
	(0.2087)	(0.1885)	(0.1624)	(0.1654)	(0.1686)	(0.1594)	(0.1431)	(0.1417)
$\Delta \ln Y_t$		1.4320***	0.8743***	0.8303***		1.3269***	0.8337***	0.7817***
		(0.4190)	(0.3000)	(0.2958)		(0.3579)	(0.2730)	(0.2773)
$\Delta \ln D_t$			0.2548**	0.1988			0.2574**	0.2165*
			(0.1146)	(0.1365)			(0.1119)	(0.1280)
$\Delta \ln C_{t-1}$				0.1531				0.1206
				(0.2187)				(0.2020)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]								
Sargan	0.0083	0.2965	0.6144	0.5503	0.0182	0.4195	0.7953	0.7440
Instrument Relevance [statistic]								
Cragg-Donald	6.8187	1.7240	1.6689	1.5671	8.7158	1.5955	1.5654	1.2921
Log-Normality Tests [p-value]								
Ser. Correl	0.8510	0.4972	0.4439	0.2247	0.8036	0.4334	0.4194	0.2253
Heterosk.	0.0539	0.0403	0.0040	0.1125	0.1434	0.0203	0.0052	0.1143
RESET	0.8214	0.1880	0.0048	0.0005	0.7910	0.3556	0.0758	0.1396
Normality	0.0006	0.1091	0.0714	0.0043	0.0012	0.0634	0.0567	0.0063

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Instrument set 1: $\Delta \ln C_{t-2}$, $\Delta \ln Y_{t-2}$, $\Delta \ln D_{t-2}$, r_{t-2}, $\Delta \ln C_{t-3}$, $\Delta \ln Y_{t-3}$, $\Delta \ln D_{t-3}$, r_{t-3}, $\Delta \ln C_{t-4}$, and a constant. Instrument Set 2: adds π_{t-2} and π_{t-3} to the Set 1. A constant was also added to the regressions.

Tables 2.7 reports the results for the Fuller-k estimator, which are similar to previous estimators (see Tables 2.5 and 2.6). Therefore, once again the results strongly support income growth rate as a predictability factor for aggregate consumption. The credit growth rate seems to be a relevant predictor too, although it loses relevance when we add consumption persistence. The Cragg-Donald test suggest that instruments are weak. Regarding the log-normality tests, there is strong evidence that residuals are not normally distributed. The heteroscedasticity and RESET tests show mixed results, depending on the specification used.

Finally, Table 2.8 display the results based on the GMM-CUE estimator, which

Table 2.7 – Fuller-k estimations of testing equations (2.8) to (2.11)

	Instrument Set 1				Instrument Set 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
r_t	-0.1476	-0.1237	0.0112	-0.0144	-0.2549	-0.0618	0.0279	0.0204
	(0.2060)	(0.1751)	(0.1575)	(0.1601)	(0.1674)	(0.1505)	(0.1396)	(0.1386)
$\Delta \ln Y_t$		1.3312***	0.8450***	0.8062***		1.2518***	0.8115***	0.7646***
		(0.3683)	(0.2821)	(0.2796)		(0.3234)	(0.2593)	(0.2636)
$\Delta \ln D_t$			0.2491**	0.1974			0.2510**	0.2121*
			(0.1107)	(0.1304)			(0.1084)	(0.1233)
$\Delta \ln C_{t-1}$				0.1453				0.1175
				(0.2086)				(0.1941)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]								
Sargan	0.0083	0.2917	0.6120	0.5483	0.0182	0.4156	0.7937	0.7426
Instrument Relevance [statistic]								
Cragg-Donald	6.8187	1.7240	1.6689	1.5671	8.7158	1.5955	1.5654	1.2921
Log-Normality Tests [p-value]								
Ser. Correl.	0.8509	0.4111	0.3957	0.2072	0.8051	0.3726	0.3788	0.2081
Heterosk.	0.0540	0.0157	0.0032	0.1092	0.1426	0.0099	0.0045	0.1171
RESET	0.8224	0.1960	0.0051	0.0006	0.7862	0.3704	0.0756	0.1390
Normality	0.0006	0.0715	0.0529	0.0035	0.0011	0.0422	0.0430	0.0050

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.Instrument set 1: $\Delta \ln C_{t-2}$, $\Delta \ln Y_{t-2}$, $\Delta \ln D_{t-2}$, r_{t-2}, $\Delta \ln C_{t-3}$, $\Delta \ln Y_{t-3}$, $\Delta \ln D_{t-3}$, r_{t-3}, $\Delta \ln C_{t-4}$, and a constant. Instrument Set 2: adds π_{t-2} and π_{t-3} to the Set 1. A constant was also added to the regressions.

relax the assumption of previous estimations that errors are i.i.d.. The kernel used is the Bartlett and bandwidth is 6. In general, the point estimates are in line with previous results in Tables (2.5) to (2.7). The income growth rate is always relevant, even at a 1% significance level. Out of four specifications, the credit growth rate is relevant, at a 5% (10%) level, two (three) times. It is worth mentioning that specifications (1) and (5) yields significant estimates of the coefficient of the interest rate, but with wrong signs (negative). However, as before, in the other specifications the interest rate is not relevant.[18] In this vein, the main message is the same: there is strong evidence in favour of the predictive content of income growth rate, which is followed by the credit growth rate. Regarding the diagnostic tests, the instruments seems to be weak as the Kleibergen-Paap statistics are low compared with the thresholds tabulated by Yogo and Stock (2005). Furthermore, there is strong evidence against Gaussian errors, and mixed results for heteroscedasticity, serial

[18] The exogeneity test rejects that specifications (1) and (5) at 10% significance level; however, this test must be viewed with caution under weak instrument problem.

correlation and neglected nonlinearities. Although the CUE-GMM estimator is robust to heteroscedasticity and autocorrelation, such problems constitute evidence against the log-normality and homoscedastic assumptions used to derive log-linear Euler equations.

Table 2.8 – CUE-GMM estimations of testing equations (2.8) to (2.11)

	Instrument Set 1				Instrument Set 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
r_t	-3.0802***	-0.1434	0.0039	-0.0268	-2.0432***	-0.0658	0.0258	0.0169
	(0.7597)	(0.1552)	(0.1346)	(0.1294)	(0.4721)	(0.1292)	(0.1148)	(0.1070)
$\Delta \ln Y_t$		1.4391***	0.8774***	0.8556***		1.3796***	0.8315***	0.7942***
		(0.2881)	(0.2602)	(0.2729)		(0.2567)	(0.2386)	(0.2502)
$\Delta \ln D_t$			0.2352**	0.1683			0.2416**	0.1983*
			(0.0991)	(0.1182)			(0.0960)	(0.1098)
$\Delta \ln C_{t-1}$				0.1494				0.1072
				(0.1902)				(0.1786)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]								
J	0.0630	0.3405	0.6276	0.5646	0.0894	0.4365	0.7999	0.7433
Instrument Relevance [statistic]								
Kleibergen	4.8331	2.0218	1.9290	1.6415	5.5912	1.7353	1.6865	1.3232
Log-Normality Tests [p-value]								
Ser. Correl.	0.0186	0.5001	0.3989	0.2073	0.0429	0.4708	0.3797	0.2156
Heterosk.	0.3627	0.0426	0.0032	0.1240	0.4352	0.0334	0.0043	0.1141
RESET	0.7474	0.1780	0.0047	0.0004	0.8608	0.3523	0.0794	0.1359
Normality	0.0009	0.1157	0.0541	0.0031	0.0037	0.0816	0.0429	0.0056

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Instrument set 1: $\Delta \ln C_{t-2}$, $\Delta \ln Y_{t-2}$, $\Delta \ln D_{t-2}$, r_{t-2}, $\Delta \ln C_{t-3}$, $\Delta \ln Y_{t-3}$, $\Delta \ln D_{t-3}$, r_{t-3}, $\Delta \ln C_{t-4}$, and a constant. Instrument Set 2: adds π_{t-2} and π_{t-3} to the Set 1. A constant was also added to the regressions.

In summary, the results from Tables 2.5 to 2.8 show evidence that the income and credit growth are relevant predictability factors for the consumption growth rate. In addition, the estimates for the coefficients of both interest rate and habit persistence do not support such factors. However, the Cragg-Donald and Kleibergen-Paap tests do not reject that instruments are weak, which cast doubt on these results, especially for the TSLS estimator. Table 2.9 displays the F-statistic of the first stage of the TSLS estimator for each endogenous variable and instrument set. The F-statistics for the interest rate is the highest, while the lowest is precisely related to income growth rate. Indeed, it is obvious that the income growth rate is quite difficult to predict. Given that the instruments are weak, it is surprisingly that the results in Tables (2.5) to (2.8) are robust across specifications, estimators and instrument sets. Despite that, we proceeded to apply valid inference under weak instruments problem.

Table 2.9 – First Stage F Statistics

	Instrument Set 1	Instrument Set 2
$r_{i,t}$	6.8187	8.7158
$\Delta \ln D_t$	4.7546	4.1421873
$\Delta \ln Y_t$	1.7240	1.6751
$\Delta \ln C_{t-1}$	4.1194	4.1301

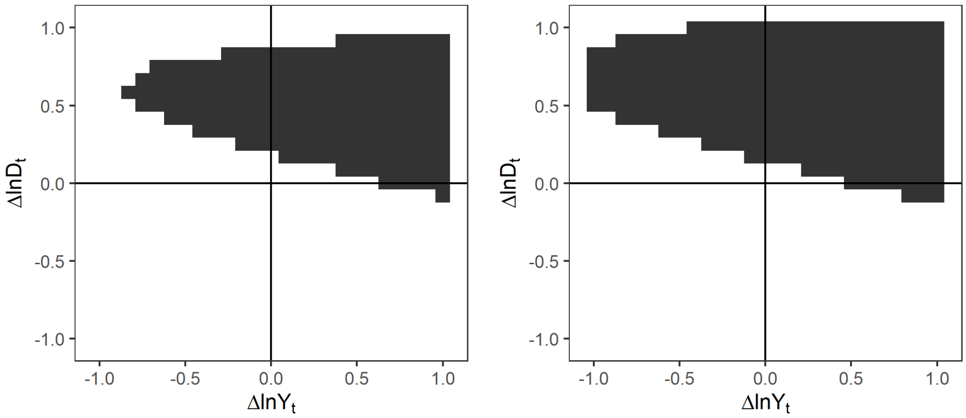
The table reports the first stage F statistics for the endogenous variables used in the TSLS, LIML, Fuller-k and GMM estimations. Instrument set 1: $\Delta \ln C_{t-2}$, $\Delta \ln Y_{t-2}$, $\Delta \ln D_{t-2}$, r_{t-2}, $\Delta \ln C_{t-3}$, $\Delta \ln Y_{t-3}$, $\Delta \ln D_{t-3}$, r_{t-3}, $\Delta \ln C_{t-4}$, and a constant. Instrument Set 2: adds π_{t-2} and π_{t-3} to the Set 1.

We estimate confidence intervals that are robust to the problem of weak instruments. To accomplish such test, we use the testing equation (2.10). The point estimates suggest that both income and credit growth are the most relevant predictors of the consumption growth rate and, for this reason, we focus on these predictors. Following Guggenberger et al. (2012) approach, we employ subset AR statistics to jointly investigate the relevance of credit and income. The results of the estimation are reported in Figures 3.1 and 3.2.

Figure 3.1 shows the robust confidence set for the coefficients of income and credit growth rates, assuming that the interest rate can be strongly identified in testing equation (2.10). For both instrument sets we reject that the coefficients of income and credit growth rates are zero. However, if the coefficient of the income growth rate is sufficiently high, the credit growth rate would not be relevant. The point estimates favor this scenario; however, it is important to note that they should be viewed with caution due to the weak instruments problem. Finally, the robust confidence set suggests that the coefficient of the income growth rate is different from zero, if the coefficient of the credit growth rate is sufficiently high.

The point estimates in Tables 2.5 to 2.8 show strong evidence that the interest rate is not a relevant predictor for consumption growth. Thus, we set the interest rate coefficient to zero in the testing equation (2.10), and estimate the robust confidence in-

Figure 2.2 – Robust Confidence Sets with Endogenous $\Delta \ln D_t$, $\Delta \ln Y_t$, r_t

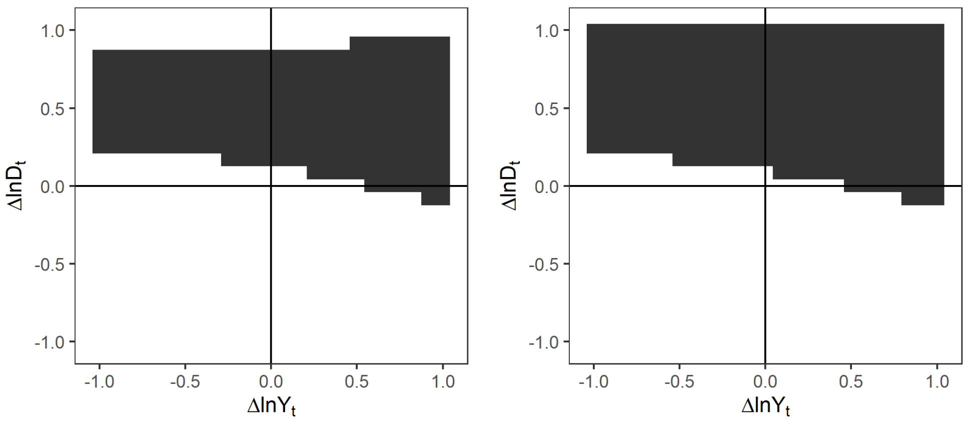


(a) Instrument Set 1 (b) Instrument Set 2

Notes: The plots the robust confidence set for credit and income at a 95% confidence level.

terval considering only the growth rates in income and credit. The results are reported in Figure 3.2. The confidence sets for both instrument lists do not contain the point (0,0), which means that at least one variable is relevant. These results aligned with the ones in Figure 3.1 and show that consumption growth can be predicted by income growth and/or credit growth.

Figure 2.3 – Robust Confidence Sets with Endogenous $\Delta \ln D_t$, $\Delta \ln Y_t$



(a) Instrument Set 1 (b) Instrument Set 2

Notes: The figures show the robust confidence set for credit and income at a 95% confidence level. Instrument set 1: $\Delta \ln C_{t-2}$, $\Delta \ln Y_{t-2}$, $\Delta \ln D_{t-2}$, r_{t-2}, $\Delta \ln C_{t-3}$, $\Delta \ln Y_{t-3}$, $\Delta \ln D_{t-3}$, r_{t-3}, $\Delta \ln C_{t-4}$, and a constant. Instrument Set 2: adds π_{t-2} and π_{t-3} to the Set 1.

Finally, there is no evidence that growth rates in income and credit are jointly irrelevant. However, if any of them has a sufficiently high coefficient, the other would not be a predictor of the consumption growth rate. It is important to note that robust intervals expand as the instruments are weaker. For instance, investigating the log-linear Euler equation (2.3), Yogo (2004) estimate non-informative confidence intervals for asset return, i.e. $(-\infty, +\infty)$. In this sense, it is possible that our instrument sets did not provide enough information to conclude that the growth rates in income and credit are relevant, regardless of the magnitude of their coefficients.

2.6 Conclusions

This paper examines the predictability of the aggregate consumption growth in Brazil, taking into account usual factors, such as expected returns on assets and anticipated growth rates in both income and credit. Previous studies found strong support for rule-of-thumb behavior, given that income growth rate predicts the consumption growth rate. Furthermore, the coefficient of income is very large, in most cases above 0.7, which implies that rule-of-thumb behavior is quantitatively important.

The rule-of-thumb behavior is generally associated with liquidity constraints. The works of Vaidyanathan (1993), Evans and Karras (1996) and Sarantis and Stewart (2003) find empirical support for this association. Ludvigson (1999) put forward a theoretical model in which consumers are liquidity constrained and the growth rates in income and credit predicts the consumption growth rate. Historically, the credit supply in Brazil is scarce, which explains the large estimates for the proportion of rule-of-thumb consumers. However, motivated by Ludvigson (1999) approach, we investigate the credit conditions directly. The point estimates of the TSLS, LIML, Fuller-k and CUE-GMM estimators show strong support for the relevance of income growth rate, and some support for the credit growth rate. To be precise, while income is relevant, at 5% significance level, in all specifications, the credit is relevant in most specifications only at 10% significance level. However, the confidence intervals that are robust to weak instruments suggest that income growth rate and/or credit growth rate are relevant predictability factors. Therefore, at least one of these two factors is able to predict the Brazilian aggregate consumption growth rate. After all, the findings suggest that Brazilian consumers are credit constrained.

Finally, is is worth mentioning that credit scores evaluations depends on consumers' income level, as modelled by Ludvigson (1999) (see equation (2.5)). Of course, in practice, other variables are taken into account. However, if income is the main factor and its relation with credit is stable, we would have difficult to recover a significant coefficient for the credit growth rate even when consumers are credit constrained. This perspective, reinforce our conclusion that Brazilian consumers are credit constrained, given that valid confidence intervals suggest that growth rate in income and credit are not jointly irrelevant.

3 Consumption (a)symmetric response to predictable income: a new test for myopia and liquidity constraint

Abstract

This paper examines whether consumption responds symmetrically or asymmetrically to predictable income. To accomplish such task, we propose an adjustment in Shea (1995a) testing equation that make straightforward to test whether consumption is more sensible to predictable income increases than decreases. Furthermore, our approach allows us to employ usual instrumental variable estimators and econometric tools developed to deal with the weak instruments problem. Our new approach yields the following results: *i)* there is overwhelming evidence that instruments are weak; *ii)* the point estimates for negative income growth are higher than those for positive income growth; *iii)* hypothesis testings indicate the same findings; *iv)* confidence sets robust to weak instruments show support for previous point estimates and hypothesis tests results. Therefore, instead of finding evidence for myopia or liquidity constraints, the findings support the "perverse asymmetry" hypothesis raised by Shea (1995a).

Keywords: Consumption smoothing; Myopia; Liquidity constraints; Hypothesis tests; Brazil.

3.1 Introduction

In a seminal paper Hall (1978) solves the consumer intertemporal problem and concludes that consumption revisions are unpredictable. More specifically, assuming a quadratic instantaneous utility and a constant interest rate, Hall (1978) reach the random walk hypothesis: $C_{t+1} = C_t + \xi_{t+1}$, where C_t is the consumption in period t and ξ_{t+1} is an innovation regarding the information set from period t, $\mathcal{I}_t$. Therefore, in accordance with life cycle-permanent income hypothesis (LCH-PIH), predictable movements in income should not affect the consumption revisions. This prediction remains valid even when relaxing certain hypotheses of Hall (1978) approach. For instance, Hansen and Singleton (1983) and Hall (1988) adopt the more appealing CRRA instantaneous utility and allow the consumer to invest in assets whose returns are time-varying, concluding that consumption growth rate depends only on the expected returns on assets.

Despite this flexibility to adjust the framework of the consumer's intertemporal problem, the failure of the LCH-PIH in aggregate data is well established because anticipated income is able to predict the consumption growth rate (Campbell and Mankiw (1989), Campbell and Mankiw (1990)).[1] According to Shea (1995a), two common explanations for such a failure is the myopia and liquidity restrictions hypotheses. Myopic behavior implies that consumers track income and, for this reason, consumption should respond equally to predictable income increases and decreases. In turn, liquidity constraints prevent consumers from taking out loans when income is temporarily low, but they can smooth consumption by using savings from previous periods. In this perspective, liquidity constraints would lead to an asymmetric pattern: consumption should be more strongly correlated with predictable income increases than declines (Altonji and Siow (1987), Shea (1995a)).

Shea (1995a) put forward a simple testing equation that examines whether consumption respond symmetrically or asymmetrically to predictable income, which allows the comparison of myopia and liquidity constraints hypotheses. After estimation, Shea (1995a) tests if the coefficient of the predictable income increases is equal or different to

[1] Indeed, earlier Flavin (1981) find evidence that consumption is excessively sensitive to current income.

the coefficient of the predictable income decreases. We propose a simple adjustment in Shea (1995a) testing equation that make straightforward to test if the coefficient of the predictable income increases is equal or greater than the coefficient of the predictable income decreases. Furthermore, instead of predicting the income growth rate after splitting the positive or negative growth periods, we predict directly income increases and income decreases. As a byproduct, this new strategy allow us to employ usual instrumental variable estimators as well as econometric tools developed to deal with weak instruments problem.[2] In particular, we present valid (robust) confidence intervals for the coefficients of income increases and income decreases.

We examine the Brazilian case using quarterly data from 1996 to 2019. This is an interest case given the evidence that consumption reacts intensively to predictable income (see, for instance, Vaidyanathan (1993), Evans and Karras (1996)). To the best of our knowledge, only Gomes (2010) and Gomes and Paz (2010) had employed the Shea (1995a) approach to the Brazilian case. Their point estimates suggest that consumption growth rate respond more strongly to predictable income increases than declines; however, the $F-test$ does not reject the symmetric null hypothesis. It is worth mentioning that Gomes (2010) and Gomes and Paz (2010) follow the empirical strategy of Shea (1995a), which means that they do not employ econometric techniques that are robust to the weak instruments problem.

Finally, our new approach yields the following results: *i)* there is overwhelming evidence that instruments are weak; *ii)* the point estimates for negative income growth are higher than the estimates for positive income growth; *iii)* the hypothesis testing indicate the same findings; *iv)* confidence sets robust to weak instruments show support for previous point estimates and hypothesis tests results. Therefore, instead of finding evidence for myopia or liquidity constraints, the findings support the "perverse asymmetry" hypothesis raised by Shea (1995a).

The rest of the paper is organized as follows. Section 3.2 discuss the consumer

[2] Neely, Roy and Whiteman (2001) and Campbell (2003) note that weak instruments are a problem in estimating consumption models because asset returns are difficult to predict. In our case, it is necessary to predict income increases and decreases, which is also not a simple task.

behavior, reviewing the LCH-PIH, the myopia and the liquidity constraints hypotheses. Section 3.3 presents previous works regarding the Brazilian case. Section 3.4 presents our new approach for comparison of the myopia and the liquidity constraints hypotheses. Section 3.5 presents and discuss the empirical results. Finally, Section 3.6 concludes.

3.2 Consumer behavior

Consider a economy lived by consumers whose preferences are represented by the CRRA instantaneous utility, given by:

$$u(C_t) = \begin{cases} \frac{C_t^{1-\gamma}}{1-\gamma}, \text{ if } \gamma > 0 \text{ and } \gamma \neq 1 \\ \ln C_t, \text{ if } \gamma = 1 \end{cases} \tag{3.1}$$

where γ is the relative risk aversion coefficient. These consumers maximize the expected lifetime utility, given by $\mathbb{E}_t \sum_{i=0}^{\infty} \beta^i u(C_{t+i})$, where $\beta \in (0, 1)$ is the intertemporal discount factor, $\mathbb{E}_t(\cdot)$ is the mathematical expectation operator, which is formed conditional on information available to the consumer up to period t, $\mathcal{I}_t$.

The consumers can transfer wealth from period t to period $t+1$ by buying individual assets, indexed by i, whose (gross) returns are given by $R_{i,t+1}$, $i = 1, ..., M$. By assuming joint conditional lognormality and homoskedasticity of consumption growth and assets returns, we reach the well-known log-linear Euler equation for the consumption growth rate:

$$\Delta \ln C_{t+1} = \mu_i + \psi \mathbb{E}_t[r_{i,t+1}] + \varepsilon_{i,t+1}, \quad i = 1, ..., M \tag{3.2}$$

where $r_{i,t+1} \equiv \ln R_{i,t+1}$, $i = 1, .., N$. The error term is an innovation regarding the consumer's information set $\mathcal{I}_t$, such as $\mathbb{E}_t[\varepsilon_{i,t+1}] = 0$. The parameter $\psi > 0$ is the elasticity of intertemporal substitution (EIS), and $\mu_i \equiv \ln \beta + 0.5\sigma_i^2$, where $\sigma_i^2 = \mathbb{V}_t[r_{i,t+1} - \gamma \Delta \ln C_{t+1}]$. Finally, the log-linear Euler equation (3.2) implies that consumer smooth consumption taking into account the investment opportunities.

Campbell and Mankiw (1989) argue that the time-series on aggregate consumption are generated by two types of consumers. One of them smooth consumption as proposed by the intertemporal consumer problem and, in accordance with the LCH-PIH, the predictable income should not affect the consumption path. The other type of consumer follows a simple rule: consume the current income, reason why they are called "rule-of-thumb consumers". Considering the Euler equation (3.2), the Campbell and Mankiw (1989) approach yields the following testing equation:

$$\Delta \ln C_{t+1} = \alpha_i + \lambda \mathbb{E}_t[\Delta \ln Y_{t+1}] + \delta \mathbb{E}_t[r_{i,t+1}] + \epsilon_{i,t+1}, \quad i = 1, ..., M \tag{3.3}$$

The parameter λ measures the prevalence of the rule-of-thumb behavior. Therefore, Campbell and Mankiw (1989) evaluate whether the predictable income growth rate and the expected returns on assets are correlated with the consumption growth rate. For US case, Campbell and Mankiw (1989) and Campbell and Mankiw (1990) findings suggest that λ is approximately 0.5. Thus, the rule-of-thumb behavior is quantitatively important and, obviously, this implies the failure of the LCH-PIH in aggregate data.

Convincingly, Shea (1995a) argues that Campbell and Mankiw (1989) approach captures a myopic behavior, because a positive and significant $\hat{\lambda}$ implies that consumption tracks predictable income, regardless of whether it increases or decreases. Under liquidity constraints the consumption smoothing is partial because consumers cannot borrow when income is temporarily low, but they are not prohibited from saving. As a result, consumption should be more strongly correlated with predictable income increases than declines, as first noted by Altonji and Siow (1987). Therefore, while myopia implies symmetric impact of predictable income on consumption, with liquidity constraints such impact would be asymmetric. Shea (1995a) put forward a testing equation that exploits these testable implications, given by:

$$\Delta \ln C_{t+1} = \alpha_i + \lambda_P \mathbb{E}_t[I^P_{t+1} \Delta \ln Y_t] + \lambda_N \mathbb{E}_t[I^N_{t+1} \Delta \ln Y_{t+1}] + \delta \mathbb{E}_t[r_{i,t+1}] + \epsilon_{i,t+1}, \quad i = 1, ..., M \tag{3.4}$$

where

$$I^P_{t+1} = \begin{cases} 1 \text{ , if } \; \Delta \ln Y_{t+1} > 0 \\ 0 \text{ , if } \; \Delta \ln Y_{t+1} \leq 0 \end{cases} \tag{3.5}$$

$$I^N_{t+1} = 1 - I^P_{t+1}$$

Furthermore, λ_P (λ_N) measures the impact of predictable income increase (decrease) on consumption growth rate. Under LCH-PIH, λ_P and λ_N should equal zero. Under myopia, λ_P and λ_N should be positive, significant and equal. Last, with liquidity constraints λ_P should be significantly positive, and should be significantly greater than λ_N.

The specifications proposed by Campbell and Mankiw (1989) and Shea (1995a) can be derived by combining the three consumers type. Suppose that the proportion of consumers who follows the standard log-linear Euler equation (3.2) is λ_1. The proportion of myopic consumers, whose consumption growth rate tracks the predictable income growth rate, is λ_2. And, λ_3 is the proportion of credit-constrained consumers, who respond more intensively to predictable income growth rate when it is positive ($\delta^P > \delta^N$). Of course, these proportions adds up to one. Table 3.1 presents such proportions and the consumption model specification for each consumer type.

Consumer type	Proportion	Model for $\Delta \ln C_t$	Parameters restrictions
LCH-PIH	λ_1	$\mu_i + \psi \mathbb{E}_t[r_{i,t+1}] + \varepsilon_{i,t+1}$	$\psi > 0$
Myopic	λ_2	$\mathbb{E}_t[\Delta \ln Y_{t+1}]$	None
Liquidity-constrained	λ_3	$\delta^P \mathbb{E}_t[I^P_{t+1} \Delta \ln Y_{t+1}] + \delta^N \mathbb{E}_t[I^N_{t+1} \Delta \ln Y_{t+1}]$	$\delta^P > \delta^N$

Notes: Proportions of each consumers type add up to 1 ($\lambda_1 + \lambda_2 + \lambda_3 = 1$). The indicator variable I^P_{t+1} takes value one if $\Delta \ln Y_{t+1} > 0$, and zero otherwise. And, $I^N_{t+1} = 1 - I^P_{t+1}$.

Table 3.1 – Consumption path for each consumer type

Following an usual strategy to confront non-nested models, we combine the consumption model for each consumer type, as follows:

$$\begin{aligned} \Delta \ln C_{t+1} =& \lambda_1 \left\{ \mu_i + \psi \mathbb{E}_t[r_{i,t+1}] + \varepsilon_{i,t+1} \right\} + \lambda_2 \mathbb{E}_t[\Delta \ln Y_{t+1}] + \\ & \lambda_3 \left\{ \delta^P \mathbb{E}_t[I^P_{t+1} \Delta \ln Y_{t+1}] + \delta^N \mathbb{E}_t[I^N_{t+1} \Delta \ln Y_{t+1}] \right\}, \quad i = 1, ..., M \end{aligned} \tag{3.6}$$

Assume that $\lambda_3 = 0$. Because there are only two consumers type, redefine $\lambda_2 \equiv \lambda$ and $\lambda_1 \equiv 1 - \lambda$. Thus, the model (3.6) specializes to Campbell and Mankiw (1989) testing equation, as follows:

$$\Delta \ln C_{t+1} = \tilde{\mu}_i + \tilde{\psi} \mathbb{E}_t[r_{i,t+1}] + \lambda \mathbb{E}_t[\Delta \ln Y_{t+1}] + \tilde{\varepsilon}_{i,t+1}, \quad i = 1, ..., M \tag{3.7}$$

where $\tilde{\mu}_i \equiv (1 - \lambda)\mu_i$, $\tilde{\psi} \equiv (1 - \lambda)\psi$, $\tilde{\varepsilon}_{i,t+1} \equiv (1 - \lambda)\varepsilon_{i,t+1}$. Obviously, if λ (λ_2) is null, the consumers smooth the consumption path according to log-linear Euler equation (3.2).

However, the larger the λ (λ_2), the larger the prevalence of the rule-of-thumb behavior (myopia hypothesis).

Given that $1 = I^P_{t+1} + I^N_{t+1}$ we rewrite the equation (3.6) to reach the testing equation developed by Shea (1995a), given by:[3]

$$\Delta \ln C_{t+1} = \tilde{\mu}_i + \tilde{\psi}\mathbb{E}_t[r_{i,t+1}] + \pi_0 \mathbb{E}_t[I^P_t \Delta \ln Y_{t+1}] + \pi_1 \mathbb{E}_t[I^N_{t+1} \Delta \ln Y_{t+1}] + \tilde{\varepsilon}_{i,t+1}, \quad i = 1, ..., M \tag{3.8}$$

where $\pi_0 \equiv \lambda_2 + \lambda_3 \delta^P$, and $\pi_1 \equiv \lambda_2 + \lambda_3 \delta^N$. Shea (1995a) performs the following hypotheses tests:

- $\mathcal{H}_0 : \pi_j = 0$ versus $\mathcal{H}_1 : \pi_j \neq 0$, for $j = 0, 1$;
- $\mathcal{H}_0 : \pi_0 = \pi_1$ versus $\mathcal{H}_1 : \pi_0 \neq \pi_1$.

The first test investigates, individually, if consumption does not depend on positive and negative predictable income growth rate. Indeed, if both parameters are null, the evidence favors the LCH-PÌH. The second hypothesis test investigates if consumption growth rate reacts symmetrically or not to predictable income growth rate. Under the null hypothesis there is evidence of myopic behavior, while the alternative hypothesis is in line with liquidity constraints.

Given that Shea (1995a) conjectures that δ^P is larger than δ^N, π_0 should be larger than π_1. Therefore, ideally, we would like to test this inequality. We put forward a simple strategy to accomplish such hypothesis test. Because $I^N_{t+1} = 1 - I^P_{t+1}$, we rewrite equation (3.6) as follows:

$$\Delta \ln C_{t+1} = \tilde{\mu}_i + \tilde{\psi}\mathbb{E}_t[r_{i,t+1}] + \pi^P_0 \mathbb{E}_t[\Delta \ln Y_{t+1}] + \pi^P_1 \mathbb{E}_t[I^P_{t+1} \Delta \ln Y_{t+1}] + \tilde{\varepsilon}_{i,t+1}, \quad i = 1, ..., M \tag{3.9}$$

where $\pi^P_0 \equiv \lambda_2 + \lambda_3 \delta^N$, and $\pi^P_1 \equiv \lambda_3(\delta^P - \delta^N)$. To investigate whether $\delta^P > \delta^N$ we simply perform the following hypothesis test:

- $\mathcal{H}_0 : \pi^P_1 = 0$ versus $\mathcal{H}_1 : \pi^P_1 > 0$.

[3] We substitute $\Delta \ln Y_{t+1}$ by $I^P_{t+1} \Delta \ln Y_{t+1} + I^N_{t+1} \Delta \ln Y_{t+1}$.

Under the null hypothesis, there is no asymmetry. However, under the alternative hypothesis, consumers react more intensely to the increase in income than to the decrease.

Alternatively, we use $I^P_{t+1} = 1 - I^N_{t+1}$ and the equation (3.6) becomes:

$$\Delta \ln C_{t+1} = \tilde{\mu}_i + \tilde{\psi}\mathbb{E}_t[r_{i,t+1}] + \pi^N_0 \mathbb{E}_t[\Delta \ln Y_{t+1}] + \pi^N_1 \mathbb{E}_t[I^N_{t+1}\Delta \ln Y_{t+1}] + \tilde{\varepsilon}_{i,t+1}, \quad i = 1, ..., M \tag{3.10}$$

where $\pi^N_0 \equiv \lambda_2 + \lambda_3\delta^P$, and $\pi^N_1 \equiv \lambda_3(\delta^N - \delta^P)$. To investigate whether $\delta^P > \delta^N$ we test:

- $\mathcal{H}_0 : \pi^N_1 = 0$ versus $\mathcal{H}_1 : \pi^N_1 < 0$.

Therefore, specifications (3.9) and (3.10) allow us to test whether $\delta^P > \delta^N$ by using a simple $t - test$. This new approach allows us to really test the liquidity constraints hypothesis.

3.3 Brazilian literature

Gomes (2010) applies the Shea (1995a) approach to the Brazilian case. In general the estimates of π_0 are positive and significant at 10%, while the estimates of π_1 are not significant. By focusing on the estimates that are significant at 10%, the average $\hat{\pi}_0$ is approximately 1.20. These results are in line with liquidity constraints. However, by means of $F - test$, Gomes (2010) does not reject the null hypothesis that the coefficients are equal ($\mathcal{H}_0 : \pi_0 = \pi_1$), which is a evidence in favor of myopia. However, the author presents two important remarks. Given the difficulty to obtain precise estimates of π_1, it seems that $F - test$ lacks power to reject the equality null hypothesis. In some years of the sample period the growth rates of consumption and income present opposite signs, which is an evidence against the myopia hypothesis.

Gomes and Paz (2010) investigate the myopia and liquidity constraints hypotheses for Brazil, Colombia, Peru, and Venezuela. Regarding the Brazilian case, most estimates of π_0 are positive and significant at 10%, while none estimates of π_1 is not significant. The average value of the significant estimates of π_0 is approximately 0.99. Once again, $F - test$ for $\pi_0 = \pi_1$ does not reject this null hypothesis for all instrument lists, at 5%

level, which weakens the evidence in favor of liquidity constraint. Not surprisingly, the authors realize that a key issue is the large standard error of π_1, which would be related with the small number of periods with negative income growth (approximately 10% of the sample periods).

Despite these econometric issues, it is worth mentioning that the results for the Brazilian case are at odds to those for the US aggregate consumption obtained by Shea (1995a). His findings suggest that consumption is more sensitive to predictable income declines than increases, which is inconsistent with both myopia and liquidity constraints hypotheses. Shea (1995a) called this result “perverse asymmetry” and mentioned that such result is qualitatively consistent with models whose intertemporal preferences exhibit loss aversion.

3.4 Econometric Methodology

This Section presents the econometric methodology. Section 3.4.1 details the data set to estimate the testing specifications (3.8), (3.9), (3.10). The Section 3.4.2 explains how such specifications are estimated and what hypotheses tests are performed.

3.4.1 Data

We use quarterly data from 1996:Q2 to 2019:Q2 (90 observations). Consumption and income data are obtained from the *Instituto Brasileiro de Geografia e Estatistica* (IBGE) being, respectively, the Final Consumption of Households and the Gross Domestic Product (GDP). The asset returns measures are the Selic interest rate and return rate of the Ibovespa index. The former comes from Central Bank of Brazil (CBB), being the short-term interest rate of the Brazilian government bond. The later is the return rate of the index of the main stocks listed in the Brazilian stock market. To calculate real series we employ the National Consumer Price Index – *Índice Nacional de Preços ao Consumidor Amplo* – from IBGE. Furthermore, we use the population series from IBGE to calculate (real) per capita series on consumption and income.[4] Finally, we remove the seasonality of real per capita consumption and income by means of the X-13 methodology. In the remainder of the study, consumption (C_t) and income (Y_t) refer to seasonally adjusted quarterly real per capita consumption and GDP, respectively. The interest rate (r_t) refers to quarterly real interest rate or asset returns rate, and the inflation rate (Π_t) is calculated from the National Consumer Price Index.

We also consider additional variables to predict the aggregate income. Indeed, these variables were selected based on both the potential they could have to predict aggregate income and their availability for the period of analysis. The credit (D_t) data corresponds to the Credit Operations Balance from the CBB. The quarterly data corresponds to the last quarter month and the was also transformed into real per capita terms. Last, its seasonality was removed, as done for the consumption and income time series.[5] From the *Fundação Centro de Estudos do Comércio Exterior* (Funcex), we use the Export Quantum index ($quantum_t$) and the Terms of Trade index (ToT_t). The first one is a measure of the Brazilian economy real exports and the second one is the index of the relative price of the Brazilian exports. These series have a monthly frequency and the the last month of the quarter value is used. The unemployment rate is obtained from the *Fundação Sistema Estadual de Análise de Dados, Pesquisa de Emprego e Desemprego* (Seade/PED). It measures the monthly unemployment rate (u_t) in the São Paulo Metropolitan Region[6] and we use the last month of each quarter. The last set of variables are confidence indices obtained from the *Federação do Comércio de Bens, Serviços e Turismo do Estado de São Paulo* (Fecomercio/SP). The *Índice de Condições Econômincas Atuais* ($icea_t$) is the Present Economic Conditions Index, the *Índice de Expectativas do Consumidor* (iec_t) is the Consumer Expectations Index and the *Índice de Confiança do consumidor* (icc_t), which is composed by the $icea_t$ and icc_t, is the Consumer Confidence Index. They are

[4] The IBGE releases the population number in annual frequency and, for this reason, we interpolate it to obtain a quarterly measure.

[5] The time series on the Credit Operations Balance of Brazilian Households starts only 2007, so we opted use the longer series and opted to use the Credit Operations Balance from the Brazilian Central Bank series.

[6] We decided to use this series because broader, nation wide unemployment surveys are unavailable for the time spam of the remaining variables we have in the dataset.

released monthly and the quarter average was used in the construction of the variables.

Using the variables described above we are able to calculate the consumption and debt share of income. So, we add two more variables to the dataset: C_t/Y_t and D_t/Y_t.

3.4.2 Econometric Model

Shea (1995a) estimates the testing specification (3.8) using the following strategy. First, he estimates the predicted income growth rate, $\widehat{\Delta \ln Y_t}$, by regressing it against five instrument lists. Second, for each instrument list, he builds the indicator variables, as follows:

$$
\begin{aligned}
\hat{I}_t^P &= \begin{cases} 1 \text{ , if } \widehat{\Delta \ln Y_t} > 0 \\ 0 \text{ , if } \widehat{\Delta \ln Y_t} \leq 0 \end{cases} \\
\hat{I}_t^N &= 1 - \hat{I}_t^P
\end{aligned} \tag{3.11}
$$

Third, Shea (1995a) multiplies $\hat{I}_t^P$ by $\widehat{\Delta \ln Y_t}$, and $\hat{I}_t^N$ by $\widehat{\Delta \ln Y_t}$, in order to estimate the specification (3.8). For the sake of comparison, we employ such strategy to estimate the specification (3.8). However, alternatively, we predict directly the variables $I_t^P \Delta \ln Y_t$ and $I_t^N \Delta \ln Y_t$, where I_t^P and I_t^N are defined in (3.5). Thus, alternatively to predict the income growth rate, we predict both positive and negative income growth rates. This approach allows us to employ econometric tools developed to handle the weak instruments problem.

For the new approach, we estimate the models using four instrumental variables (IV) estimators: two-stage least squares (TSLS), limited information maximum likelihood (LIML), Fuller-k and continuously updated GMM (CUE-GMM). The LIML and Fuller-k provide more reliable point estimates and inferences under weak instruments than does TSLS. Indeed, as discussed by Stock, Wright and Yogo (2002), LIML and Fuller-k estimators are partially robust to the weak instrument problem. Thus, following Yogo (2004), we employ these estimators besides the TSLS. In addition, to handle with heteroscedastic and serial correlated errors, we employ the CUE-GMM estimator.

To estimate the models of interest, we need instrument variables that are not only exogenous, but also correlated with the endogenous variables. Thus, in order to test the instruments validity, we rely on the Sargan test of overidentifying restrictions, where the null hypothesis is that instruments are exogenous. Of course, we are aware that weak instruments problem makes the Sargan test unreliable.

Regarding the presence of weak instruments, we inspect the F-statistic of the first-stage regression of the TSLS estimator, and we employ the tests developed by Cragg and Donald (1993) and Kleibergen and Paap (2006). The Cragg-Donald statistic is based on the eigenvalue of the matrix version of the F-statistic from the first-stage TSLS regression. This test assumes that error term is i.i.d and its critical values were tabulated by Yogo and Stock (2005). When we employ the CUE-GMM, we report the Kleibergen-Paap statistic, which allows the use of heteroscedasticity and autocorrelation consistent (HAC) estimators for the covariance matrix. In this case, the critical values are the ones tabulated by Yogo and Stock (2005) for the LIML case. We also report an underidentification test – the Anderson LM test for LIML, Fuller-k and TSLS or Kleibergen-Paap LM for the GMM-CUE estimator – to evaluate whether the instruments are irrelevant or not.

We also employ confidence intervals that are (fully) robust to weak instruments. Such confidence intervals are based on similar tests as the Anderson-Rubin (AR) one (Anderson, Rubin et al. (1949)). Guggenberger et al. (2012) developed a test based on AR statistic, which is suitable for many endogenous variables case. Basically, the test uses the LIML estimates for the strongly identified parameters, allowing us to construct robust confidence interval to a subset of endogenous variables. The author shows that this subset AR test has correct asymptotic size, while subset tests based on the Lagranger Multiplier statistic are distorted asymptotically and, because the LM statistic appears in the subset Conditional Likelihood (CLR) subset test, Guggenberger et al. (2012) conjecture that the latter test is also distorted.[7]

Hypothesis tests on the estimated coefficients are performed using a F–test for the specifications following specification (3.8) and one-tailed t-tests for specifications (3.9) and (3.10). Our new approach allows us to test the perverse asymmetry hypothesis by simply

[7] Inference on a subset of parameters can be done by projection methods (see, for instance, Dufour and Taamouti (2005)). However, Guggenberger et al. (2012) also shows that the subset AR has non-worse power than projection-type methods.

change the inequality of the alternative hypothesis. Table 3.2 summarizes the hypotheses tests of interest for each model.

Model	Hypothesis Test	Interpretation
(3.8)	$\mathcal{H}_0 : \pi_0 = \pi_1$	Myopia
	$\mathcal{H}_1 : \pi_0 \neq \pi_1$	Liquidity constraints or perverse asymmetry
(3.9)	$\mathcal{H}_0 : \pi_1^P = 0$	Myopia
	$\mathcal{H}_1 : \pi_1^P > 0$	Liquidity constraints
(3.9)	$\mathcal{H}_0 : \pi_1^P = 0$	Myopia
	$\mathcal{H}_1 : \pi_1^P < 0$	Perverse asymmetry
(3.10)	$\mathcal{H}_0 : \pi_1^N = 0$	Myopia
	$\mathcal{H}_1 : \pi_1^N < 0$	Liquidity constraints
(3.10)	$\mathcal{H}_0 : \pi_1^N = 0$	Myopia
	$\mathcal{H}_1 : \pi_1^N > 0$	Perverse asymmetry

Table 3.2 – Hypotheses Tests

The log-linear representation of the consumer's Euler equations comes from log-normality and homocedasticity assumptions. These auxiliary assumptions implies that the error term of log-linear Euler equation (3.2) is conditionally Gaussian, homoscedastic and uncorrelated with elements of the conditioning set $\mathcal{I}_t$. Furthermore, the error term must be independent of any function of the variables in $\mathcal{I}_t$. Following Gomes and Issler (2017), we investigate these restrictions by means of residual-based tests of normality, conditional homoskedasticity and serial correlation, and the Ramsey Regression Equation Specification Error Test (RESET). It is worth mentioning that we apply versions of these diagnostic tests suitable for instrumental variable setting.

We investigate whether residuals are normally distributed using the test developed by D'agostino, Belanger and Jr (1990), whose null hypothesis is that the series has normal distribution. The heteroscedasticity is examined using the test for instrumental variables developed by Pagan and Hall (1983) whose null hypothesis is that residuals are homoskedastic. To do so, we use the full set of instruments as indicator variables hypothesized to be related to the heteroscedasticity in the log-linear Euler equations. For serial correlation, we use a test proposed by Cumby and Huizinga (1992). The null hypothesis is that the residuals of the regression is a moving average up to order q against the alternative that the autocorrelations are nonzero at lags greater than q. We use $q = 0$, which means that we test whether the residual series is uncorrelated against the alternative that there is serial correlation of first order. The test is robust to conditional heteroscedasticity and an autocorrelation-robust covariance matrix is computed using the Bartlett kernel. Finally, for testing the omission of higher order variables, we use Pesaran and Taylor (1999) pesaran1999diagnostics version of the RESET test. Under the null that there are no neglected nonlinearities, and the residuals should be uncorrelated with low-order polynomials in the forecast values of the dependent variable. We employ a polynomial of third degree.

3.5 Results

In Section 3.5.1 form the instrument lists used to estimate the specifications (3.8), (3.9) and (3.10). In Section 3.5.2 we report the estimation of specification (3.8) using the Shea (1995a) approach. Finally, Section 3.5.3 reports the results from our new methodology.

3.5.1 Instrument Sets

To estimate the specifications (3.8), (3.9) and (3.10) we need a instrument list capable to predict the income growth rate (increase and decrease) and assets returns (interest rate). Usually, the instrument lists are based on lagged variables that appear in the testing equations. However, we explore additional variables in an attempt to minimize the weak instruments problem. The variables candidates to be in the instrument sets are the second and third lags of the variables described on Section 3.4.1: consumption growth ($\Delta \ln C_t$), income growth ($\Delta \ln Y_t$), debt growth ($\Delta \ln D_t$), inflation rate (Π_t), interest rate (r_t), unemployment rate (u_t), terms of trade (ToT_t), export quantum index ($quantum_t$), present economic conditions index ($icea_t$), consumer expectations index (iec_t),consumer confidence index (icc_t), consumption-income ratio (C_t/Y_t) and debt-income ratio (D_t/Y_t).

To select the most relevant instruments for the endogenous variables, forward and backward stepwise selection methods are used. In the forward selection, the algorithm starts with an empty model and in the step (i) it considers adding all the variables and chooses the most significant one, in the next step (ii), if the significance level is bellow a predetermined threshold, adds the variable. After that repeat step (i) and (ii) no variable has statistical significance bellow the threshold. The backward selection starts with the dependent regressed against all the available regressors. In the step (i) it considers dropping all variables and chooses the least significant and, in step (ii) it drops the variable if the significance level is above the predetermined threshold.

These selection methods are used for each endogenous variables – ΔY_t, $I_t^N \Delta \ln Y_t$, $I_t^P \Delta \ln Y_t$ and $r_{i,t}$ –, and the Wald test is used in each step of the algorithm. The threshold for the significance level is 0.05, unless the number of variables selected by the procedure is smaller than four, given that the testing equations have the maximum of 3 endogenous variables. When this happens, we raise the the significance level until we have a minimum of 4 variables for each of the endogenous variables, which is the minimum number of instruments necessary to apply the Sargan overidentification test. After that, we have two sets of variables for each variable: one selected via forward and and another selected using the backward method. Finally, the set with the higher F statistic is chosen. Table 3.3 show the results of this strategy.

The only variable that is present in all instrument sets is the inflation rate lagged twice. Most of the selected predictors are lagged variables included in the testing equation, but especially for the positive and negative income growth, the alternative predictors we considered were selected instead the lagged income growth and interest rate. As expected, the interest rate is the variable with the highest F statistic. Table 3.4 summarizes the instrument set that will be used for each endogenous variable for the testing specifications (3.8), (3.9) and (3.10).

In the next section we use the selected instrument sets in the estimation of the proposed models. In addition to the sets described in Table 3.4, we also use the union of the sets referring to the endogenous variables present in the specification being estimated. For instance, in the specification (3.8) the endogenous variables are the interest rate and both

Table 3.3 – Selected Instruments

	$\Delta \ln Y_t$	$I_t^P \Delta \ln Y_t$	$I_t^N \Delta \ln Y_t$	$r_{i,t}$
C_{t-2}/Y_{t-2}	-0.2151***			
	(0.0812)			
Π_{t-2}	-0.4956***	-0.2216*	-0.2105***	0.9237***
	(0.1663)	(0.1186)	(0.0756)	(0.1483)
D_{t-2}/Y_{t-2}	-0.1171**			
	(0.0520)			
$\Delta \ln Y_{t-3}$	-0.1645**			
	(0.0739)			
ToT_{t-3}		-0.0004***		
		(0.0001)		
u_{t-3}			0.0008***	
			(0.0003)	
$\Delta \ln C_{t-3}$			-0.0656**	
			(0.0304)	
icc_{t-2}		0.0004***		
		(0.0001)		
iec_{t-3}		-0.0003*	0.0002***	
		(0.0001)	(0.0000)	
$icea_{t-2}$				0.0001**
				(0.0001)
$r_{i,t-2}$				0.8083***
				(0.0932)
C_{t-3}/Y_{t-3}				0.2303***
				(0.0825)
constant	0.2683***	0.0454***	-0.0349***	-0.1688***
	(0.0726)	(0.0131)	(0.0091)	(0.0558)
T	90.0000	90.0000	90.0000	90.0000
R^2	0.2092	0.2080	0.2561	0.5453
F	5.6212	5.5812	7.3167	25.4837

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table shows the selected instrument set for each variable. The variables appearing as instruments are: consumption (C), income (Y), inflation rate (Π), debt (D), terms of trade (ToT), unemployment in the Metropolitan Area of São Paulo (u), consumer confidence index (icc), consumer expectation index (iec), actual economic condition index ($ieca$) and the selic rate (r_i).

positive and negative income growth rate. Using Shea (1995a) approach, the instrument sets are: $\mathbb{S}$, $\mathbb{Y}$, and $\mathbb{S} \cup \mathbb{Y}$. Because our new approach predicts income growth rate increases and decreases, the instrument sets are: $\mathbb{S}$, $\mathbb{Y}^P$, $\mathbb{Y}^N$ and $\mathbb{S} \cup \mathbb{Y}^P \cup \mathbb{Y}^N$.

Table 3.4 – Instrument Sets Summary

Instrument Set	Variables
$\mathbb{Y}$	Π_{t-2}, C_{t-2}/Y_{t-2}, D_{t-2}/Y_{t-2}, $\Delta \ln Y_{t-3}$
$\mathbb{Y}^P$	Π_{t-2}, ToT_{t-3}, icc_{t-2}, iec_{t-3}
$\mathbb{Y}^N$	Π_{t-2}, u_{t-3}, $\Delta \ln Y_{t-3}$, iec_{t-3}
$\mathbb{S}$	Π_{t-2}, $icea_{t-2}$, $r_{i,t-2}$, C_{t-3}/Y_{t-3}

3.5.2 Shea's approach

In this section, we present the results based on the same procedure used by Shea (1995a). Table 3.5 shows the results of the first stage regressions. The first line of the table shows the dependent variable and the second line, the instrument set used in each column. Because the endogenous variables are the income growth rate and the interest rate, we also used the union of the instrument sets for those variables in the first stage. The results in table 3.5 show that it is easier to predict the interest rate than the income growth rate, as can be seem in the F statistics.

Table 3.5 – Shea (1995a) strategy - First Stage

Dependent Variable	$\Delta \ln Y_t$			$r_{i,t}$		
Instrument Set	$\mathbb{Y}$	$\mathbb{S}$	$\mathbb{Y} \cup \mathbb{S}$	$\mathbb{Y}$	$\mathbb{S}$	$\mathbb{Y} \cup \mathbb{S}$
Π_{t-2}	-0.4956***	-0.3289	-0.6505***	0.1200	0.9237***	0.7478***
	(0.1663)	(0.2117)	(0.2357)	(0.1394)	(0.1483)	(0.1709)
C_{t-2}/Y_{t-2}	-0.2151***		-0.1910	0.2977***		0.2364
	(0.0812)		(0.2022)	(0.0680)		(0.1467)
D_{t-2}/Y_{t-2}	-0.1171**		-0.1896**	-0.2784***		-0.1198**
	(0.0520)		(0.0798)	(0.0436)		(0.0579)
$\Delta \ln Y_{t-3}$	-0.1645**		-0.1579**	0.0131		0.0218
	(0.0739)		(0.0759)	(0.0619)		(0.0550)
$icea_{t-2}$		0.0000	0.0000		0.0001**	0.0002***
		(0.0001)	(0.0001)		(0.0001)	(0.0001)
$r_{i,t-2}$		0.0965	-0.1931		0.8083***	0.6243***
		(0.1331)	(0.1776)		(0.0932)	(0.1288)
C_{t-3}/Y_{t-3}		-0.1452	0.0820		0.2303***	0.1009
		(0.1177)	(0.1927)		(0.0825)	(0.1397)
constant	0.2683***	0.0939	0.2791***	0.1205*	-0.1688***	-0.1089
	(0.0726)	(0.0796)	(0.0966)	(0.0609)	(0.0558)	(0.0700)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
R^2	0.2092	0.1149	0.2254	0.4182	0.5453	0.5735
F	5.6212	2.7572	3.4083	15.2727	25.4837	15.7519

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

After running the first stage regressions, we estimate the second stage regression and report the results in Table 3.6. For all instrument sets, the coefficient for $\hat{I}_t^P\widehat{\Delta \ln Y_t}$ is statistically different from zero and larger than the coefficient for $\hat{I}_t^N\widehat{\Delta \ln Y_t}$. Indeed, we do not reject that the coefficient for $\hat{I}_t^N\widehat{\Delta \ln Y_t}$ is equal zero for any instrument set. So far, the evidence is in favor of the liquidity constraints hypothesis. However, when we formally test whether these coefficients are the same ($\pi_0 = \pi_1$), we do not reject such null hypothesis. In this sense, we do not reject the myopia hypothesis. These results are in line with those in Gomes (2010) and Gomes and Paz (2010). It seems that consumers face liquidity constraints, but the statistical test has no power to detect it.

Table 3.6 – Shea (1995a) strategy

	$\mathbb{Y}$	$\mathbb{S}$	$\mathbb{Y} \cup \mathbb{S}$
$\hat{I}_t^N\widehat{\Delta \ln Y_t}$	0.4698	0.2790	0.5026
	(0.6216)	(0.8052)	(0.5109)
$\hat{I}_t^P\widehat{\Delta \ln Y_t}$	1.1904***	1.7232***	1.1633***
	(0.3079)	(0.4171)	(0.3292)
$\hat{r}_{i,t}$	-0.2936*	-0.0874	-0.1736
	(0.1533)	(0.1394)	(0.1326)
constant	0.0040	-0.0031	0.0016
	(0.0041)	(0.0044)	(0.0040)
T	90.0000	90.0000	90.0000
R^2	0.2434	0.2228	0.2214
Test for $\mathcal{H}_0 : \pi_0 = \pi_1$ [p-value]			
$\mathcal{H}_1 : \pi_0 \neq \pi_1$	0.3765	0.1696	0.3642

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.5.3 The new approach

In this section we focus on the results based on the new approach where we estimate the specifications (3.8), (3.9) and (3.10) applying conventional instrumental variables estimators. Because the results across the estimators are similar, we report in this Section those base on LIML estimator. The results based on TSLS, Fuller-k and GMM-CUE estimators are reported in the Appendix A.

Tables 3.7 to 3.9 report the results using LIML estimator for specifications (3.8), (3.9) and (3.10), respectively. The first line in each table indicates the instrument set used and the first column describe the variables included in the specification and the tests performed. From the second to the last columns, the results for each instrument set are reported.

Table 3.7 reports the results for the testing equation (3.8), and its version without the interest rate. The coefficient of predictable income decrease are positive and significant, at 5%, for the four instrument sets. Based on the Anderson LM test, these are the sets of instruments that reject the null hypothesis that the model is underidentified. In this sense, when the model is identified, there is evidence that consumers react to predictable income decrease. Regarding the predictable income increase and the expected interest rate, they are not relevant, at 5% significance level, across all instrument sets. By focusing on cases where the model is identified, the Cragg-Donald test suggest that the instruments are weak. Indeed,the first-stage F statistic are very low, except for the interest rate. Although the Sargan test does not reject any specification, its results should be viewed with caution due to the weak instruments problem.

By focusing on myopia and liquidity constraints testing, we notice that the null hypothesis $\pi_0 = \pi_1$ is rejected, at 5% significance level, only for two specifications (see Table 3.7). What does these two specifications have in common? First, they do not contain the interest rate. Second, they reject the under-identification null hypothesis of Anderson LM test. Third, they present the two largest Cragg-Donald statistic. Therefore, when the model is identified and the instruments are not so weak, we reject the myopia hypothesis. These findings reinforce the importance of verifying whether the instruments are weak and of applying techniques developed to deal with such a problem.

Table 3.8 reports the results for the testing specification (3.9), in which the coefficient of predictable income increase, $\pi_1^P = \lambda_3(\delta^P - \delta^N)$, tells us whether consumers react more intensively to income increases than decreases. Once again, four specifications reject the null hypothesis that the model is underidentified (Anderson LM test). By focusing on such specifications, the point estimates suggest that $\delta^N > \delta^P$ because $\pi_1^P < 0$. Excluding the interest rate, this coefficient becomes statistically different from zero at the 5% significance level. With the interest rate, it is only significant at 10%. For all specifications,

Table 3.7 – LIML estimations based on specification (3.8)

	$\mathbb{Y}^P$	$\mathbb{Y}^N$	$\mathbb{S}$	$\mathbb{Y}^P \cup \mathbb{Y}^N \cup \mathbb{S}$	$\mathbb{Y}^P$	$\mathbb{Y}^N$	$\mathbb{Y}^P \cup \mathbb{Y}^N$
$I_t^N \Delta \ln Y_t$	1.8906***	2.7040	1.4141	1.8798***	2.1649***	3.8862	1.8537***
	(0.6739)	(2.3910)	(1.1573)	(0.5162)	(0.5462)	(3.6315)	(0.4547)
$I_t^P \Delta \ln Y_t$	0.3816	-0.9983	1.2598*	0.4661	0.3365	-2.3844	0.3342
	(0.3260)	(2.8758)	(0.7516)	(0.3663)	(0.3368)	(4.5483)	(0.3293)
$r_{i,t}$	-0.1757	-0.1888	-0.0651	-0.0677			
	(0.3035)	(0.3530)	(0.1734)	(0.1304)			
constant	0.0131**	0.0299	0.0005	0.0100*	0.0111**	0.0442	0.0098**
	(0.0059)	(0.0342)	(0.0104)	(0.0055)	(0.0050)	(0.0582)	(0.0047)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
Sargan	0.8293	0.6088	0.8638	0.3770	0.8394	0.8192	0.5632
Test for $\mathcal{H}_0 : \pi_0 = \pi_1$ [p-value]							
$\mathcal{H}_1 : \pi_0 \neq \pi_1$	0.0846	0.4787	0.9312	0.0664	0.0155	0.4397	0.0257
Instrument Relevance [statistic]							
Anderson LM	6.4754**	0.7334	3.6755	19.1943***	15.9515***	0.8815	18.7059***
Cragg-Donald	1.6475	0.1746	0.9048	2.4096	4.5777	0.2102	3.6296
First-Stage F [statistic]							
$I_t^N \Delta \ln Y_t$	4.6316	7.3166	2.5171	3.0923	4.6316	7.3166	4.8074
$I_t^P \Delta \ln Y_t$	5.5812	1.7369	2.1434	2.6417	5.5812	1.7369	3.9720
$r_{i,t}$	4.2762	5.8685	25.4837	12.0186	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.4824	0.3585	0.4237	0.5235	0.7355	0.3832	0.6236
Heterosk.	0.0733	0.4798	0.1083	0.1906	0.0549	0.9287	0.1755
RESET	0.8916	0.9524	0.9972	0.4303	0.7990	0.9175	0.5596
Normality	0.0019	0.0706	0.1325	0.0041	0.0028	0.0452	0.0081

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.

the Cragg-Donald test shows signs that instruments are weak, which compromises the Sargan test. Indeed, the first-stage F statistics point out the difficult to predict $\Delta \ln Y_t$ and $I_t^P \Delta \ln Y_t$.

Regarding the myopia and liquidity constraints tests, we dot not reject the null hypothesis $\pi_1^P = 0$ in favor of the alternative hypothesis $\pi_1^P > 0$ (see Table 3.8). Therefore, we find no evidence in favor of liquidity constraints hypothesis. We test for "perverse assymetria" by confronting the null hypothesis $\pi_1^P = 0$ against the alternative hypothesis $\pi_1^P < 0$. In such case, we reject the null hypothesis, at 5% significance level, as long as the Anderson LM test indicates that the model is not underidentified and the Cragg-Donald

Table 3.8 – LIML estimations based on specification (3.9)

	$\mathbb{Y}$	$\mathbb{Y}^P$	$\mathbb{S}$	$\mathbb{Y} \cup \mathbb{Y}^P \cup \mathbb{S}$	$\mathbb{Y}$	$\mathbb{Y}^P$	$\mathbb{Y} \cup \mathbb{Y}^P$
$\Delta \ln Y_t$	-0.9713	1.8906***	1.4141	1.9641***	5.6311	2.1649***	2.2571***
	(13.9704)	(0.6739)	(1.1573)	(0.6046)	(5.9476)	(0.5462)	(0.6228)
$I_t^P \Delta \ln Y_t$	3.2480	-1.5090*	-0.1543	-1.5502*	-7.3313	-1.8284**	-1.9473**
	(22.3805)	(0.8749)	(1.7868)	(0.9152)	(9.5520)	(0.7553)	(0.9132)
$r_{i,t}$	-0.4212	-0.1757	-0.0651	-0.1089			
	(0.9467)	(0.3035)	(0.1734)	(0.1362)			
constant	-0.0120	0.0131**	0.0005	0.0117*	0.0451	0.0111**	0.0117*
	(0.1204)	(0.0059)	(0.0104)	(0.0062)	(0.0596)	(0.0050)	(0.0060)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
Sargan	0.0862	0.8293	0.8638	0.1942	0.2188	0.8394	0.2048
Test for $\mathcal{H}_0 : \pi_1^P = 0$ [p-value]							
$\mathcal{H}_1 : \pi_1^P > 0$	0.4425	0.9559	0.5343	0.9530	0.7776	0.9912	0.9821
$\mathcal{H}_1 : \pi_1^P < 0$	0.5575	0.0441	0.4657	0.0470	0.2224	0.0088	0.0179
Instrument Relevance [statistic]							
Anderson LM	2.9896	6.4754**	3.6755	18.9579***	3.6039	15.9515***	18.1368***
Cragg-Donald	0.7301	1.6475	0.9048	2.1082	0.8864	4.5777	2.9565
First-Stage F [statistic]							
$\Delta \ln Y_t$	5.6211	5.2361	2.7572	2.6441	5.6211	5.2361	3.7260
$I_t^P \Delta \ln Y_t$	4.3765	5.5812	2.1434	2.3877	4.3765	5.5812	3.5220
$r_{i,t}$	15.2726	4.2762	25.4837	10.7948	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.7796	0.4824	0.4237	0.5678	0.2944	0.7355	0.8014
Heterosk.	0.4974	0.0733	0.1083	0.1965	0.8630	0.0549	0.0845
RESET	0.0125	0.8916	0.9972	0.3661	0.6870	0.7990	0.7314
Normality	0.0287	0.0019	0.1325	0.0025	0.0000	0.0028	0.0018

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.

statistics are not that low. Therefore, we find evidence that $\delta^N > \delta^P$ when the instruments are not so weak.

Finally, Table 3.9 reports the results for specification (3.10), in which the coefficient of predictable income decrease, $\pi_1^N = \lambda_3(\delta^N - \delta^P)$, tells us whether consumers react more intensively to income increases than decreases. With this testing equation, no coefficient is statistically different from zero, at 5% level. Indeed, the Anderson LM test rejects the underidenification null hypothesis, at 10% significance level, only for two instrument specifications. Focusing on these specifications, π_1^P is differently from zero, at

Table 3.9 – LIML estimations based on specification (3.10)

	$\mathbb{Y}$	$\mathbb{Y}^N$	$\mathbb{S}$	$\mathbb{Y} \cup \mathbb{Y}^N \cup \mathbb{S}$	$\mathbb{Y}$	$\mathbb{Y}^N$	$\mathbb{Y} \cup \mathbb{Y}^N$
$I_t^N \Delta \ln Y_t$	-3.2480	3.7023	0.1543	0.8837	7.3313	6.2706	0.2730
	(22.3805)	(5.2262)	(1.7868)	(0.9506)	(9.5520)	(8.1158)	(1.2004)
$\Delta \ln Y_t$	2.2767	-0.9983	1.2598*	0.7231	-1.7002	-2.3844	1.0711*
	(8.4223)	(2.8758)	(0.7516)	(0.4719)	(3.6690)	(4.5483)	(0.6156)
$r_{i,t}$	-0.4212	-0.1888	-0.0651	-0.1318			
	(0.9467)	(0.3530)	(0.1734)	(0.1286)			
constant	-0.0120	0.0299	0.0005	0.0078	0.0451	0.0442	0.0007
	(0.1204)	(0.0342)	(0.0104)	(0.0065)	(0.0596)	(0.0582)	(0.0083)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
Sargan	0.0862	0.6088	0.8638	0.3826	0.2188	0.8192	0.2646
Test for $\mathcal{H}_0 : \pi_1^N = 0$ [p-value]							
$\mathcal{H}_1 : \pi_1^P > 0$	0.5575	0.2403	0.4657	0.1776	0.2224	0.2209	0.4103
$\mathcal{H}_1 : \pi_1^P < 0$	0.4425	0.7597	0.5343	0.8224	0.7776	0.7791	0.5897
Instrument Relevance [statistic]							
Anderson LM	2.9896	0.7334	3.6755	14.9146*	3.6039	0.8815	11.5084*
Cragg-Donald	0.7301	0.1746	0.9048	1.5692	0.8864	0.2102	1.7175
First-Stage F [statistic]							
$I_t^N \Delta \ln Y_t$	3.7910	7.3166	2.5171	3.2287	3.7910	7.3166	4.0826
$\Delta \ln Y_t$	5.6211	4.6889	2.7572	2.8508	5.6211	4.6889	3.4590
$r_{i,t}$	15.2726	5.8685	25.4837	11.4796	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.7796	0.3585	0.4237	0.3697	0.2944	0.3832	0.4073
Heterosk.	0.4974	0.4798	0.1083	0.1677	0.8630	0.9287	0.0699
RESET	0.0125	0.9524	0.9972	0.6246	0.6870	0.9175	0.5418
Normality	0.0287	0.0706	0.1325	0.0069	0.0000	0.0452	0.0554

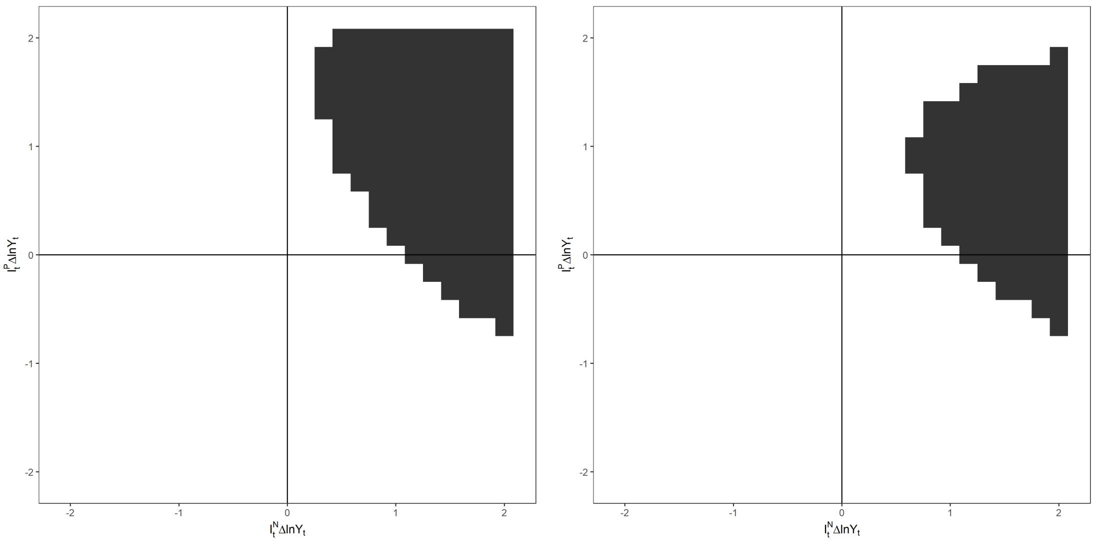
Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.

10% significance level, and the point estimates suggest that $\delta^N > \delta^P$ because $\pi_1^N > 0$. It is worth mentioning that Cragg-Donald statistics indicate that the instruments are weak, and the first-stage F statistics ratify the difficult to predict $\Delta \ln Y_t$ and $I_t^N \Delta \ln Y_t$. Not surprisingly, when testing the null hypothesis $\pi_1^N = 0$ against the alternative hypothesis $\pi_1^N > 0$ or $\pi_1^N < 0$, we do not reject the null hypothesis.

Comparing the Cragg-Donald statistics in Tables 3.7, 3.8 and 3.9, it seems that specifications (3.8) and (3.9) are better specified than specification (3.10). In other words, given our instruments sets, it is easier predict $\Delta \ln Y_t$ and $I_t^P \Delta \ln Y_t$ than $I_t^N \Delta \ln Y_t$. However, in all cases the diagnostic tests in Tables 3.7, 3.8 and 3.9 show evidence that instrument are weak. For this reason, we compute robust confidence intervals based on the Anderson, Rubin et al. (1949) statistics for specifications (3.8), (3.9) and (3.10) and their versions without the interest rate as it revealed being not significant in the regressions. For each model we use instrument set with the highest Cragg and Donald (1993) statistic (reported in Tables 3.7, 3.8 and 3.9). The results are reported on Figures 3.1, 3.2 and 3.3.

Figure 3.1 shows the confidence sets based on the equation (3.8). Both specifications indicate that the coefficient of $I_t^N \Delta \ln Y_t$, π_1, is greater than zero for any value of the coefficient of $I_t^P \Delta \ln Y_t$, π_0. Furthermore, when π_1 is large – approximately greater than one –, we can see that $\pi_0 = 0$ is included in the confidence set. Indeed, the point estimates for π_1 are between 1.85 and 2.16 for the specifications in which the Anderson LM test rejects that the model is underidentified (see Table 3.7). Taking this into account, there is evidence that consumers react more intensely to income decreases than increases, which is a evidence in favor of the "perverse assymetria" hypothesis.

Figure 3.1 – Confidence Set for $I_t^P \Delta \ln Y_t$ and $I_t^N \Delta \ln Y_t$

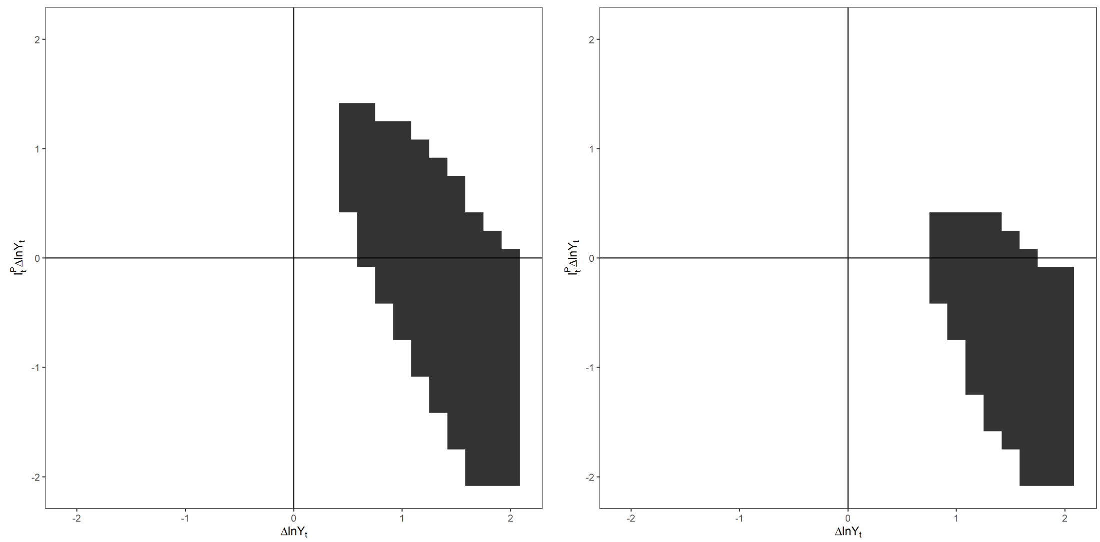


(a) With Selic (b) Without Selic

Notes: The plots the robust confidence set for credit and income at a 95% confidence level. The instrument set for each specification was chosen based on the highest Cragg and Donald (1993) statistic in Table 3.7.

Figure 3.2 reports the confidence set for the specification (3.9). For both specifications, the coefficient of $\Delta \ln Y_t$, π_0^P, is greater than zero for any value of the coefficient of $I_t^P \Delta \ln Y_t$, π_1^P. For large values of π_0^P, the confidence sets suggest that $\pi_1^P = 0$. It is worth mentioning that, the estimates of π_0^P in Table 3.8 – when the underidentification null hypothesis is rejected – range from 1.89 to 2.25. Taking into account the results in both Table 3.8 and Figure 3.2, the conclusions are similar to the ones from model (3.8) and and we have evidence for the "perverse asymmetry" as well.

Figure 3.2 – Confidence Set for $I_t^P \Delta \ln Y_t$ and $I_t \Delta \ln Y_t$



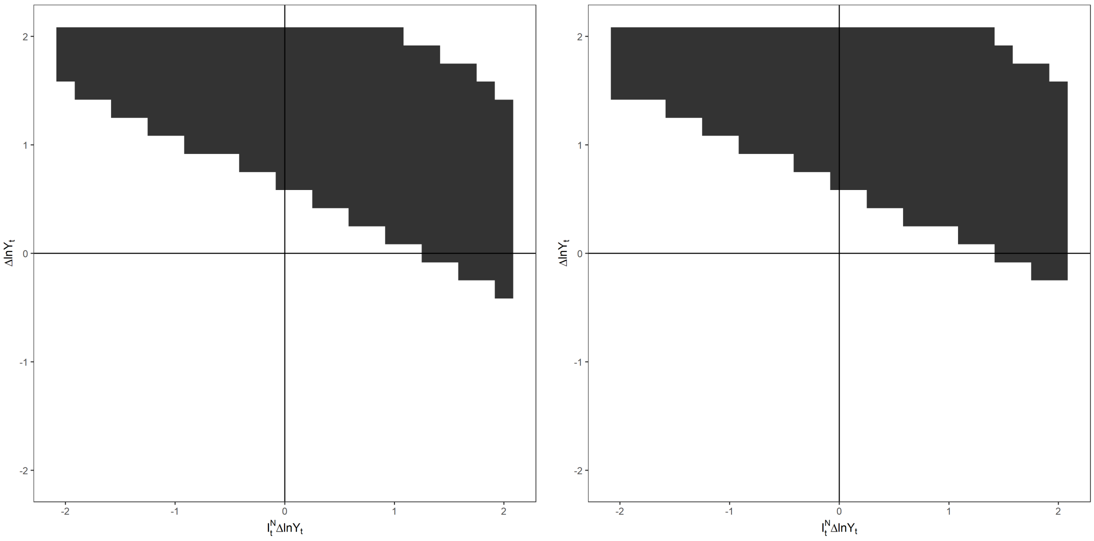
(a) With Selic (b) Without Selic

Notes: The plots the robust confidence set for credit and income at a 95% confidence level. The instrument set for each specification was chosen based on the highest Cragg and Donald (1993) statistic in Table 3.8.

Figure 3.3 shows the confidence sets based on the specification (3.10). The diagnostics tests in Tables 3.7, 3.8 and 3.9 suggest that specification (3.10) is more affected than the specifications (3.8) and (3.9). Not by chance, the Figure 3.3 show confidence sets that are less informative. They show that the coefficients are not equal to zero, but any one of them can be null. When $\pi_0^N \geq 0.5$, note that $\pi_1^N = 0$ is a feasible value, indicating for myopia. However, for $\pi_0^N < 0.5$ the plots suggests that $\pi_1^N > 0$, which is in favor of "perverse asymmetry" hypothesis.

Alike the results of Shea (1995a) and Shea (1995b), this section results show evidence that the "perverse asymmetry" is the reason of the LCH-PIH failure. Interestingly, the evidence found in this section contrasts with the ones found in section 3.5.2, where we used the Shea (1995a) approach, as in Gomes (2010) and Gomes and Paz (2010). The

Figure 3.3 – Confidence Set for $I_t^N \Delta \ln Y_t$ and $\Delta \ln Y_t$



(a) With Selic (b) Without selic

Notes: The plots the robust confidence set for credit and income at a 95% confidence level. The instrument set for each specification was chosen based on the highest Cragg and Donald (1993) statistic in Table 3.9.

main difference between Shea (1995a) and our new approach is how the positive/negative income growth is calculated. While in Shea (1995a), $\hat{I}_t^P$ is calculated using $\widehat{\Delta \ln Y_t}$, in the new approach the indicator variable I_t^P is calculated with the realized value of $\Delta \ln Y_t$ and, after that, we calculate the $E_t[I_t^P \Delta \ln Y_t]$.

3.6 Conclusions

According to the LCH-PIH, predictable income changes should not affect the consumers' consumption choice. However, it's well documented in the literature its failure in aggregate data (see, for example, Campbell and Mankiw (1989), Campbell and Mankiw (1990)). Trying to understand the failure reason, Shea (1995a) tests two hypothesis for this failure: myopia and liquidity constraints.

In the case of myopia, consumption should respond equally to increases and declines of income growth. Under liquidity constraints, consumption should be more strongly correlated with predictable income increases than declines. However, Shea (1995a) finds that aggregate consumption is more sensitive to predictable income declines than to predictable income increases, which is inconsistent with both myopia and with liquidity constraints.

In this work, we adapt Shea (1995a) strategy so that we could confront these hypothesis, and the "perverse asymmetry" as well, in a more straightforward way. Our proposed approach also allows us to use the usual instrumental variables estimators and weak instrument robust tools. We we Brazilian quarterly data from 1991:Q2 to 2019:Q2 and find evidence that consumption growth responds more to negative predictable income growth than to positive predictable income growth. Those results are in line with the findings of Shea (1995a) using US data, but contrasts with the findings of Gomes (2010) that used Brazilian data as well.

4 Predictability of Aggregate Consumption Growth: a case for structural breaks?

Abstract

This paper evaluates the consumption predictability taking into account four factors: intertemporal substitution (returns on assets), habit formation (lagged consumption), rule-of-thumb behavior (current income) and credit conditions (credit level). In general, the literature estimates such models assuming the following auxiliary assumptions: log-normality of consumption and assets returns, parameters constancy over time and that valid instruments are available. We adopt a strategy that evaluates those assumptions and that valid instruments are available. More specifically, we use structural break tests to deal with the parameter stability and use robust confidence intervals given the evidence that instruments are weak. The results show that the relevant predictability factors change over time. From Jun-59 to Dec-83, both variables and debt growth are relevant. From Jan-84 to Dec-06, there is no evidence of rule-of-thumb behavior anymore and habit persistence is the only relevant factor. In the last sub-sample, after Jan-07, habit is not relevant anymore and there is not enough information to estimate the coefficients for income and debt growth.

Keywords: Consumption predictability; Euler equation; Structural breaks; Weak instruments; US.

4.1 Introduction

Browning and Crossley (2001) convincingly argue that the life-cycle framework is better viewed as a source of models that can be taken to the data. In this vein, the life-cycle framework (or tradition) leads to a life-cycle model with empirical content only when particular assumptions regarding the economic environment and the consumers preferences are chosen. After elaborating a specific model, the consumers behavior is frequently summarized by Euler equations, which describe the evolution of consumption along an optimal path.

In practice, before estimating any Euler equation, additional auxiliary assumptions are made. For the most part, the literature on consumption decision assume that the joint conditional distribution of consumption and assets returns is log-normal. Furthermore, the assumptions behind the econometric approach used to estimate the Euler equations can also be viewed as auxiliary assumptions. On this matter, we emphasize the usual assumptions on the stability of the parameters over time and the availability of suitable instruments – exogenous, but correlated with the endogenous variables. Given all these auxiliary assumptions, when an Euler equation is rejected, it is not clear who to blame. Should the model itself be revised or should an auxiliary assumption be avoided?

Obviously, to some extent, we can investigate the auxiliary assumptions. However, since the seminal paper of Hansen and Singleton (1983), the log-normality assumption is used as it was part of the procedure to derive the testing equations. In other words, the well-known time-series representation for the consumption growth rate is due to the log-normality assumption, and this formulation gives rise to the literature on consumption predictability (Hall (1988), Kiley (2010) and Everaert and Pozzi (2014)). Maybe for this reason, the analysis of the log-normality assumption is not usual. An exception is Gomes and Issler (2017) who applied several residual-based tests after estimating log-linear Euler equations, such as normality tests.

Regarding the stability of the parameters, the Euler equations come from structural models and, consequently, depend on structural parameters. Although such strategy is a response to the Lucas' Critique, it is not possible to ensure that such parameters are constant over a long period. Besides, when we couple a log-linear Euler equation with rule-of-thumb behavior, it is questionable whether we can still see all parameters as being structural. As proposed by Campbell and Mankiw (1989), rule-of-thumb consumers consume their entire current income, which is assumed to be a fixed proportion λ of aggregate income. Although there is no reason to argue that λ is constant over time, usually the literature assumes that it is constant and just few authors have not assumed such a hypothesis (Bacchetta and Gerlach (1997) and Brady (2008)).

The error term of the log-linear Euler equation is a rational expectation forecast error, being an innovation regarding the consumer information set. For this reason, lagged variables should be exogenous instruments. However, due to temporal aggregation, Hall (1988) suggests the use of variables lagged at least twice. This becomes a common practice in the literature, once researchers have been concerned with instruments exogeneity. However, such practice tend to amplify the problem of weak instruments because, in general, the higher the lag, the lower the correlation between the instrument and the endogenous variable. Yogo (2004) estimates log-linear Euler equations, recovering the elasticity of intertemporal substitution (EIS) for eleven developed countries. Using instruments lagged twice, he find strong evidence that instruments are weak, specially when stock returns are employed. After estimating confidence intervals robust to weak instruments, Yogo (2004) concludes that the EIS is not significant different from zero. Unfortunately, in many cases the intervals are not informative, being $(-\infty, +\infty)$ (see also Gomes (2013)). From our point of view, this particularity prevents us from learning anything about the EIS, or any other parameter of interest.

To take these issues into account, we propose a novel strategy to investigate the log-linear Euler equations based on four steps. First, we delineate a setup to minimize the problem of weak instruments. We discard assets whose returns are difficult to predict and we use instruments lagged just once. To balance the temporal aggregation problem, we use monthly data instead of the quarterly and annually frequencies used by Hall (1988). Second, to investigate possible structural breaks we employ the methodology proposed by

Hall, Han and Boldea (2012a), which is able to deal with endogenous regressors. Therefore, differently from Brady (2008), who searches for breaks in the time-series on consumption and credit, we directly examine the log-linear Euler equations.[1] Third, for each sub-sample we perform several diagnostic tests to evaluate the weak instruments problem and the log-normality assumption. Fourth, we employ estimators robust to serial correlations and homoskedasticity, and, when necessary, we employ confidence intervals robust to the weak instruments.

We apply such strategy to a consumption model that captures the following sources of predictability: intertemporal substitution (returns on assets), habit formation (lagged consumption), rule-of-thumb behavior (current income) and credit conditions (credit level). These factors were selected based on the findings from Campbell and Mankiw (1990), Sommer (2007), Brady (2008), Kiley (2010), and Everaert and Pozzi (2014).

Analyzing the US case from Jun-59 to Jan-18, our strategy reduces the problem of the weak instruments, making the robust conficence intervals more informative. Because we also consider the possibility of parameter instability, we learn that the correlation of the endogenous variables with consumption growth change over time. According to our results, the findings of previous works that favored rule-of-thumb and habit persistence hold in the past. For the most recent period of our analysis, from Jan-07 to Jan-18 there is little evidence that these two factors were important, but there is evidence for intertemporal substitution. Regarding the credit conditions (debt), there is some evidence of its relevance in the period from Jun-59 to Dec-83.

The rest of the paper is organized as follows. Section 4.2 briefly reviews the relevant consumption models for our work. Section 4.3 discusses the econometric methodology, describing the diagnostic tests, structural break test and robust inference. Section 4.4 presents the results and section 4.5 concludes.

[1] This structural break analysis also motives the use of monthly data in order to increase the number of observations in each sub-sample.

4.2 Consumption Predictability

In this section we present important results from the literature on consumption predictability that motivate our work. Section 4.2.1 describes the standard model in macroeconomics, which is based on the *constant-relative-risk-aversion* (CRRA) instantaneous utility. Section 4.2.2 adds habit formation, capturing consumption growth rate persistence. Section 4.2.3 discuss the rule-of-thumb behavior as well as its connection with credit constraints.

4.2.1 Canonical consumption model

As discussed by Gomes and Issler (2017), the standard approach in macroeconomics consists of a single-good economy of identical consumers, who choose consumption and asset holdings to maximize the lifetime well-being, given by $\mathbb{E}_t\left[\sum_{i=0}^{\infty}\beta^i u(C_{t+i})\right]$, where $u(\cdot)$ is the instantaneous utility, C_t is the consumption level in period t, $\beta \in (0,1)$ is the intertemporal discount factor, and the mathematical operator $\mathbb{E}_t(\cdot)$ is formed conditional on information available to the consumer up to period t. The CRRA instantaneous utility integrates the traditional approach, which is given by:

$$u(C_t) = \frac{C_t^{1-\gamma} - 1}{1-\gamma} \tag{4.1}$$

where γ is the constant relative risk aversion coefficient. The representative consumer can transfer wealth from one period to the next by buying individual assets indexed by i, $i = 1, ..., N$, whose gross return is $R_{i,t}$. In this setup, the well-known consumer Euler equation is given by[2]

$$\mathbb{E}_{t-1}\left[\beta\left(\frac{C_t}{C_{t-1}}\right)^{-\gamma} R_{i,t}\right] = 1,\ i = 1, ..., N \tag{4.2}$$

By assuming joint conditional lognormality and homoskedasticity of $\left(\frac{C_t}{C_{t-1}}, R_{1,t}, ..., R_{N,t}\right)$, we reach the usual log-linear Euler equation representation:[3]

$$\Delta \ln C_t = \psi(ln\beta + 0.5\sigma_i^2) + \psi r_{i,t} + \varepsilon_{i,t},\ i = 1, ..., N \tag{4.3}$$

[2] See, for instance, Hansen and Singleton (1982).

[3] Suppose that $H_{i,t}$ is conditionally log-normal. Then, $\mathbb{E}_{t-1}[H_{i,t}] = \exp\{\mathbb{E}_{t-1}[h_{i,t}] + 0.5\mathbb{V}_{t-1}[h_{i,t}]\}$, where $h_{i,t} \equiv \ln H_{i,t}$. Define $\sigma_{i,t} \equiv \mathbb{V}_{t-1}[h_{i,t}]$. Under homoskedasticity it becomes constant over time, i.e. σ_i.

where $\psi \equiv 1/\gamma$ is the EIS, $\sigma_i^2 \equiv \mathbb{V}[r_{i,t} - \psi^{-1}\Delta \ln C_t]$, $r_{i,t} \equiv \ln R_{i,t}$, and $\varepsilon_{i,t} \equiv \Delta \ln C_t - \mathbb{E}_{t-1}[\Delta \ln C_t] - \psi\,(r_{i,t} - \mathbb{E}_{t-1}[r_{i,t}])$. Thus, the error term depends, by construction, on shocks to assets returns and on shocks to the growth rates of aggregate consumption. Therefore, assets returns are endogenous variables. Despite that, the error term is an innovation regarding the consumers' information set from period $t-1$, $\mathcal{I}_{t-1}$, such as $\varepsilon_{i,t}|\mathcal{I}_{t-1} \sim \mathcal{N}(0, \psi^2\sigma_i^2)$, for $i = 1, ..., N$. Consequently, the log-normality assumption can be assessed by residual-based tests of normality, homoskedasticity and serial correlation (Gomes and Issler (2017)).[4]

Following Araujo and Issler (2011), Gomes and Issler (2017) apply the Generalized Taylor Expansion – hereafter GTE – to Euler equation (4.2), obtaining the following model for the consumption growth rate:

$$\Delta \ln C_t = \psi \ln \beta + \psi r_{i,t} + \psi \mathbb{E}_{t-1}[z_{i,t}] + \varepsilon_{i,t},\, ,\ i = 1, ..., N \tag{4.4}$$

where $\mathbb{E}_{t-1}[z_{i,t}]$ captures the higher-order terms of the GTE. Therefore, if log-normality does not hold, the estimation of model (4.3) will generate the omitted-variable bias. Indeed, the omission of $\mathbb{E}_{t-1}[z_{i,t}]$ cast doubt on the validity of any instrument that belong to the conditioning set used by the econometrician, once it potentially depends on the elements of the information set $\mathcal{I}_{t-1}$. Thus, after estimating the log-linear Euler equation (4.3), we evaluate the omission of non-linear terms related to $\mathbb{E}_{t-1}[z_{i,t}]$. To accomplish such task, we apply versions of the regression specification error test (RESET) designed to deal with endogenous covariates. After estimating the model (4.3) using quarterly and annual data, Gomes and Issler (2017) finds evidence against the log-normality assumption, especially due to serial correlation and non-normality of the residuals.

Under log-normality and homoskedastic assumptions, the canonical consumption model leads to the log-linear Euler equation (4.3), which captures the intertemporal substitution factor. Indeed, the EIS measures the consumer's willingness to adjust the planned consumption in response to investment opportunities. Several studies have estimated the model (4.3) to recover that parameter. Mankiw (1981), Hall (1988) and Campbell and

4 Obviously, we must employ homoskedasticity and serial correlation tests that take in account the endogeneity problem.

Mankiw (1989) find barely statistically significant estimates of EIS that were below 0.25. Patterson and Pesaran (1992) and Hahm (1998) obtains significant EIS estimates, but below 0.40. More recently, Campbell (2003) could not reject that the EIS is equal to zero.

Neely, Roy and Whiteman (2001) and Campbell (2003) notice that weak instrument is a problem when estimating log-linear Euler equations because asset returns and consumption growth rate are difficult to predict.[5] It is worth mentioning that, if instruments are weak, standard IV point estimates, hypothesis tests, and confidence intervals are unreliable (Stock, Wright and Yogo (2002)). Yogo (2004) finds evidence that most EIS estimates for eleven developed countries, including the U.S. ones, are plagued by weak instruments. So, using methods robust to such problem, he concludes that the EIS is less than 1 and not significantly different from 0 for all eleven developed countries analyzed (see also Gomes and Paz (2011)). It is worth noting that, for stock returns, most (robust) confidence intervals are not informative, being $(-\infty, +\infty)$. From our point of view, the conservative interpretation of such intervals is that we have no information about the parameter of interest. Despite that, the log-linear Euler equation (4.3) holds for any asset held by the consumer which enable us to avoid assets whose returns are difficult to predict, such as stocks.

4.2.2 Habit formation

Habit formation takes place when the marginal utility of current consumption depends on the habit level. When habit is external, as in Abel (1990) "catching up with the Joneses" formulation, the habit level depends on the aggregate consumption per capita, $\bar{C}_t$, instead of the consumer's own consumption, C_t. Likewise, and in line with Kiley (2010) and Everaert and Pozzi (2014), we assume the following instantaneous utility:

$$u(C_t, \bar{C}_{t-1}) = \frac{1}{1-\gamma}\left(\frac{C_t}{\bar{C}_{t-1}^{\alpha}}\right)^{1-\gamma} \tag{4.5}$$

[5] Hansen and Singleton (1983) estimates the reverse model where the asset return is the dependent variable and the consumption growth rate is the independent variables.

where $\alpha \geq 0$ measures the strength of habit formation. For the instantaneous utility (4.5), the consumer Euler equation becomes:

$$\mathbb{E}_{t-1}\left[\beta\left(\frac{C_t}{C_{t-1}}\right)^{-\gamma}\left(\frac{C_{t-1}}{C_{t-2}}\right)^{\alpha(\gamma-1)} R_{i,t}\right] = 1,\ i = 1, ..., N \tag{4.6}$$

Consumers' own past consumption appear in the Euler equation (4.6) because, in equilibrium, identical consumers choose the same level of consumption (Abel (1990), Campbell and Cochrane (1999)). Note that, without habit formation ($\alpha = 0$), we fall back to the usual Euler equation (4.2). Under log-normality and homoskedasticity, the Euler equation (4.6) becomes:

$$\Delta \ln C_t = \psi(\ln \beta + 0.5\sigma_i^2) + \alpha(1-\psi)\Delta \ln C_{t-1} + \psi r_{i,t} + \varepsilon_{i,t} \tag{4.7}$$

where the lagged consumption growth rate comes from habit formation. Because the information set is from period $t-1$, as before $\sigma_i^2 = \mathbb{V}[r_{i,t} - \psi^{-1}\Delta \ln C_t]$, $\varepsilon_{i,t} = \Delta \ln C_t - \mathbb{E}_{t-1}[\Delta \ln C_t] - \psi\left(r_{i,t} - \mathbb{E}_{t-1}[r_{i,t}]\right)$, and $\varepsilon_{i,t}|\mathcal{I}_{t-1} \sim \mathcal{N}(0, \psi^2\sigma_i^2)$, for $i = 1, ..., N$, which can be evaluated by means of residual-based tests.

Following the approach of Gomes and Issler (2017), we apply the GTE to Euler equation (4.6). To do so, notice that the GTE of the exponential function around x, with increment h, is given by:

$$e^{x+h} = e^x + he^x + \frac{h^2 e^{x+\lambda(h)\cdot h}}{2},\ \text{with } \lambda(h) : \mathbb{R} \to (0,1)\,. \tag{4.8}$$

Dividing (4.8) by e^x yields:

$$e^h = 1 + h + \frac{h^2 e^{\lambda(h)\cdot h}}{2}, \tag{4.9}$$

which does not depend on x. Define

$$h \equiv \ln\left(\beta\left(\frac{C_t}{C_{t-1}}\right)^{-\gamma}\left(\frac{C_{t-1}}{C_{t-2}}\right)^{\alpha(\gamma-1)} R_{i,t}\right) \tag{4.10}$$

After substituting 4.10 on 4.9, it is possible to see that the the Euler equation (4.6) becomes[6]:

$$\Delta \ln C_t = \psi \ln \beta + \psi r_{i,t} + \alpha(\psi - 1)\Delta \ln C_{t-1} + \psi \mathbb{E}_{t-1}[z_{i,t}] + \varepsilon_{i,t} \tag{4.11}$$

[6] To further details, see Gomes and Issler (2017).

where $z_{i,t} \equiv h^2 e^{\lambda(h_{i,t})\cdot h_{i,t}}/2$. As before, $\mathbb{E}_{t-1}[z_{i,t}]$ captures the higher-order terms of the Taylor expansion, and in general it will be a function of the variables in the conditioning set used by the econometrician to compute $\mathbb{E}_{t-1}[\cdot]$ (Gomes and Issler (2017)). For this reason, after estimating the log-linear Euler equation (4.7), we apply RESET tests to evaluate the omission of non-linear terms related to $\mathbb{E}_{t-1}[z_{i,t}]$.

Regarding the strength of the habit formation, studies of time-nonseparable preferences yield mixed conclusions. For instance, Dunn and Singleton (1986), Eichenbaum, Hansen and Singleton (1988), Muellbauer (1988) and Heaton (1993) find very little evidence of habit formation, while Ferson and Constantinides (1991), Fuhrer (2000), Tallarini and Zhang (2005) find large and statistically significant amounts of habit formation. Weber (2002) investigates different time-nonseparable preferences and his findings are not robust. While some specifications yield significant and positive habit coefficient, others lead to negative coefficients suggesting local durability. Despite this controversy, Sommer (2007) and Kiley (2010) investigates habit formation along with other sources of consumption predictability, concluding that lagged consumption growth rate has predictive content for the consumption growth rate.

4.2.3 Rule-of-thumb behavior and credit constraints

Mankiw (1981) evaluates the model (4.3) by adding covariates that, under the null hypothesis, should be not relevant. However, his findings suggest that the anticipated income growth rate predicts the consumption growth rate. Not by chance, Campbell and Mankiw (1989) argues that the time series data on consumption are best viewed as generated not by a single consumer, but by two consumers type. The first type follows the model (4.3), which means that she/he smooths the consumption path taking in account the expected asset returns.[7] The second type follows the rule of thumb of consuming the current income. To identify the model, Campbell and Mankiw (1989) assume that the current income of the rule-of-thumb consumers is the proportion λ of the aggregate income. As a result, Campbell and Mankiw (1989) put forward a testing equation in which

[7] To be precise, Campbell and Mankiw (1989) starts with the quadratic utility, and after that move to CRRA one.

expected returns on assets and anticipated income growth rate predict the consumption growth rate. Using G7 data, Campbell and Mankiw (1989) and Campbell and Mankiw (1990) findings suggest that the rule-of-thumb behavior is widespread. Regarding the U.S. economy, approximately 50% of total income belongs to rule-of-thumb consumers.

The rule-of-thumb behavior is generally associated to lack of credit (Vaidyanathan (1993), Engelhardt (1996), and Garcia, Lusardi and Ng (1997)). Consumers would like to smooth consumption, but the lack of credit leads consumption to track the current income instead of the permanent income. Unfortunately, CAMPBELL; MANKIW's (1989) approach does not deliver a theoretical connection between rule-of-thumb behavior and credit conditions. This gap was filled by Campbell and Mankiw (1990), who developed a model in which consumers face borrowing constraints that varies stochastically with income. Using simulated series from her model, Ludvigson (1999) estimates the following specification:

$$\Delta \ln C_t = \theta_0 + \theta_1 r_{i,t} + \theta_2 \Delta \ln Y_t + \theta_3 \Delta \ln D_t + \varepsilon_{i,t} \tag{4.12}$$

where D_t is the level of credit. Her findings suggest that $\theta_2 \neq 0$ and $\theta_3 \neq 0$. More important, the tighter the credit constraints in the simulations, the larger were the estimates of θ_2. Campbell and Mankiw (1990) also estimates the specification (4.12) using effective data of the US economy, concluding that $\theta_2 \neq 0$ and $\theta_3 \neq 0$. In this sense, her model correctly predicts the statistically significant correlation between consumption growth rate and both the expected growth rates in income and credit.[8]

Brady (2008) investigates whether the sharp and sustained increase in consumer credit put in motion in the 1980s in the U.S. led consumption smoothing to be a reality. To accomplish such task, Brady (2008) investigates structural breaks in aggregate time series on consumption and credit and, the break dates were used to define the sub-samples. After that, Brady (2008) estimates the model (4.12) for each sub-sample. The results point out that consumption smoothing is evident in the data after the mid-1980s and into the 2000s, because income and credit growth rates lose relevance. Although very interesting,

[8] Prior to Campbell and Mankiw (1990), Bacchetta and Gerlach (1997) analyze empirically five countries, including the US, and their findings suggests that credit growth rate is relevant to predict the consumption growth rate in all cases.

this analysis has one caveat. Structural breaks in the time series on consumption and/or credit do not imply breaks in the parameters of the testing equation (4.12). As detailed in Section 4.3, we employ the methodology proposed by Hall, Han and Boldea (2012a) to search for structural breaks directly in the models of interest.

Kiley (2010) and Everaert and Pozzi (2014) examine the aggregate consumption growth taking into account several predictability factors, such as intertemporal substitution, habit formation and rule-of-thumb behavior. Using techniques robust to weak instrument problems, Kiley (2010) analysis shows support for habit persistence and rule-of-thumb behavior for U.S. case. Everaert and Pozzi (2014) analyze a panel of 15 OECD countries, and their results support current disposable income growth as the only variable with significant predictive power for aggregate consumption growth. However, differently from Campbell and Mankiw (1990) and Brady (2008), the work of Kiley (2010) and Everaert and Pozzi (2014) do not take into account direct measures of credit, nor the possibility of structural breaks in the parameters.

4.3 Econometric Methodology

In this section we detail the methodology we use to examine the consumption growth predictability. Section 4.3.1 describes the econometric methodology, including the econometric specifications, the estimators and the robust confidence intervals. In section 4.3.2 we present the tests to assess the properties of the residuals and the instruments relevance. Finally, section 4.3.3 describes the endogenous structural break test we use to assess the stability of the parameters.

4.3.1 Econometric Model

We report the results based on three different specifications. All of them include the habit persistence and the interest rate. The first one adds the income and debt growth rates. The second specification adds only the income growth while the third adds only the debt growth. The specifications are:

$$\Delta \ln C_t = \theta_0 + \theta_1 \Delta \ln C_{t-1} + \theta_2 r_{i,t} + \theta_3 \Delta \ln Y_t + \theta_4 \Delta \ln D_t + \varepsilon_t \tag{4.13}$$

$$\Delta \ln C_t = \theta_0 + \theta_1 \Delta \ln C_{t-1} + \theta_2 r_{i,t} + \theta_4 \Delta \ln D_t + \varepsilon_t, \tag{4.14}$$

$$\Delta \ln C_t = \theta_0 + \theta_1 \Delta \ln C_{t-1} + \theta_2 r_{i,t} + \theta_3 \Delta \ln Y_t + \varepsilon_t \tag{4.15}$$

As usual, the error term of equations (4.13), (4.14) and (4.15) are assumed to be correlated with the explanatory variables. Indeed, the error term in the equations depend, by construction, on shocks to assets returns and on shocks to the growth rates of aggregate consumption, debt or income. In this setup, the parameters can be identified only if valid instruments are available. The instruments cannot be correlated with the error term and have to be correlated with the endogenous regressors. The latter condition means that the instruments need to be able to predict the endogenous regressors, otherwise the weak instrument problem arises. Theoretically, the error term is an innovation, being orthogonal to any lagged variable. So, the natural choice for the instruments are the lagged variables. Given this scenario, to mitigate the weak instrument problem, we employ as part of our econometric strategy two different instrument sets. The Instrument Set 1 uses the first lag of habit, interest, income, credit and inflation and the Instrument Set 2 uses the second lags of the same variables.

For estimation, some instrumental variables (IV) estimators, such as the limited information maximum likelihood (LIML) and Fuller-k, provide more reliable point estimates and inferences under weak instruments than does the two-stage least squares (TSLS). Indeed, as discussed by Stock, Wright and Yogo (2002), LIML and Fuller-k estimators are partially robust to the weak instrument problem. Thus, following Yogo (2004), we employ these estimators. In addition, to handle with heteroscedastic and serial correlated errors, we employ the continuously updated GMM (CUE-GMM) estimator.

Finally, we also employ confidence interval that are (fully) robust to weak instruments. In the context of just one endogenous there are three statistics we could use:

the Anderson-Rubin statistic (AR) (anderson1949estimation), Lagranger Multiplier (LM) (Kleibergen02) and the Conditional Likelihood Ratio (CLR) (Moreira03). Andrews07 indicates the use of the Moreira03 Conditional Likelihood Ratio (CLR) because it has the strongest asymptotic power (under the conditions discussed in their paper). The specifications we consider in this paper have many endogenous variables in the right hand side of the test equation, which means we have fewer options considered reliable.

When there are many endogenous variables, an alternative is to focus on a subset of the parameters. We use the Guggenberger et al. (2012) test that is based on the Anderson-Rubin (AR) statistic (Anderson, Rubin et al. (1949)) that uses the limited information maximum likelihood (LIML) estimates for the strongly identified parameters. The author shows that this subset AR test has correct asymptotic size, while subset tests based on the Lagranger Multiplier statistic are distorted asymptotically and, because the LM statistic appears in the subset Conditional Likelihood (CLR) subset test, Guggenberger et al. (2012) conjecture that the latter test is also distorted[9].

4.3.2 Diagnostic Tests

To estimate the models of interest, we need instruments that are not only exogenous, but correlated with the endogenous variables. In order to test the instruments validity, we rely on the Sargan test of overidentifying restrictions, where the null hypothesis is that instruments are exogenous. Of course, we are aware that weak instruments problem make the Sargan test unreliable.

Regarding the presence of weak instruments, we inspect the F-statistic of the first-stage regression of the TSLS estimator, and we employ the tests developed by Cragg and Donald (1993) and Kleibergen and Paap (2006). The Cragg-Donald statistic is based on the eigenvalue of the matrix version of the F-statistic from the first-stage TSLS regression. This test assumes that error term is i.i.d and its critical values were tabulated by Yogo (2004). When the i.i.d. assumption is no longer valid, the reported statistic is the

[9] Another alternative to make inference on a subset of parameters is to use projection methods, as in Dufour and Taamouti (2005). However, Guggenberger et al. (2012) also shows that the subset AR has non-worse power than projection-type methods.

Kleibergen-Paap statistic, which allows the use of heteroscedasticity and autocorrelation consistent (HAC) estimators for the covariance matrix. Thus, we employ such test along with GMM-CUE estimator. In this case, the critical values are the ones tabulated by Yogo and Stock (2005) for the LIML case.

The log-linear representation of the consumer's Euler equations comes from log-normality and homocedasticity assumptions. These auxiliary assumptions implies that the error term is conditionally Gaussian, homoscedastic and uncorrelated with elements of the conditioning set $\mathcal{I}_{t-1}$. Furthermore, the error term must be independent of any function of the variables in $\mathcal{I}_{t-1}$. Following Gomes and Issler (2017), we investigate these restrictions by means of residual-based tests of normality, conditional homoskedasticity and serial correlation, and the Ramsey Regression Equation Specification Error Test (RESET). It is worth mentioning that we apply versions of these diagnostic tests suitable for instrumental variable setting.

To investigate whether residuals are normally distributed, we use the test developed by D'agostino, Belanger and Jr (1990), whose the null hypothesis is that the series has normal distribution. For heteroscedasticity, we use a test for instrumental variables developed by Pagan and Hall (1983) where the null hypothesis is that residuals are homoskedastic. To do so, we use the full set of instruments as indicator variables hypothesized to be related to the heteroscedasticity in the log-linear Euler equations. For serial correlation, we use a test proposed by Cumby and Huizinga (1992). The null hypothesis is that the residuals of the regression is a moving average up to order q against the alternative that the autocorrelations are nonzero at lags greater than q. We use $q = 0$, which means that we test whether the residual series is uncorrelated against the alternative that there is serial correlation of first order. The test is robust to conditional heteroscedasticity and an autocorrelation-robust covariance matrix is computed using the Bartlett kernel. Finally, for testing the omission of higher order variables, we use the Pesaran and Taylor (1999) version of the RESET test. Under the null that there are no neglected nonlinearities, and the residuals should be uncorrelated with low-order polynomials in the forecast values of the dependent variable. We employ a polynomial of third degree.

4.3.3 Structural break tests

Parameter instability is tested using a methodology proposed by Hall, Han and Boldea (2012b). It allows us to estimate the break points simultaneously with the model parameters. Their methodology can also handle endogenous regressors in the test equation and, consequently, allows us to test the presence of breaks directly in the consumer's Euler equation.

The methodology developed by Hall, Han and Boldea (2012b) is an extension of the structural break tests from Bai and Perron (1998). The latter developed a method for determining the structural breaks of linear models in an Ordinary Least Squares (OLS) framework and the former extends these tests by allowing for endogenous regressors that are estimated via a Two Stage Least Squares (TSLS) based procedure.

As in BaiPerron98, the testing procedure consists on partitioning the data and testing if coefficients are different from in each partition. But the main difference when testing breaks with endogenous regressors is the possibility of presence of breaks in the first stage as well, which makes the procedure and derivation of test statistics much more complicated than the Bai and Perron (1998) break test.

In the case of stable first stage, we incorporate the usual first stage estimates in the second stage equation and use two suitable tests to find the break dates. The first is a test of no break against m breaks and the second is a sequential test of m breaks against $m+1$ breaks. The first test is performed using a F statistic. In order to perform the second test, the following strategy is used: in the first step, use the $Sup - F_T(1;p)$ statistic to test the null hypothesis of no breaks. In the second step, use the $F_T(2|1)$ to test the hypothesis of one break against the hypothesis of 2 breaks. If $F_T(2|1)$ is not statistically significant, $\hat{m}_T = 1$. Otherwise, we go to the next step. In the l^{th} step, test $F_T(l+1|l)$ and, if the statistic is not significant, conclude there are l break points; otherwise, we continue until we reach a limit L. If all statistics found in these sequence are significant, conclude that there are, at least, L break points[10].

[10] More details on the break dates estimation can be found on Hall12

When the reduced form is unstable, Hall12 use tests with fixed break points, on the dates we found a break in the first stage, combined with the tests derived for the case when the reduced form is stable. In order to perform the tests, we follow the procedure the described bellow:

1. Estimate the reduced form and test for multiple changes in parameters using, for example, the methods in BaiPerron98.

2. If the reduced form is judged stable, test for changes in the parameter of the structural equation using the statistics derived by Hall12.

3. If the reduced form is unstable, estimate the number of breaks using, for example, the methods in BaiPerron98. Next, using the estimated breaks in the reduced form, test and estimate the breaks in the structural equation using the following procedure:

   a) Divide the sample using the breaks estimated in the reduced form;

   b) Using the divided sample, test the presence of breaks in the structural equation in each subsample;

   c) Conditional on the breaks found in the previous step, test if there is a break in the same location of the breaks found in the reduced form;

   d) The number of breaks is the sum of the breaks found in the structural equation in the two previous steps.

Note that the coefficients of the test equation and the break dates are estimated jointly.

4.4 Results

In this section, we report the results. Section 4.4.1 presents the data and some descriptive statistics. Section 4.4.2 presents the point estimates and instruments sets we adopted. Section 4.4.3 reports the results from the investigation of the parameter stability using the endogenous structural break tests. Finally, section 4.4.4 covers the results from the robust confidence sets estimation.

4.4.1 Data and descriptive statistics

We use monthly data extracted from the National Income and Product Accounts (NIPA) and the Federal Reserve Economic Data (Fred), covering the period from Jun-59 to Jan-18.

The consumption variable (C_t) is defined as the per capita real consumption of non-durables and services. For the calculation, we use the seasonally adjusted aggregate consumption of non-durables and services obtained from the NIPA tables and transformed it into "real per capita" dividing by the population and deflating by the personal consumption expenditure index (π_t), both available in the NIPA tables. The income variable (Y_t) is defined as the the per capita disposable income, where the disposable income variable is the seasonally adjusted disposable personal income obtained from the NIPA tables and is also divided by the population and deflated using the personal consumption expenditure index.

The credit (D_t) and interest rate (r_t) come from the Fred data base. The consumer credit is the seasonally adjusted total consumer credit outstanding and the interest rate is the 3 month treasury bill. Both variables were deflated using the personal expenditures index. The consumer credit was also transformed into per capita values using the population from the NIPA tables. Table 4.1 shows the summary statistics of the data, and figure 4.1 plots the time series evolution. The variables are defined as the annual percentual change.

4.4.2 Specification and Estimators Comparison

In this section we compare three different specifications for the consumption model using two instrument sets and four estimation methods. The results are reported on tables 4.2, 4.3 and 4.4. Each table contains the results for one specification. The Instrument Set 1 includes the first lag of consumption, habit, interest, income, credit and inflation; the

Table 4.1 – Descriptive Statistics

	mean	sd	min	median	max
$\Delta \ln C$	2.2339	4.2708	-15.4685	2.2047	21.8391
$\Delta \ln Y$	2.0623	8.6377	-77.7148	2.1601	65.8857
Π	3.2140	2.9647	-13.6525	2.7205	14.5722
r	1.2381	2.7846	-8.1844	1.2283	13.8423
$\Delta \ln D$	3.1330	6.7209	-39.3652	3.3333	51.4435

Notes: The table shows the mean, standard deviation, minimum, median and maximum for the consumption, credit and income annualized monthly real growth rate of the per capita series, the annual real interest rate and the annual inflation.

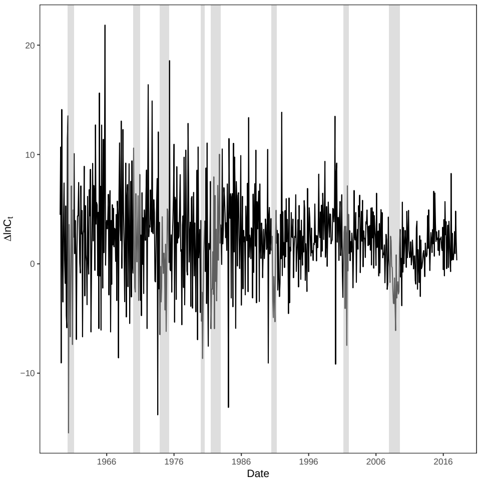
Instrument Set 2 includes the second lag of the consumption, habit, interest, income, credit and inflation.

Table 4.2 present the results for the specification (4.13).The Instrument Set 1 point estimates show strong support for habit persistence and debt, little support for income (also estimated with an unexpected sign) and no support for interest rate. When we look at the estimates obtained with Instrument Set 2, there is evidence only for rule-of-thumb behaviour. However, comparing the diagnostics, Instrument Set 1 results suffer less with weak instruments, as indicated by Cragg-Donald and First-Satage F statistics. Regarding the exogeneity test, when using Instrument Set 2, the Sargan test rejects the four estimation methods. The serial correlation test is not rejected just for the TSLS when using Instrument Set 2, but normality was rejected for all specifications. The diagnostic tests suggest that the Instrument Set 1 results are more reliable.

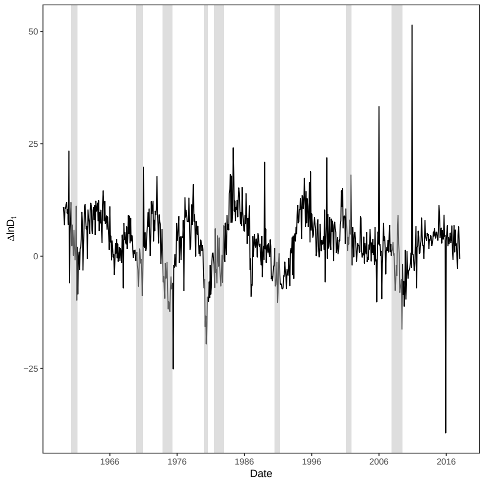
Table 4.3 show the results for the specification (4.14), without income growth. The estimates using Instrument Set 1 indicate that habit and debt are important factors, but with the Instrument Set 2, they indicate that debt is now relevant (when compared to the results in table 4.2). The diagnostics with the Instrument Set 1 reject the presence of weak instruments, as indicated by the high First-Stage F and Cragg-Donald statistics, and the Sargan, serial correlation RESET tests are not rejected. The diagnostics for the Instrument Set 2 indicate that the regressions are affected by weak instruments and the specification is rejected by the Sargan test.

Table 4.4 specification excludes the debt growth instead of income growth when

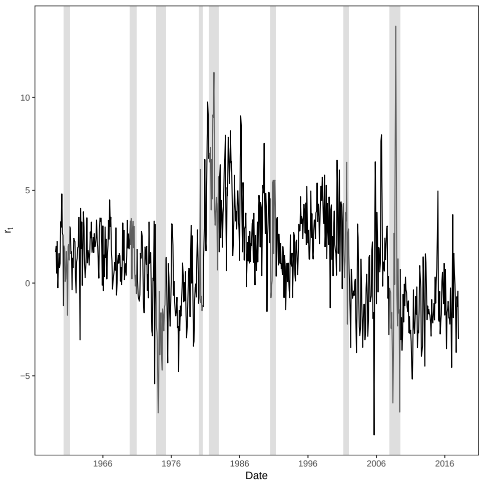
Figure 4.1 – Growth Rate of the Series



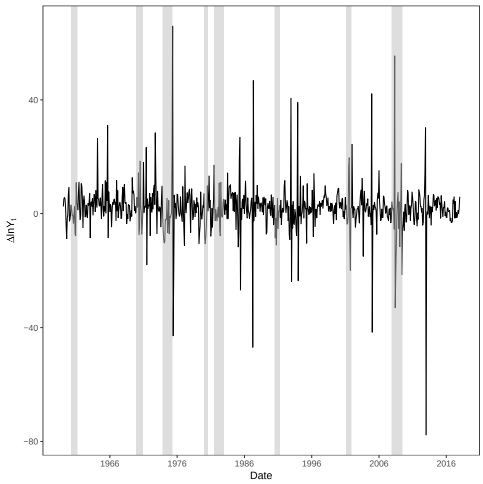
(a) Consumption



(b) Credit



(c) Interest



(d) Income

Notes: The plots show the consumption, credit and income annualized real growth rate of the per capita series and the annual real interest rate. The grey areas represent the recession dates from the NBER.

compared with table 4.3. As we can notice, habit remains significant in the estimation with Instrument Set 1 and interest and income are not relevant. The point estimates with Instrument Set 2 show support for income as in table 4.2 results. The inclusion of the income in the equation makes the weak instrument problem reappear. As the First-Stage F statistics suggest, the income variable is difficult to predict and the Cragg-Donald statistic indicate the presence of weak instruments. The serial correlation test shows that it is adequate to estimate the regression using the first lags as instruments.

Table 4.2 – Specification (4.13)

	Instruments: Set 1				Instruments: Set 2			
	TSLS	LIML	Fuller-k	GMM-CUE	TSLS	LIML	Fuller-k	GMM-CUE
$\Delta \ln C_{t-1}$	-0.2282***	-0.2284***	-0.2283***	-0.2284***	-0.1034	0.5053	0.2845	0.6072
	(0.0422)	(0.0434)	(0.0427)	(0.0441)	(0.1547)	(0.6485)	(0.4275)	(0.4910)
$r_{i,t}$	0.1134	0.1176	0.1153	0.1184	0.0470	-0.1074	-0.0515	-0.1107
	(0.0968)	(0.0998)	(0.0982)	(0.1059)	(0.0996)	(0.2902)	(0.2070)	(0.2199)
$\Delta \ln Y_t$	-0.2132*	-0.2413*	-0.2264*	-0.2412**	0.2639**	1.2650	0.8999*	1.5013***
	(0.1154)	(0.1239)	(0.1193)	(0.1183)	(0.1295)	(0.8499)	(0.5218)	(0.4243)
$\Delta \ln D_t$	0.2304***	0.2402***	0.2350***	0.2402***	0.0606	-0.1829	-0.0945	-0.2271
	(0.0649)	(0.0681)	(0.0664)	(0.0691)	(0.0566)	(0.2417)	(0.1570)	(0.1577)
Constant	2.3229***	2.3454***	2.3335***	2.3441***	1.6763***	-0.7823	0.1133	-1.3525
	(0.2732)	(0.2827)	(0.2776)	(0.2985)	(0.4516)	(2.2682)	(1.4380)	(1.3904)
T	705	705	705	705	705	705	705	705
First-Stage F [statistic]								
$\Delta \ln C_{t-1}$					9.3372			
$r_{i,t}$	132.5546				65.1893			
$\Delta \ln Y_t$	7.8760				3.6600			
$\Delta \ln D_t$	52.0612				42.5329			
Instrument Relevance [statistic]								
Cragg-Donald	4.7192	4.7192	4.7192	4.5873	2.4043	2.4043	2.4043	2.2028
Exogeneity Tests [p-value]								
Sargan	0.3609	0.3708	0.3680	0.3836	0.0000	0.0024	0.0020	0.0039
Log-normality Tests [p-value]								
Ser. Correl.	0.6767	0.5493	0.6181	0.5494	0.2334	0.0126	0.0129	0.0145
Heterosk.	0.2450	0.3158	0.2781	0.3156	0.7812	0.9105	0.9359	0.8985
RESET	0.5724	0.5979	0.5840	0.5987	0.4510	0.2617	0.2537	0.2836
Normality	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The Instrument Set 1 uses the first lag of habit, interest, income, credit and inflation; the Instrument Set 2 uses the second lag of the consumption, habit, interest, income, credit and inflation.

Table 4.3 – Specification (4.14)

	Instruments: Set 1				Instruments: Set 2			
	TSLS	LIML	Fuller-k	GMM-CUE	TSLS	LIML	Fuller-k	GMM-CUE
$\Delta \ln C_{t-1}$	-0.2291***	-0.2292***	-0.2292***	-0.2292***	-0.2725*	-0.3425	-0.3366	-0.2121
	(0.0362)	(0.0362)	(0.0362)	(0.0368)	(0.1416)	(0.2208)	(0.2152)	(0.1438)
$r_{i,t}$	0.0743	0.0738	0.0740	0.0738	0.1121	0.1164	0.1159	0.1060
	(0.0811)	(0.0813)	(0.0812)	(0.0866)	(0.0931)	(0.0985)	(0.0982)	(0.0996)
$\Delta \ln D_t$	0.1750***	0.1755***	0.1753***	0.1757***	0.1292***	0.1351***	0.1345***	0.1210**
	(0.0457)	(0.0459)	(0.0458)	(0.0479)	(0.0461)	(0.0520)	(0.0516)	(0.0481)
Constant	2.1081***	2.1072***	2.1076***	2.1066***	2.2999***	2.4318***	2.4212***	2.1987***
	(0.2202)	(0.2205)	(0.2203)	(0.2355)	(0.3433)	(0.4592)	(0.4507)	(0.3551)
T	705	705	705	705	705	705	705	705
First-Stage F [statistic]								
$\Delta \ln C_{t-1}$					10.6166			
$r_{i,t}$	165.6115				75.6711			
$\Delta \ln D_t$	63.3649				50.7290			
Instrument Relevance [statistic]								
Cragg-Donald	62.5313**	62.5313**	62.5313**	56.9270**	9.3613	9.3613	9.3613	9.0376
Exogeneity Tests [p-value]								
Sargan	0.3261	0.3261	0.3261	0.3391	0.0000	0.0000	0.0000	0.0000
Log-normality Tests [p-value]								
Ser. Correl.	0.7038	0.7055	0.7047	0.7046	0.8388	0.5855	0.6043	0.9036
Heterosk.	0.0408	0.0409	0.0409	0.0410	0.0483	0.0528	0.0524	0.0434
RESET	0.6281	0.6284	0.6283	0.6316	0.4298	0.6864	0.6681	0.2826
Normality	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01. The Instrument Set 1 uses the first lag of habit, interest, income, credit and inflation; the Instrument Set 2 uses the second lag of the consumption, habit, interest, income, credit and inflation.

Table 4.4 – Specification (4.15)

	Instruments: Set 1				Instruments: Set 2			
	TSLS	LIML	Fuller-k	GMM-CUE	TSLS	LIML	Fuller-k	GMM-CUE
$\Delta \ln C_{t-1}$	-0.1981***	-0.1967***	-0.1971***	-0.1992***	0.0837	0.5290	0.4301	0.5621
	(0.0400)	(0.0412)	(0.0408)	(0.0423)	(0.1945)	(0.4495)	(0.3833)	(0.3928)
$r_{i,t}$	0.1744*	0.1833*	0.1805*	0.2005*	0.0318	-0.0810	-0.0560	-0.0565
	(0.0926)	(0.0963)	(0.0951)	(0.1055)	(0.1149)	(0.2139)	(0.1884)	(0.1535)
$\Delta \ln Y_t$	-0.1374	-0.1715	-0.1606	-0.1779*	0.3875***	0.9006**	0.7848**	1.0239***
	(0.1010)	(0.1111)	(0.1079)	(0.1050)	(0.1353)	(0.3831)	(0.3168)	(0.2714)
Constant	2.7410***	2.7967***	2.7790***	2.7946***	1.2143**	-0.6883	-0.2620	-1.0453
	(0.2715)	(0.2868)	(0.2818)	(0.3055)	(0.5969)	(1.5349)	(1.2845)	(1.2009)
T	705	705	705	705	705	705	705	705
First-Stage F [statistics]								
$\Delta \ln C_{t-1}$					8.3617			
$r_{i,t}$	163.9069				78.1584			
$\Delta \ln Y_t$	7.7162				4.2151			
Exogeneity Tests [statistics]								
Sargan	0.1691	0.1778	0.1769	0.2475	0.0004	0.0061	0.0057	0.0087
Instrument Relevance [p-value]								
Cragg-Donald	7.0348	7.0348	7.0348	7.0418	3.2671	3.2671	3.2671	3.0814
Log-normality Tests [p-value]								
Ser. Correl.	0.7229	0.7828	0.7607	0.7383	0.0672	0.0073	0.0085	0.0087
Heterosk.	0.0182	0.0296	0.0253	0.0326	0.8667	0.8704	0.8829	0.8562
RESET	0.9643	0.9745	0.9709	0.9836	0.1078	0.1124	0.1006	0.1275
Normality	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The Instrument Set 1 uses the first lag of habit, interest, income, credit and inflation; the Instrument Set 2 uses the second lag of the consumption, habit, interest, income, credit and inflation.

Overall, the results from tables 4.2, 4.3 and 4.4 show that, with Instrument Set 1, we find more statistically significant and stable estimates across the estimation methods (especially if we consider the habit formation coefficients), the First-Stage F statistics for all the endogenous are higher, the Cragg-Donald statistics are higher (but not always enough to reject the instruments are weak instrument) and the instrument exogeneity tests are not rejected. The log-normality tests, however, indicate that for both sets the residuals are not normal. It´s also important to notice that the null hypothesis of no serial correlation is never rejected.

Regarding the predictability factors, for the Instrument Set 1, habit and debt are important predictors. For Instrument Set 2, income is relevant. These results are very likely to be contested because the instrument diagnostics indicate a weak instrument problem, especially with Instrument Set 2. Because the diagnostics are favorable to the use of first lags in the instrument set, in the next section we use this set in order to test the stability of the coefficients.

4.4.3 Endogenous Breaks

We now employ endogenous break tests in order to assess the parameters' stability. Based on the diagnostics from section 4.3.2, we choose the instrument set containing the first lag of the endogenous variables, consumption growth and deflator to perform the tests. The results are reported in table 4.5 where the header contains the period found in the break tests and the body of the table shows the estimated coefficients for each subsample.

When performing the break tests, we limit the number of breaks in the first stage regression to one break for each endogenous variable and another break in the second stage regression. With Specification 1, there were two breaks in the first stage: Feb-81 and Sep-95, but none of them are present in the second stage in which a break was found in Dec-06. For the Specification 2, we found two breaks in the first stage as well: one in May-75 and another in Sep-95. However, both breaks were not present in the second stage. In the second stage equation, we found a break in Dec-06 as well.

Table 4.5 – Endogenous Breaks – Instruments: Set 1

	Specification 1		Specification 2	
	Jun-59 Dec-06	Jan-07 Jan-18	Jun-59 Dec-06	Jan-07 Jan-18
Constant	2.5656**	-0.1365**	2.5482**	-0.2215**
	(0.061)	(0.0393)	(0.0649)	(0.043)
$\Delta \ln Y_t$			0.0343	-0.0864
			(0.0988	(0.1285
$r_{i,t}$	0.0097	-0.6219**	-0.0332	-0.6597**
	(0.0919)	(0.1827)	(0.0919)	(0.2051)
$\Delta \ln C_{t-1}$	-0.2588**	-0.02	-0.2614**	-0.02
	(0.046)	(0.0925)	(0.0452)	(0.1029)
$\Delta \ln D_t$	0.1628*	0.367**	0.169	0.4514**
	(0.095)	(0.1444)	(0.1134)	(0.1894)

Results estimated using Hall12 algorithm. The header shows the beginning and ending dates of the sub-samples generated after the computation of break dates. The coefficients in the body of the table were jointly estimated with the break date.

The results in table 4.5 indicate that, after Jan-07, both credit and interest rate became more relevant to predict the consumption and income never was relevant. However, the interest rate coefficient has an unexpected sign and we should interpret those results with caution, especially when we include the income in the specification, because it´s likely that the results are affected by the weak instruments problem. Despite this issue, the coefficients present clear differences before and after the break and we are going to use the break date in order to generate confidence intervals that are robust to weak instruments in the next section.

The break test from the table 4.5 indicate the presence of a break in Dec-06 and Brady (2008) also found a break in Dec-83. Thus, we use those breaks to divide our sample and re-estimate the coefficients for three different sub-samples. The estimations are performed using TSLS and the results are reported in table 4.6.

The results from table 4.6 indicate that the the habit was important prior to Jan-07, the debt is relevant prior to Jan-84 and after Jan-07, the income is not correlated with consumption and the interest rate is important after Jan-07. We must notice, however, that the specifications with income are affected by the weak instrument problem, as we

Table 4.6 – Sub-Sample Estimation (Instruments: Set 1)

	Specification 1			Specification 2		
	Jun-59 Dec-83	Jan-84 Dec-06	Jan-07 Jan-18	Jun-59 Dec-83	Jan-84 Dec-06	Jan-07 Jan-18
$\Delta \ln C_{t-1}$	-0.2530***	-0.3056***	-0.2868	-0.2534***	-0.3042***	-0.2684
	(0.0595)	(0.0567)	(0.2380)	(0.0539)	(0.0572)	(0.2102)
$r_{i,t}$	0.0899	0.0246	-0.6568**	0.0286	0.0253	-0.6431**
	(0.2433)	(0.1382)	(0.3155)	(0.1550)	(0.1399)	(0.2923)
$\Delta \ln D_t$	0.2515*	0.0744	0.5142*	0.2507***	0.0810	0.4638**
	(0.1409)	(0.0684)	(0.3056)	(0.0623)	(0.0679)	(0.2185)
$\Delta \ln Y_t$	-0.1395	0.0415	-0.0488			
	(0.4235)	(0.0730)	(0.1668)			
constant	2.6325***	2.8133***	-0.0485	2.3661***	2.8716***	-0.0143
	(0.6542)	(0.4037)	(0.5711)	(0.4026)	(0.3943)	(0.5163)
T	296.0000	276.0000	133.0000	296.0000	276.0000	133.0000
First-Stage F [statistic]						
$r_{i,t}$	54.4168	43.6661	8.8017	68.2563	54.7077	10.7808
$\Delta \ln D_t$	51.7254	23.0370	1.5041	59.4429	28.7635	1.8400
$\Delta \ln Y_t$	3.0647	6.4812	2.0273			
Exogeneity Tests [p-value]						
Sargan	0.0008	0.2990	0.8328	0.0258	0.2669	0.8001
Instrument Relevance [statistic]						
Cragg-Donald	0.5519	6.1136	0.5688	48.7497**	24.2859**	1.5530
Log-normality Tests [p-value]						
Ser. Correl.	0.7076	0.6083	0.8945	0.3310	0.6122	0.8901
Heterosk.	0.8194	0.0118	0.9964	0.5705	0.0105	0.9800
RESET	0.1152	0.1388	0.9473	0.4256	0.1709	0.9505
Normality	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

can see from the Cragg-Donald statistic and the First-Stage F statistic for the income growth. In the sub-samples prior to Jan-07, just the income has weak instruments, but after Jan-07 the debt also suffers from this problem[11].

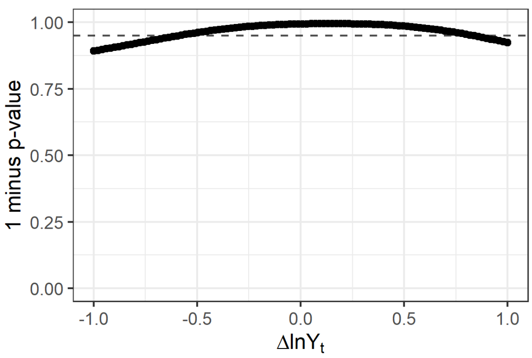
A weakness of this procedure is that the breaks and coefficients are estimated jointly and, due to weak instruments, they may be not so reliable. In the next session, we use the break dates from table 4.6 and generate robust confidence intervals for the variables with weak instruments.

[11] The interest rate also have a First-Stage F statistic bellow the rule-of-thumb threshold of 10, but we focus on income and debt growth that have much lower statistics

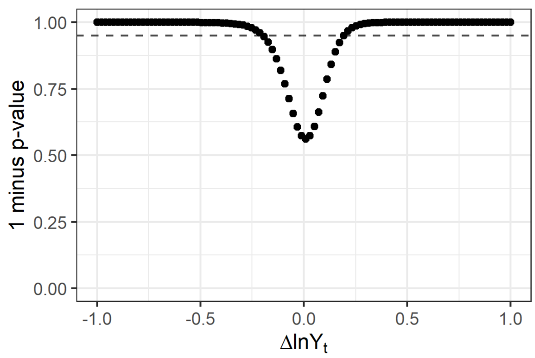
4.4.4 Robust Confidence Sets

Table 4.6 results show that from the period from Jun-59 to Dec-06 it is difficult to predict the income growth and from Jan-07 to Jan-18 both income and debt growth are difficult to predict. To overcome this problem, we also report the results using robust confidence sets based on the Subset AR. The specification used to generate the intervals includes habit persistence, income growth, interest rate and credit growth (equation (4.13)) and robust intervals are calculated for the each sub-sample for the variables with low first-stage F statistics. Thus, for the period of Jun-59/Dec-83 and Jan-84/Dec-06, we assume income growth is weakly identified (and the remainder variables are strongly identified) and for the period of Jan-07-Jan-18, we assume both income and debt growth are weakly identified. Figure 4.2 reports the results for each sub-sample.

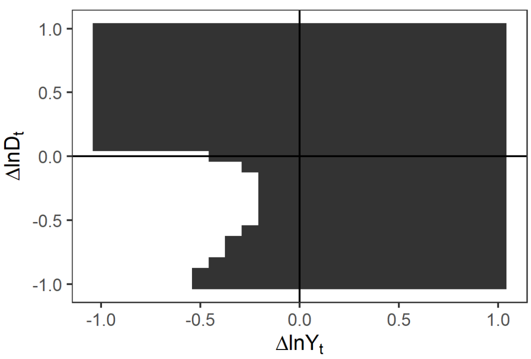
Figure 4.2 – Subset AR - Break in December 1983 and December 2006



(a) before 1983m12



(b) 84m01 until 2006m12



(c) after 2007m01

Confidence sets generated by the Subset AR. In panels (a) and (b) the 95% confidence interval for the income growth coefficient is given by values on the x-axis where the *1 minus p-value* is bellow the threshold of 0.95. In panel (c) the shaded area corresponds to the 95% confidence set for the income and debt growth coefficients.

In figure 4.2, panel (a) shows the results for the period before Dec-83. We reject that income growth is not relevant, but its coefficient may be both positive or negative. In the period from Jan-84 to Dec-06, panel (b), we cannot reject that the coefficient of income is different from zero. Finally, panel (c) show the confidence set for the period post Jan-07 and the results are not much informative, since we cannot reject both coefficients are positive or zero.

In line with Brady (2008) results, we find that income growth is statistically relevant in the beginning of the sample and later it was not relevant anymore. However, in the most recent period, after Jan-07[12], we do not have enough information to conclude that consumers are smoothing consumption. Kiley (2010) does not consider the parameters could change over time and concludes that habit persistence and rule-of-thumb behavior are relevant factors. However these results show that, indeed those two variables were important in the past but in the past decade there no evidence for habit persistence and we do not have much information on debt and income growth.

4.5 Conclusions

This work investigates the consumption growth predictability for the US. To accomplish this task, we build a consumption model that takes into account four factors: intertemporal substitution (returns on assets), habit formation (lagged consumption), rule-of-thumb behavior (current income) and credit conditions (credit level).

In general, the literature estimates such models assuming the following auxiliary assumptions: log-normality of consumption and assets returns, parameters constancy over time and that valid instruments are available. Concerned with these issues, we (*i*) employ many diagnostic tests to evaluate the specifications used, (*ii*) test the stability of the parameters and (*iii*) consider the use of the first lag of endogenous and dependent variables in the instrument set to mitigate the weak instruments problem.

The common practice in the literature is the use of instruments lagged at least twice, however, instruments lagged once reduces the weak instruments problem and they

[12] Brady (2008) data ends in Sep-05 and there is no intersection between our most recent sub-sample and his data.

have a better performance in the diagnostics when compared to the second lags instrument set. However, even with the use of the first lag, some endogenous variables are still difficult to predict and we employ robust confidence sets for some coefficients. Moreover, we find evidence of parameter instability and, for this reason, we also use the endogenous structural break tests in the testing specifications.

Finally, we generate robust confidence intervals for the sub-samples defined by the break dates Dec-83 and Dec-06. The results show that from Jun-59 to Dec-83, habit persistence, income and debt growth are relevant predictors. From Jan-84 to Dec-06, there is not evidence for rule-of-thumb behavior and habit persistence is the only relevant factor. In the last sub-sample, after Jan-07, habit is not relevant anymore and there is not enough information to estimate the coefficients for income and debt growth.

Bibliography

ABEL, A. B. Asset prices under habit formation and catching up with the joneses. **American Economic Review and Statistics**, v. 80, n. 2, p. 38–42, 1990.

ALTONJI, J. G.; SIOW, A. Testing the response of consumption to income changes with (noisy) panel data. **The Quarterly Journal of Economics**, MIT Press, v. 102, n. 2, p. 293–328, 1987.

ANDERSON, T. W.; RUBIN, H. et al. Estimation of the parameters of a single equation in a complete system of stochastic equations. **The Annals of Mathematical Statistics**, Institute of Mathematical Statistics, v. 20, n. 1, p. 46–63, 1949.

ARAUJO, F.; ISSLER, J. V. A stochastic discount factor approach to asset pricing using panel data asymptotics. Graduate School of Economics, Getulio Vargas Foundation, Working Paper Series 717. 2011.

BACCHETTA, P.; GERLACH, S. Consumption and credit constraints: International evidence. **Journal of Monetary Economics**, Elsevier, v. 40, n. 2, p. 207–238, 1997.

BAI, J.; PERRON, P. Estimating and testing linear models with multiple structural changes. **Econometrica**, p. 47–78, 1998.

BLANCHARD, O. J.; MANKIW, N. G. "consumption: Beyond certainty equivalence. **American Economic Review**, v. 78, n. 2, p. 173–177, 1988.

BRADY, R. R. Structural breaks and consumer credit: Is consumption smoothing finally a reality? **Journal of macroeconomics**, Elsevier, v. 30, n. 3, p. 1246–1268, 2008.

BROWNING, M.; CROSSLEY, T. F. The life-cycle model of consumption and saving. **Journal of Economic Perspectives**, v. 15, n. 3, p. 3–22, 2001.

CAMPBELL, J. Y. Consumption-based asset pricing. In: CONSTANTINIDES, G. M.; HARRIS, M.; STULZ, R. M. (Ed.). **Handbook of the Economics of Finance**. [S.l.]: Elsevier, 2003. v. 1B, cap. 13, p. 801–885.

CAMPBELL, J. Y.; COCHRANE, J. H. By force of habit. a consumption-based explanation of aggregate stock market behavior. **Journal of Political Economy**, v. 107, p. 205–251, 1999.

CAMPBELL, J. Y.; MANKIW, N. G. Consumption, income, and interest rates: Reinterpreting the time series evidence. **NBER macroeconomics annual**, MIT Press, v. 4, p. 185–216, 1989.

_____. Permanent income, current income, and consumption. **Journal of Business & Economic Statistics**, Taylor & Francis, v. 8, n. 3, p. 265–279, 1990.

_____. The response of consumption to income: a cross-country investigation. **European economic review**, Elsevier, v. 35, n. 4, p. 723–756, 1991.

CAVALCANTI, C. B. Intertemporal substitution in consumption: an american investigation for brazil. **Brazilian Review of Econometrics**, v. 13, n. 2, p. 203–229, 1993.

CRAGG, J. G.; DONALD, S. G. Testing identifiability and specification in instrumental variable models. **Econometric Theory**, Cambridge Univ Press, v. 9, n. 02, p. 222–240, 1993.

CUMBY, R.; HUIZINGA, J. Testing the autocorrelation structure of disturbances in ordinary least squares and instrumental variables regressions. **Econometrica**, Wiley-Blackwell, v. 60, n. 1, p. 185–195, 1992.

D'AGOSTINO, R. B.; BELANGER, A.; JR, R. B. D. A suggestion for using powerful and informative tests of normality. **The American Statistician**, Taylor & Francis, v. 44, n. 4, p. 316–321, 1990.

DEATON, A. S. Saving and liquidity constraints. **Econometrica**, v. 59, p. 1221–1248, 1991.

DUFOUR, J.-M.; TAAMOUTI, M. Projection-based statistical inference in linear structural models with possibly weak instruments. **Econometrica**, Wiley Online Library, v. 73, n. 4, p. 1351–1365, 2005.

DUNN, K. B.; SINGLETON, K. J. Modeling the term structure of interest rates under non-separable utility and durability of goods. **Journal of Financial Economics**, v. 17, n. 1, p. 27–55, 1986.

EICHENBAUM, M. S.; HANSEN, L. P.; SINGLETON, K. J. A time series analysis of representative agent models of consumption and leisure choice under uncertainty. **The Quarterly Journal of Economics**, MIT Press, v. 103, n. 1, p. 51–78, 1988.

ENGELHARDT, G. V. Consumption, down payments and liquidity constraints. **Journal of Money, Credit and Banking**, v. 28, p. 255–271, 1996.

EPSTEIN, L. G.; ZIN, S. E. Substitution, risk aversion and the temporal behavior of consumption and asset returns: a theoretical framework. **Econometrica**, v. 57, p. 937–979, 1989.

______. Substitution, risk aversion, and the temporal behavior of consumption and asset returns: An empirical analysis. **Journal of Political Economy**, JSTOR, v. 99, n. 2, p. 263–286, 1991.

EVANS, P.; KARRAS, G. Private and government consumption with liquidity constraints. **Journal of International Money and Finance**, Elsevier, v. 15, n. 2, p. 255–266, 1996.

EVERAERT, G.; POZZI, L. The predictability of aggregate consumption growth in oecd countries: a panel data analysis. **Journal of Applied Econometrics**, Wiley Online Library, v. 29, n. 3, p. 431–453, 2014.

FERSON, W. E.; CONSTANTINIDES, G. M. Habit persistence and durability in aggregate consumption: Empirical tests. **Journal of Financial Economics**, v. 29, n. 2, p. 199–240, 1991.

FLAVIN, M. A. The adjustment of consumption to changing expectations about future income. **Journal of political economy**, The University of Chicago Press, v. 89, n. 5, p. 974–1009, 1981.

FUHRER, J. C. Habit formation in consumption and its implications for monetary-policy models. **American Economic Review**, v. 90, n. 3, p. 367–390, 2000.

GARBER, G. et al. Household debt and recession in brazil. In: **Handbook of US Consumer Economics**. [S.l.]: Elsevier, 2019. p. 97–119.

GARCIA, R.; LUSARDI, A.; NG, S. Excess sensitivity and asymmetries in consumption: An empirical investigation. **Journal of Money, Credit and Banking**, v. 29, p. 157–176, 1997.

GOMES, F. A. R. Consumo no brasil: teoria da renda permanente, formação de hábito e restrição à liquidez. **Revista Brasileira de Economia**, SciELO Brasil, v. 58, n. 3, p. 381–402, 2004.

______. Consumo no brasil: comportamento otimizador, restrição de crédito ou miopia? **Revista brasileira de Economia**, SciELO Brasil, v. 64, n. 3, p. 261–275, 2010.

______. Gasto do governo e consumo privado: Substitutos ou complementares? **Revista Brasileira de Economia**, SciELO Brasil, v. 67, n. 2, p. 219–234, 2013.

GOMES, F. A. R.; ISSLER, J. V. Testing consumption optimality using aggregate data. **Macroeconomic Dynamics**, Cambridge University Press, v. 21, n. 5, p. 1119–1140, 2017.

GOMES, F. A. R.; ISSLER, J. V.; SALVATO, M. A. Principais características do consumo de duráveis no brasil e testes de separabilidade entre duráveis e não-duráveis. **Revista brasileira de Economia**, SciELO Brasil, v. 59, n. 1, p. 33–60, 2005.

GOMES, F. A. R.; PAZ, L. S. Especificações para a função consumo: Testes para países da américa do sul. **Pesquisa e Planejamento Econômico**, Instituto de Pesquisa Econômica Aplicada (Ipea), v. 34, n. 1, p. 39–55, 2004.

______. Consumption in south america: myopia or liquidity constraints? **Economia Aplicada**, SciELO Brasil, v. 14, n. 2, p. 129–145, 2010.

______. Narrow replication of yogo (2004) estimating the elasticity of intertemporal substitution when instruments are weak. **Journal of Applied Econometrics**, v. 26, p. 1215–1216, 2011.

GUGGENBERGER, P. et al. On the asymptotic sizes of subset anderson–rubin and lagrange multiplier tests in linear instrumental variables regression. **Econometrica**, Wiley Online Library, v. 80, n. 6, p. 2649–2666, 2012.

HAHM, J. H. Consumption adjustment to real interest rates: Intertemporal substitution revisited. **Journal of Economic Dynamics and Control**, v. 22, p. 293–320, 1998.

HALL, A. R.; HAN, S.; BOLDEA, O. Inference regarding multiple structural changes in linear models with endogenous regressors. **Journal of econometrics**, Elsevier, v. 170, n. 2, p. 281–302, 2012.

______. Inference regarding multiple structural changes in linear models with endogenous regressors. **Journal of Econometrics**, Elsevier, v. 170, n. 2, p. 281–302, 2012.

HALL, R. E. Stochastic implications of the life cycle-permanent income hypothesis: theory and evidence. **Journal of political economy**, The University of Chicago Press, v. 86, n. 6, p. 971–987, 1978.

______. Intertemporal substitution in consumption. **Journal of political economy**, The University of Chicago Press, v. 96, n. 2, p. 339–357, 1988.

HANSEN, L. P.; SINGLETON, K. J. Generalized instrumental variables estimation of nonlinear rational expectations models. **Econometrica: Journal of the Econometric Society**, JSTOR, p. 1269–1286, 1982.

______. Stochastic consumption, risk aversion, and the temporal behavior of asset returns. **Journal of political economy**, The University of Chicago Press, v. 91, n. 2, p. 249–265, 1983.

HEATON, J. The interaction between time-nonseparable preferences and time aggregation. **Econometrica**, v. 61, n. 2, p. 353–385, 1993.

ISSLER, J. V.; ROCHA, F. d. P. Consumo, restrição à liquidez, e bem-estar no brasil. **Economia Aplicada**, v. 4, n. 4, p. 637–665, 2000.

JAPPELLI, T.; PAGANO, M. Consumption and capital market imperfections: An international comparison. **The American Economic Review**, JSTOR, p. 1088–1105, 1989.

JÚNIOR, F. A. de B.; DELALIBERA, B. R.; NETO, V. R. de P. Predictability of aggregate consumption in brazil: habits, non-separability between consumption and leisure, or credit constraint? **Brazilian Review of Econometrics**, v. 38, n. 1, p. 75–95, 2018.

KILEY, M. T. Habit persistence, nonseparability between consumption and leisure, or rule-of-thumb consumers: Which accounts for the predictability of consumption growth? **The Review of Economics and Statistics**, MIT Press, v. 92, n. 3, p. 679–683, 2010.

KLEIBERGEN, F.; PAAP, R. Generalized reduced rank tests using the singular value decomposition. **Journal of econometrics**, Elsevier, v. 133, n. 1, p. 97–126, 2006.

LUDVIGSON, S. Consumption and credit: a model of time-varying liquidity constraints. **Review of Economics and Statistics**, MIT Press, v. 81, n. 3, p. 434–447, 1999.

MANKIW, N. G. The permanent income hypothesis and the real interest rate. **Economics Letters**, Elsevier, v. 7, n. 4, p. 307–311, 1981.

MUELLBAUER, J. Habits, rationality and myopia in the life cycle consumption function. **Annales d'Economie et de Statistique**, v. 9, p. 47–70, 1988.

MÜLLER, K. Sectoral credit around the world, 1940-2014. **Available at SSRN 2923239**, 2017.

NEELY, C. J.; ROY, A.; WHITEMAN, C. H. Risk aversion versus intertemporal substitution: a case study of identification failure in the intertemporal consumption capital asset pricing model. **Journal of Business & Economic Statistics**, Taylor & Francis, v. 19, n. 4, p. 395–403, 2001.

PAGAN, A. R.; HALL, A. D. Diagnostic tests as residual analysis. **Econometric Reviews**, Taylor & Francis, v. 2, n. 2, p. 159–218, 1983.

PATTERSON, K. D.; PESARAN, B. The intertemporal elasticity of substitution in consumption in the united states and the united kingdom. **Review of Economics and Statistics**, v. 74, p. 573–584, 1992.

PESARAN, M. H.; TAYLOR, L. W. Diagnostics for iv regressions. **Oxford Bulletin of Economics and Statistics**, Wiley Online Library, v. 61, n. 2, p. 255–281, 1999.

REIS, E. et al. Renda permanente e poupança precaucional: Evidências empíricas para o brasil no passado recente. **Pesquisa e Planejamento Econômico**, v. 28, n. 2, p. 233–272, 1998.

SARANTIS, N.; STEWART, C. Liquidity constraints, precautionary saving and aggregate consumption: an international comparison. **Economic Modelling**, Elsevier, v. 20, n. 6, p. 1151–1173, 2003.

SHEA, J. Myopia, liquidity constraints, and aggregate consumption: a simple test. **Journal of money, credit and banking**, JSTOR, v. 27, n. 3, p. 798–805, 1995.

_____. Union contracts and the life-cycle/permanent-income hypothesis. **The American Economic Review**, JSTOR, p. 186–200, 1995.

SOMMER, M. Habit formation and aggregate consumption dynamics. **The BE journal of macroeconomics**, De Gruyter, v. 7, n. 1, 2007.

STOCK, J. H.; WRIGHT, J. H.; YOGO, M. A survey of weak instruments and weak identification in generalized method of moments. **Journal of Business & Economic Statistics**, Taylor & Francis, v. 20, n. 4, p. 518–529, 2002.

TALLARINI, T.; ZHANG, H. External habits and the cyclicality of expected stock returns. **Journal of Business**, v. 78, p. 1023–1048, 2005.

VAIDYANATHAN, G. Consumption, liquidity constraints and economic development. **Journal of Macroeconomics**, Elsevier, v. 15, n. 3, p. 591–610, 1993.

WEBER, C. E. Intertemporal non-separability and “rule of thumb” consumption. **Journal of Monetary Economics**, Elsevier, v. 49, n. 2, p. 293–308, 2002.

WEIL, P. The equity premium puzzle and the risk-free rate puzzle. **Journal of Monetary Economics**, v. 89, p. 401–421, 1989.

YOGO, M. Estimating the elasticity of intertemporal substitution when instruments are weak. **Review of Economics and Statistics**, MIT Press, v. 86, n. 3, p. 797–810, 2004.

YOGO, M.; STOCK, J. H. Identification and inference for econometric models. In: ANDREWS, D. W. K.; STOCK, J. H. (Ed.). **Essays in Honor of Thomas Rothenberg**. Cambridge: Cambridge University Press, 2005. cap. 5, p. 80–108.

APPENDIX A – TSLS, GMM and Fuller-k Results

This Appendix presents the estimation of equations 3.8, 3.9 and 3.10 for other three estimators: two-stage least square (TSLS), continuously updating GMM (CUE-GMM) and Fuller-k.

Table A.1 – TSLS estimations based on specification (3.8)

	$\mathbb{Y}^P$	$\mathbb{Y}^N$	$\mathbb{S}$	$\mathbb{Y}^P \cup \mathbb{Y}^N \cup \mathbb{S}$	$\mathbb{Y}^P$	$\mathbb{Y}^N$	$\mathbb{Y}^P \cup \mathbb{Y}^N$
$I_t^N \Delta \ln Y_t$	1.8869***	2.2673	1.4146	1.6203***	2.1394***	2.8597	1.7405***
	(0.6715)	(1.5866)	(1.1515)	(0.4210)	(0.5375)	(1.7730)	(0.4191)
$I_t^P \Delta \ln Y_t$	0.3820	-0.4656	1.2563*	0.4727	0.3394	-1.0767	0.3563
	(0.3253)	(1.8821)	(0.7478)	(0.2922)	(0.3320)	(2.1734)	(0.3000)
$r_{i,t}$	-0.1763	-0.2189	-0.0651	-0.0771			
	(0.3024)	(0.2736)	(0.1730)	(0.1187)			
constant	0.0131**	0.0236	0.0005	0.0091**	0.0110**	0.0274	0.0091**
	(0.0059)	(0.0226)	(0.0104)	(0.0046)	(0.0049)	(0.0279)	(0.0043)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
Sargan	0.8292	0.5754	0.8637	0.3421	0.8384	0.7416	0.5519
Test for $\mathcal{H}_0 : \pi_0 = \pi_1$ [p-value]							
$\mathcal{H}_1 : \pi_0 \neq \pi_1$	0.0844	0.4254	0.9290	0.0633	0.0155	0.3119	0.0263
Instrument Relevance [statistic]							
Anderson LM	6.4754**	0.7334	3.6755	19.1943***	15.9515***	0.8815	18.7059***
Cragg-Donald	1.6475	0.1746	0.9048	2.4096	4.5777	0.2102	3.6296
First-Stage F [statistic]							
$I_t^N \Delta \ln Y_t$	4.6316	7.3166	2.5171	3.0923	4.6316	7.3166	4.8074
$I_t^P \Delta \ln Y_t$	5.5812	1.7369	2.1434	2.6417	5.5812	1.7369	3.9720
$r_{i,t}$	4.2762	5.8685	25.4837	12.0186	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.4812	0.5168	0.4223	0.4330	0.7224	0.4382	0.5764
Heterosk.	0.0734	0.1662	0.1067	0.2331	0.0551	0.5543	0.1898
RESET	0.8915	0.9213	0.9972	0.3327	0.7965	0.8239	0.5187
Normality	0.0019	0.0355	0.1311	0.0038	0.0032	0.1222	0.0080

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.

Table A.2 – TSLS estimations based on specification (3.9)

	$\mathbb{Y}$	$\mathbb{Y}^P$	$\mathbb{S}$	$\mathbb{Y} \cup \mathbb{Y}^P \cup \mathbb{S}$	$\mathbb{Y}$	$\mathbb{Y}^P$	$\mathbb{Y} \cup \mathbb{Y}^P$
$\Delta \ln Y_t$	1.3208	1.8869***	1.4146	1.5127***	2.0566**	2.1394***	1.7907***
	(1.0597)	(0.6715)	(1.1515)	(0.4181)	(1.0066)	(0.5375)	(0.4549)
$I_t^P \Delta \ln Y_t$	-0.5277	-1.5049*	-0.1584	-1.0552*	-1.6703	-1.7999**	-1.3985**
	(1.6611)	(0.8721)	(1.7774)	(0.6134)	(1.5813)	(0.7438)	(0.6597)
$r_{i,t}$	-0.2527	-0.1763	-0.0651	-0.1186			
	(0.1576)	(0.3024)	(0.1730)	(0.1164)			
constant	0.0083	0.0131**	0.0005	0.0096**	0.0102	0.0110**	0.0090**
	(0.0096)	(0.0059)	(0.0104)	(0.0045)	(0.0100)	(0.0049)	(0.0044)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
Sargan	0.0771	0.8292	0.8637	0.1533	0.0769	0.8384	0.1599
Test for $\mathcal{H}_0 : \pi_1^P = 0$ [p-value]							
$\mathcal{H}_1 : \pi_1^P > 0$	0.6243	0.9560	0.5354	0.9555	0.8531	0.9912	0.9816
$\mathcal{H}_1 : \pi_1^P < 0$	0.3757	0.0440	0.4646	0.0445	0.1469	0.0088	0.0184
Instrument Relevance [statistic]							
Anderson LM	2.9896	6.4754**	3.6755	18.9579**	3.6039	15.9515***	18.1368***
Cragg-Donald	0.7301	1.6475	0.9048	2.1082	0.8864	4.5777	2.9565
First-Stage F [statistic]							
$\Delta \ln Y_t$	5.6211	5.2361	2.7572	2.6441	5.6211	5.2361	3.7260
$I_t^P \Delta \ln Y_t$	4.3765	5.5812	2.1434	2.3877	4.3765	5.5812	3.5220
$r_{i,t}$	15.2726	4.2762	25.4837	10.7948	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.3344	0.4812	0.4223	0.4019	0.6798	0.7224	0.5709
Heterosk.	0.0547	0.0734	0.1067	0.2400	0.0196	0.0551	0.0700
RESET	0.5743	0.8915	0.9972	0.2322	0.4959	0.7965	0.6277
Normality	0.0028	0.0019	0.1311	0.0021	0.0043	0.0032	0.0080

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.

Table A.3 – TSLS estimations based on specification (3.10)

	$\mathbb{Y}$	$\mathbb{Y}^N$	$\mathbb{S}$	$\mathbb{Y} \cup \mathbb{Y}^N \cup \mathbb{S}$	$\mathbb{Y}$	$\mathbb{Y}^N$	$\mathbb{Y} \cup \mathbb{Y}^N$
$I_t^N \Delta \ln Y_t$	0.5277	2.7329	0.1584	0.8379	1.6703	3.9364	0.6208
	(1.6611)	(3.4283)	(1.7774)	(0.6750)	(1.5813)	(3.8924)	(0.7640)
$\Delta \ln Y_t$	0.7931	-0.4656	1.2563*	0.6182*	0.3863	-1.0767	0.7573**
	(0.6503)	(1.8821)	(0.7478)	(0.3287)	(0.6310)	(2.1734)	(0.3816)
$r_{i,t}$	-0.2527	-0.2189	-0.0651	-0.1229			
	(0.1576)	(0.2736)	(0.1730)	(0.1161)			
constant	0.0083	0.0236	0.0005	0.0079	0.0102	0.0274	0.0038
	(0.0096)	(0.0226)	(0.0104)	(0.0049)	(0.0100)	(0.0279)	(0.0053)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
Sargan	0.0771	0.5754	0.8637	0.3450	0.0769	0.7416	0.2203
Test for $\mathcal{H}_0 : \pi_1^N = 0$ [p-value]							
$\mathcal{H}_1 : \pi_1^N > 0$	0.3757	0.2138	0.4646	0.1089	0.1469	0.1573	0.2093
$\mathcal{H}_1 : \pi_1^N < 0$	0.6243	0.7862	0.5354	0.8911	0.8531	0.8427	0.7907
Instrument Relevance [statistic]							
Anderson LM	2.9896	0.7334	3.6755	14.9146*	3.6039	0.8815	11.5084*
Cragg-Donald	0.7301	0.1746	0.9048	1.5692	0.8864	0.2102	1.7175
First-Stage F [statistic]							
$I_t^N \Delta \ln Y_t$	3.7910	7.3166	2.5171	3.2287	3.7910	7.3166	4.0826
$\Delta \ln Y_t$	5.6211	4.6889	2.7572	2.8508	5.6211	4.6889	3.4590
$r_{i,t}$	15.2726	5.8685	25.4837	11.4796	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.3344	0.5168	0.4223	0.3366	0.6798	0.4382	0.3822
Heterosk.	0.0547	0.1662	0.1067	0.2147	0.0196	0.5543	0.0704
RESET	0.5743	0.9213	0.9972	0.6219	0.4959	0.8239	0.6093
Normality	0.0028	0.0355	0.1311	0.0029	0.0043	0.1222	0.0102

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.

Table A.4 – CUE-GMM estimations based on specification (3.8)

	$\mathbb{Y}^P$	$\mathbb{Y}^N$	$\mathbb{S}$	$\mathbb{Y}^P \cup \mathbb{Y}^N \cup \mathbb{S}$	$\mathbb{Y}^P$	$\mathbb{Y}^N$	$\mathbb{Y}^P \cup \mathbb{Y}^N$
$I_t^N \Delta \ln Y_t$	1.8909***	2.8688	1.4093	2.2704***	2.1822***	3.6376	1.9466***
	(0.6483)	(2.2949)	(1.0523)	(0.4915)	(0.5343)	(2.7308)	(0.4295)
$I_t^P \Delta \ln Y_t$	0.3793	-1.1415	1.2554**	0.1012	0.3234	-1.9271	0.2469
	(0.3139)	(2.4852)	(0.6143)	(0.3438)	(0.3305)	(3.0453)	(0.3083)
$r_{i,t}$	-0.1761	-0.1844	-0.0644	-0.0426			
	(0.2873)	(0.4735)	(0.1424)	(0.1421)			
constant	0.0131**	0.0319	0.0005	0.0146***	0.0113**	0.0388	0.0110**
	(0.0056)	(0.0307)	(0.0089)	(0.0054)	(0.0049)	(0.0402)	(0.0044)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
J	0.8224	0.6559	0.8412	0.3352	0.8341	0.8662	0.5479
Test for $\mathcal{H}_0 : \pi_0 = \pi_1$ [p-value]							
$\mathcal{H}_1 : \pi_0 \neq \pi_1$	0.0733	0.3953	0.9213	0.0027	0.0120	0.3283	0.0077
Instrument Relevance [statistic]							
Kleibergen LM	3.0762	0.7207	2.5929	14.3631**	13.1880***	0.8431	14.0275**
Kleibergen F	0.8501	0.1727	0.6736	2.3757	4.6074	0.2021	3.6184
First-Stage F [statistic]							
$I_t^N \Delta \ln Y_t$	4.9143	8.2657	2.3331	3.5035	4.9143	8.2657	5.4355
$I_t^P \Delta \ln Y_t$	6.5248	1.6090	2.0232	3.1363	6.5248	1.6090	4.5102
$r_{i,t}$	1.4305	1.9025	17.7241	8.0870	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.4840	0.3400	0.4207	0.9191	0.7503	0.3719	0.7096
Heterosk.	0.0735	0.5789	0.1057	0.3269	0.0558	0.8659	0.1831
RESET	0.8846	0.9548	0.9972	0.7222	0.7987	0.9138	0.6072
Normality	0.0019	0.0657	0.1278	0.0033	0.0026	0.0595	0.0086

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.

Table A.5 – CUE-GMM estimations based on specification (3.9)

	$\mathbb{Y}$	$\mathbb{Y}^P$	$\mathbb{S}$	$\mathbb{Y} \cup \mathbb{Y}^P \cup \mathbb{S}$	$\mathbb{Y}$	$\mathbb{Y}^P$	$\mathbb{Y} \cup \mathbb{Y}^P$
$\Delta \ln Y_t$	1.0906	1.8909***	1.4093	2.7860***	6.6647*	2.1822***	2.5453***
	(1.0245)	(0.6483)	(1.0523)	(0.6650)	(3.6336)	(0.5343)	(0.5585)
$I_t^P \Delta \ln Y_t$	-0.0018	-1.5116*	-0.1540	-3.3960***	-9.5069	-1.8587**	-2.4919***
	(1.5612)	(0.8439)	(1.5589)	(0.9847)	(5.8817)	(0.7401)	(0.8119)
$r_{i,t}$	-0.2745**	-0.1761	-0.0644	-0.0884			
	(0.1334)	(0.2873)	(0.1424)	(0.2056)			
constant	0.0050	0.0131**	0.0005	0.0242***	0.0601	0.0113**	0.0154***
	(0.0087)	(0.0056)	(0.0089)	(0.0075)	(0.0378)	(0.0049)	(0.0055)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
J	0.0897	0.8224	0.8412	0.2451	0.3447	0.8341	0.2163
Test for $\mathcal{H}_0 : \pi_1^P = 0$ [p-value]							
$\mathcal{H}_1 : \pi_1^P > 0$	0.5005	0.9616	0.5392	0.9996	0.9452	0.9931	0.9986
$\mathcal{H}_1 : \pi_1^P < 0$	0.4995	0.0384	0.4608	0.0004	0.0548	0.0069	0.0014
Instrument Relevance [statistic]							
Kleibergen LM	2.2160	3.0762	2.5929	14.2694*	2.5767	13.1880***	14.4869**
Kleibergen F	0.5532	0.8501	0.6736	2.0618	0.6476	4.6074	2.8022
First-Stage F [statistic]							
$\Delta \ln Y_t$	6.0941	6.5296	2.7508	3.3167	6.0941	6.5296	4.5922
$I_t^P \Delta \ln Y_t$	4.4742	6.5248	2.0232	2.7761	4.4742	6.5248	4.1137
$r_{i,t}$	5.4029	1.4305	17.7241	6.5795	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.3113	0.4840	0.4207	0.3286	0.2129	0.7503	0.9091
Heterosk.	0.0757	0.0735	0.1057	0.6290	0.9790	0.0558	0.1562
RESET	0.6137	0.8846	0.9972	0.9952	0.8784	0.7987	0.8371
Normality	0.0112	0.0019	0.1278	0.0255	0.0008	0.0026	0.0009

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.

Table A.6 – CUE-GMM estimations based on specification (3.10)

	$\mathbb{Y}$	$\mathbb{Y}^N$	$\mathbb{S}$	$\mathbb{Y} \cup \mathbb{Y}^N \cup \mathbb{S}$	$\mathbb{Y}$	$\mathbb{Y}^N$	$\mathbb{Y} \cup \mathbb{Y}^N$
$I_t^N \Delta \ln Y_t$	0.0018	4.0102	0.1540	1.3613**	9.5069	5.5647	0.8667
	(1.5612)	(4.7182)	(1.5589)	(0.6747)	(5.8817)	(5.6922)	(0.7321)
$\Delta \ln Y_t$	1.0888*	-1.1415	1.2554**	0.5287	-2.8422	-1.9271	0.8528**
	(0.5836)	(2.4852)	(0.6143)	(0.3263)	(2.4296)	(3.0453)	(0.3636)
$r_{i,t}$	-0.2745**	-0.1844	-0.0644	-0.1272			
	(0.1334)	(0.4735)	(0.1424)	(0.1135)			
constant	0.0050	0.0319	0.0005	0.0107**	0.0601	0.0388	0.0044
	(0.0087)	(0.0307)	(0.0089)	(0.0048)	(0.0378)	(0.0402)	(0.0050)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
J	0.0897	0.6559	0.8412	0.2871	0.3447	0.8662	0.1595
Test for $\mathcal{H}_0 : \pi_1^N = 0$ [p-value]							
$\mathcal{H}_1 : \pi_1^P > 0$	0.4995	0.1989	0.4608	0.0234	0.0548	0.1655	0.1198
$\mathcal{H}_1 : \pi_1^P < 0$	0.5005	0.8011	0.5392	0.9766	0.9452	0.8345	0.8802
Instrument Relevance [statistic]							
Kleibergen LM	2.2160	0.7207	2.5929	10.4657	2.5767	0.8431	7.9015
Kleibergen F	0.5532	0.1727	0.6736	1.4053	0.6476	0.2021	1.4755
First-Stage F [statistic]							
$I_t^N \Delta \ln Y_t$	3.5748	8.2657	2.3331	3.5715	3.5748	8.2657	4.5866
$\Delta \ln Y_t$	6.0941	4.6120	2.7508	3.3924	6.0941	4.6120	4.0212
$r_{i,t}$	5.4029	1.9025	17.7241	7.4566	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.3113	0.3400	0.4207	0.4879	0.2129	0.3719	0.4832
Heterosk.	0.0757	0.5789	0.1057	0.1575	0.9790	0.8659	0.0532
RESET	0.6137	0.9548	0.9972	0.7270	0.8784	0.9138	0.6301
Normality	0.0112	0.0657	0.1278	0.0029	0.0008	0.0595	0.0381

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.

Table A.7 – Fuller-k estimations based on specification (3.8)

	$\mathbb{Y}^P$	$\mathbb{Y}^N$	$\mathbb{S}$	$\mathbb{Y}^P \cup \mathbb{Y}^N \cup \mathbb{S}$	$\mathbb{Y}^P$	$\mathbb{Y}^N$	$\mathbb{Y}^P \cup \mathbb{Y}^N$
$I_t^N \Delta \ln Y_t$	1.8155***	1.8456*	1.4182	1.8274***	2.0907***	2.3151**	1.8108***
	(0.6249)	(0.9707)	(0.9866)	(0.4962)	(0.5214)	(1.0676)	(0.4410)
$I_t^P \Delta \ln Y_t$	0.3902	0.0350	1.1511*	0.4680	0.3449	-0.3985	0.3428
	(0.3126)	(1.1081)	(0.6417)	(0.3505)	(0.3229)	(1.2671)	(0.3180)
$r_{i,t}$	-0.1867	-0.2427	-0.0672	-0.0697			
	(0.2807)	(0.2179)	(0.1606)	(0.1279)			
constant	0.0129**	0.0175	0.0016	0.0098*	0.0107**	0.0187	0.0095**
	(0.0057)	(0.0137)	(0.0089)	(0.0053)	(0.0048)	(0.0163)	(0.0045)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
Sargan	0.8022	0.4630	0.7792	0.3756	0.8308	0.5547	0.5616
Test for $\mathcal{H}_0 : \pi_0 = \pi_1$ [p-value]							
$\mathcal{H}_1 : \pi_0 \neq \pi_1$	0.0812	0.3730	0.8595	0.0654	0.0156	0.2345	0.0258
Instrument Relevance [statistic]							
Anderson LM	6.4754**	0.7334	3.6755	19.1943***	15.9515***	0.8815	18.7059***
Cragg-Donald	1.6475	0.1746	0.9048	2.4096	4.5777	0.2102	3.6296
First-Stage F [statistic]							
$I_t^N \Delta \ln Y_t$	4.6316	7.3166	2.5171	3.0923	4.6316	7.3166	4.8074
$I_t^P \Delta \ln Y_t$	5.5812	1.7369	2.1434	2.6417	5.5812	1.7369	3.9720
$r_{i,t}$	4.2762	5.8685	25.4837	12.0186	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.4586	0.9225	0.3801	0.5024	0.6979	0.6876	0.6049
Heterosk.	0.0758	0.0779	0.0701	0.1967	0.0557	0.1865	0.1806
RESET	0.8876	0.8816	0.9965	0.4113	0.7916	0.7502	0.5444
Normality	0.0019	0.0039	0.0877	0.0044	0.0040	0.0957	0.0082

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.

Table A.8 – Fuller-k estimations based on specification (3.9)

	$\mathbb{Y}$	$\mathbb{Y}^P$	$\mathbb{S}$	$\mathbb{Y} \cup \mathbb{Y}^P \cup \mathbb{S}$	$\mathbb{Y}$	$\mathbb{Y}^P$	$\mathbb{Y} \cup \mathbb{Y}^P$
$\Delta \ln Y_t$	1.2977	1.8155***	1.4182	1.8925***	2.9523	2.0907***	2.1669***
	(1.7886)	(0.6249)	(0.9866)	(0.5732)	(1.8639)	(0.5214)	(0.5883)
$I_t^P \Delta \ln Y_t$	-0.4273	-1.4253*	-0.2671	-1.4689*	-3.0471	-1.7458**	-1.8388**
	(2.8415)	(0.8173)	(1.5088)	(0.8634)	(2.9688)	(0.7221)	(0.8609)
$r_{i,t}$	-0.2660	-0.1867	-0.0672	-0.1111			
	(0.1880)	(0.2807)	(0.1606)	(0.1330)			
constant	0.0078	0.0129**	0.0016	0.0114*	0.0185	0.0107**	0.0112**
	(0.0157)	(0.0057)	(0.0089)	(0.0059)	(0.0186)	(0.0048)	(0.0057)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
Sargan	0.0818	0.8022	0.7792	0.1933	0.1511	0.8308	0.2033
Test for $\mathcal{H}_0 : \pi_1^P = 0$ [p-value]							
$\mathcal{H}_1 : \pi_1^P > 0$	0.5596	0.9576	0.5701	0.9537	0.8462	0.9911	0.9823
$\mathcal{H}_1 : \pi_1^P < 0$	0.5596	0.9576	0.5701	0.9537	0.8462	0.9911	0.9823
Instrument Relevance [statistic]							
Anderson LM	2.9896	6.4754**	3.6755	18.9579**	3.6039	15.9515***	18.1368***
Cragg-Donald	0.7301	1.6475	0.9048	2.1082	0.8864	4.5777	2.9565
First-Stage F [statistic]							
$\Delta \ln Y_t$	5.6211	5.2361	2.7572	2.6441	5.6211	5.2361	3.7260
$I_t^P \Delta \ln Y_t$	4.3765	5.5812	2.1434	2.3877	4.3765	5.5812	3.5220
$r_{i,t}$	15.2726	4.2762	25.4837	10.7948	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.3307	0.4586	0.3801	0.5343	0.7165	0.6979	0.7512
Heterosk.	0.0508	0.0758	0.0701	0.1984	0.1534	0.0557	0.0781
RESET	0.5962	0.8876	0.9965	0.3436	0.5944	0.7916	0.7140
Normality	0.0045	0.0019	0.0877	0.0029	0.0001	0.0040	0.0028

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.

Table A.9 – Fuller-k estimations based on specification (3.10)

	$\mathbb{Y}$	$\mathbb{Y}^N$	$\mathbb{S}$	$\mathbb{Y} \cup \mathbb{Y}^N \cup \mathbb{S}$	$\mathbb{Y}$	$\mathbb{Y}^N$	$\mathbb{Y} \cup \mathbb{Y}^N$
$I_t^N \Delta \ln Y_t$	0.4273	1.8106	0.2671	0.8838	3.0471	2.7136	0.3885
	(2.8415)	(2.0322)	(1.5088)	(0.8924)	(2.9688)	(2.2825)	(1.0814)
$\Delta \ln Y_t$	0.8704	0.0350	1.1511*	0.7009	-0.0948	-0.3985	0.9846*
	(1.0859)	(1.1081)	(0.6417)	(0.4415)	(1.1569)	(1.2671)	(0.5516)
$r_{i,t}$	-0.2660	-0.2427	-0.0672	-0.1302			
	(0.1880)	(0.2179)	(0.1606)	(0.1262)			
constant	0.0078	0.0175	0.0016	0.0078	0.0185	0.0187	0.0016
	(0.0157)	(0.0137)	(0.0089)	(0.0062)	(0.0186)	(0.0163)	(0.0075)
T	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000	90.0000
Exogeneity Tests [p-value]							
Sargan	0.0818	0.4630	0.7792	0.3816	0.1511	0.5547	0.2622
Test for $\mathcal{H}_0 : \pi_1^N = 0$ [p-value]							
$\mathcal{H}_1 : \pi_1^P > 0$	0.4404	0.1877	0.4299	0.1624	0.1538	0.1189	0.3601
$\mathcal{H}_1 : \pi_1^P < 0$	0.5596	0.8123	0.5701	0.8376	0.8462	0.8811	0.6399
Instrument Relevance [statistic]							
Anderson LM	2.9896	0.7334	3.6755	14.9146*	3.6039	0.8815	11.5084*
Cragg-Donald	0.7301	0.1746	0.9048	1.5692	0.8864	0.2102	1.7175
First-Stage F [statistic]							
$I_t^N \Delta \ln Y_t$	3.7910	7.3166	2.5171	3.2287	3.7910	7.3166	4.0826
$\Delta \ln Y_t$	5.6211	4.6889	2.7572	2.8508	5.6211	4.6889	3.4590
$r_{i,t}$	15.2726	5.8685	25.4837	11.4796	.	.	.
Log-Normality Tests [p-value]							
Ser. Correl	0.3307	0.9225	0.3801	0.3632	0.7165	0.6876	0.3968
Heterosk.	0.0508	0.0779	0.0701	0.1738	0.1534	0.1865	0.0641
RESET	0.5962	0.8816	0.9965	0.6265	0.5944	0.7502	0.5647
Normality	0.0045	0.0039	0.0877	0.0059	0.0001	0.0957	0.0396

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The table columns report the results for the instrument set on its header. The variables in each set can be found on table 3.4.