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CONSUMPTION (A)SYMMETRIC RESPONSE TO PREDICTABLE INCOME: A NEW TEST FOR MYOPIA AND LIQUIDITY CONSTRAINTS

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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 over-whelming 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 e vidence 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.

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) reaches 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 lifecycle-permanent income hypothesis (LCH-PIH), predictable movements in income should not affect the consumption revisions. This prediction remains valid even when relaxing certain hypotheses made by Hall (1978). 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; 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 current 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

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

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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 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 and 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 2 discuss the consumer behavior, reviewing the LCH-PIH, the myopia and the liquidity constraints hypotheses. Section 3 presents previous works regarding the Brazilian case. Section 4 presents our new approach for comparison of the myopia and the liquidity constraints hypotheses. Section 5 presents and discuss the empirical results. Finally, Section 6 concludes.

2. CONSUMER BEHAVIOR

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

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

[2] Neely et al. (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.

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:

$$\Delta \ln C_{t+1} = \mu_i + \psi \mathbb{E}_t[r_{i,t+1}] + \varepsilon_{i,t+1}, \quad i = 1,...,N \tag{2}$$

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 $\sigma_i^2 = \mathbb{V}_t[r_{i,t+1} - \gamma \Delta \ln C_{t+1}]$.[3] Finally, the log-linear Euler equation (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 (2), the Campbell and Mankiw (1989) approach yields the following testing equation:

$$\Delta \ln C_{t+1} = \alpha_i + \lambda \mathbb{E}_t[\Delta \ln Y_{t+1}] + \delta \mathbb{E}_t[r_{i,t+1}] + \varepsilon_{i,t+1}, \quad i = 1,...,N \tag{3}$$

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:

$$\Delta \ln C_{t+1} = \alpha_i + \lambda_P \mathbb{E}_t[I_{t+1}^P \Delta \ln Y_t] + \lambda_N \mathbb{E}_t[I_{t+1}^N \Delta \ln Y_{t+1}] + \delta \mathbb{E}_t[r_{i,t+1}] + \varepsilon_{i,t+1}, \quad i = 1,...,N \tag{4}$$

where

$$\begin{aligned} I_{t+1}^P &= \begin{cases} 1\text{ , if } \Delta \ln Y_{t+1} > 0 \\ 0\text{ , if } \Delta \ln Y_{t+1} \leq 0 \end{cases} \\ I_{t+1}^N &= 1 - I_{t+1}^P \end{aligned} \tag{5}$$

[3] $\mathbb{V}_t$ is the variance conditional on information available up to period t, $\mathcal{I}_t$.

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 types. Suppose that the proportion of consumers who follows the standard log-linear Euler equation (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 presents such proportions and the consumption model specification for each consumer type.

TABLE I

CONSUMPTION PATH 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	$\delta^P \mathbb{E}_t[I^P_{t+1} \Delta \ln Y_{t+1}] + \delta^N \mathbb{E}_t[I^N_{t+1} \Delta \ln Y_{t+1}]$	$\delta^P > \delta^N$

Note: 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, $I^N_{t+1} = 1 - I^P_{t+1}$.

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

$$\begin{aligned} \Delta \ln C_{t+1} = & \lambda_1 \{\mu_i + \psi \mathbb{E}_t[r_{i,t+1}] + \varepsilon_{i,t+1}\} + \lambda_2 \mathbb{E}_t[\Delta \ln Y_{t+1}] + \\ & \lambda_3 \left\{\delta^P \mathbb{E}_t[I^P_{t+1} \Delta \ln Y_{t+1}] + \delta^N \mathbb{E}_t[I^N_{t+1} \Delta \ln Y_{t+1}]\right\}, \quad i = 1, \ldots, N \end{aligned} \tag{6}$$

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 (6) specializes to Campbell and Mankiw (1989) testing equation, as follows:

$$\Delta \ln C_{t+1} = \tilde{\mu}_i + \tilde{\psi} \mathbb{E}_t[r_{i,t+1}] + \lambda \mathbb{E}_t[\Delta \ln Y_{t+1}] + \tilde{\varepsilon}_{i,t+1}, \quad i = 1, \ldots, N \tag{7}$$

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

Given that $I^P_{t+1} + I^N_{t+1} = 1$, we rewrite the equation (6) to reach the testing equation developed by Shea (1995a), given by:[4]

$$\Delta \ln C_{t+1} = \tilde{\mu}_i + \tilde{\psi} \mathbb{E}_t[r_{i,t+1}] + \pi_0 \mathbb{E}_t[I^P_t \Delta \ln Y_{t+1}] + \pi_1 \mathbb{E}_t[I^N_{t+1} \Delta \ln Y_{t+1}] + \tilde{\varepsilon}_{i,t+1}, \quad i = 1, \ldots, M \tag{8}$$

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 $\mathcal{H}_1 : \pi_0 \neq \pi_1$.

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

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 (6) as follows:

$$\Delta \ln C_{t+1} = \tilde{\mu}_i + \tilde{\psi}\mathbb{E}_t[r_{i,t+1}] + \pi_0^P \mathbb{E}_t[\Delta \ln Y_{t+1}] + \pi_1^P \mathbb{E}_t[I^P_{t+1}\Delta \ln Y_{t+1}] + \tilde{\varepsilon}_{i,t+1}, \quad i = 1,\ldots,M \tag{9}$$

where $\pi_0^P \equiv \lambda_2 + \lambda_3\delta^N$, and $\pi_1^P \equiv \lambda_3(\delta^P - \delta^N)$. To investigate whether $\delta^P > \delta^N$ we simply perform the following hypothesis test:

- $\mathcal{H}_0 : \pi_1^P = 0$ versus $\mathcal{H}_1 : \pi_1^P > 0$.

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 (6) becomes:

$$\Delta \ln C_{t+1} = \tilde{\mu}_i + \tilde{\psi}\mathbb{E}_t[r_{i,t+1}] + \pi_0^N \mathbb{E}_t[\Delta \ln Y_{t+1}] + \pi_1^N \mathbb{E}_t[I^N_{t+1}\Delta \ln Y_{t+1}] + \tilde{\varepsilon}_{i,t+1}, \quad i = 1,\ldots,M \tag{10}$$

where $\pi_0^N \equiv \lambda_2 + \lambda_3\delta^P$, and $\pi_1^N \equiv \lambda_3(\delta^N - \delta^P)$. To investigate whether $\delta^P > \delta^N$ we test:

- $\mathcal{H}_0 : \pi_1^N = 0$ versus $\mathcal{H}_1 : \pi_1^N < 0$.

Therefore, specifications (9) and (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. 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. Take into account 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 $\pi_0 = \pi_1$. 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 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 a result is qualitatively consistent with models whose intertemporal preferences exhibit loss aversion.

4. ECONOMETRIC METHODOLOGY

This Section presents the econometric methodology. Section 4.1 details the data set to estimate the testing specifications (8), (9), (10). The Section 4.2 explains how such specifications are estimated and what hypotheses tests are performed.

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.[5] 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 asset return (r_t) refers to the quarterly real interest 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 it was also transformed into real per capita terms. Last, its seasonality was removed, as done for the consumption and income time series.[6] 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[7] 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 a present economic conditions index, the *Índice de Expectativas do Consumidor* (iec_t) is a consumer expectations index, and the *Índice de Confiança do consumidor* (icc_t), which is composed by the $icea_t$ and icc_t, is a consumer confidence index. They are 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. Thus, we add two more variables to the dataset: C_t/Y_t and D_t/Y_t.

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

[6]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.

[7]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.

4.2. *Econometric Model*

Shea (1995a) estimates the specification (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:

$$\begin{aligned} \hat{I}_t^P &= \begin{cases} 1\,, \text{ if } \widehat{\Delta \ln Y_t} > 0 \\ 0\,, \text{ if } \widehat{\Delta \ln Y_t} \leq 0 \end{cases} \\ \hat{I}_t^N &= 1 - \hat{I}_t^P \end{aligned} \tag{11}$$

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 (8). For the sake of comparison, we employ such strategy too. 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 (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 et al. (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 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.[8]

Hypothesis tests on the estimated coefficients are performed using a F–test for the specifications following specification (8) and one-tailed t-tests for specifications (9) and (10). Our new approach allows us to test the perverse asymmetry hypothesis by simply change the inequality of the alternative hypothesis. Table II summarizes the hypotheses tests of interest for each model.

TABLE II

HYPOTHESES TESTS

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

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 (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 et al. (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 Hashem Pesaran and

[8]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.

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.

5. RESULTS

In Section 5.1 we form the instrument lists used to estimate the specifications (8), (9) and (10). In Section 5.2 we report the estimation of specification (8) using the Shea (1995a) approach. Finally, Section 5.3 reports the results from our new methodology.

5.1. *Instrument Sets*

To estimate the specifications (8), (9) and (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 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, we employ forward and backward stepwise selection methods. In both methods, we have a set of candidate regressors that includes all variables we are considering adding to the model and a test statistic that is used to decide if a candidate variable will be added or dropped. In the forward selection, the algorithm starts with an empty model. In the step (i), it considers adding all the candidate regressors one-by-one; in the next step (ii), it adds the most significant variable if the significance level is bellow a predetermined threshold. After that, steps (i) and (ii) are repeated until no variable has statistical significance bellow the threshold. The backward selection starts with all the candidate regressors included in the model. In the step (i), it considers dropping all variables one-by-one; in step (ii), it drops the least significant variable if the significance level is above the predetermined threshold. After that, steps (i) and (ii) are repeated until no variable has statistical significance above the 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 another selected using the backward method. Finally, the set with the higher F statistic is chosen. Table III 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, alternative predictors were selected instead the lagged income growth and interest rate. As expected, the interest rate is the variable with the highest F statistic. Table IV summarizes the instrument set that will be used for each endogenous variable to estimate the specifications (8), (9) and (10).

TABLE III

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

Note: 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).

TABLE IV

INSTRUMENT SETS SUMMARY

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

In the next session, we use the selected instrument sets in the estimation of the proposed models. In addition to the sets described in Table IV, we also use the union of the sets referring to the endogenous variables present in the specification being estimated. For instance, in the specification (8) the endogenous variables are the interest rate and both 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 $\mathbb{S} \cup \mathbb{Y}^P \cup \mathbb{Y}^N$.

5.2. *Shea's approach*

In this section, we present the results based on the same procedure used by Shea (1995a). Table V 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 V show that it is easier to predict the interest rate than the income growth rate, as can be seem in the F statistics.

TABLE V
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

Note: 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 VI. 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.

5.3. *The new approach*

In this section we focus on the results based on the new approach where we estimate the specifications (8), (9) and (10) applying conventional instrumental variables estimators. Because the results across the estimators are similar, we report in this Section those based on LIML estimator.

TABLE VI

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

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

The results based on TSLS, Fuller-k and GMM-CUE estimators are reported in the Appendix 6.

Tables VII to IX report the LIML estimations of the specifications (8), (9) and (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 VII reports the results for the testing equation (8), and its version without the interest rate. The coefficient of predictable income decrease is positive and significant, at 5%, for 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 VII). 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 both verifying whether the instruments are weak and applying techniques developed to deal with such a problem. Finally, regarding the log-normality tests, there is evidence against the normality assumption.

Table VIII reports the results for the specification (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

TABLE VII

LIML ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.

is only significant at 10%. For all specifications, 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 VIII). 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 statistics are not that low. Therefore, we find evidence that $\delta^N > \delta^P$ when the instruments are not so weak. Last, once again, the log-normality tests suggest that normality assumption is rejected.

Table IX reports the results for specification (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 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 $\Delta \ln Y_t$

TABLE VIII

LIML ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.

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 VII, VIII and IX, it seems that specifications (8) and (9) are better specified than specification (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 VII, VIII and IX show evidence that instrument are weak. For this reason, we compute robust confidence intervals based on the Anderson et al. (1949) statistics for specifications (8), (9) and (10) and their versions without the interest rate because is was not rlevant in previous regressions. For each model we use instrument set with the highest Cragg and Donald (1993) statistic (reported in Tables VII, VIII and IX). The results are reported on Figures 1, 2 and 3.

Figure 1 shows the confidence sets based on the equation (8). Including or excluding the interest rate, 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 VII). Taking this into account, there is evidence that consumers

TABLE IX

LIML ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.

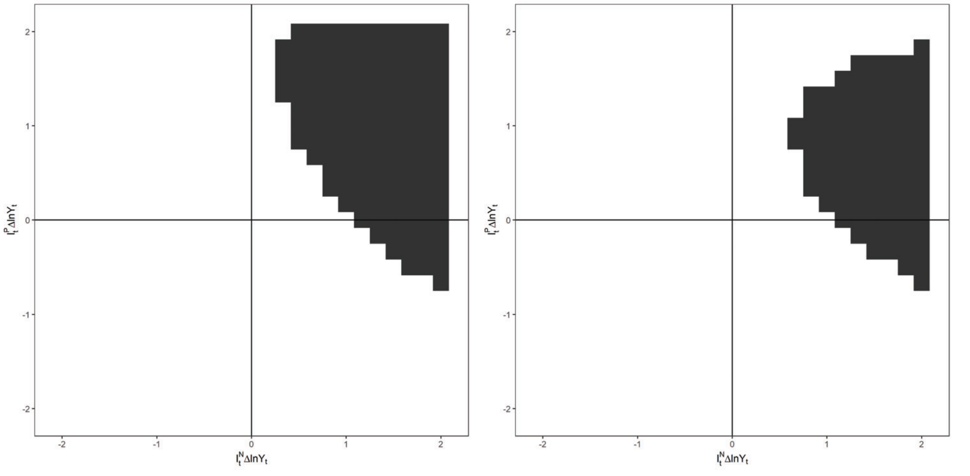
react more intensely to income decreases than increases, which is a evidence in favor of the "perverse assymetria" hypothesis.

Figure 2 reports the confidence set for the specification (9). Including or excluding the interest rate, 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 VIII – when the underidentification null hypothesis is rejected – range from 1.89 to 2.25. Taking into account these results, the conclusions are similar to the ones from model (8) and we have evidence for the "perverse asymmetry"as well.

Figure 3 shows the confidence sets based on the specification (10). The diagnostics tests in Tables VII, VIII and IX suggest that specification (10) is more affected by the weak instrument problem than the specifications (8) and (9). Not by chance, the Figure 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 5.2, where we used the Shea

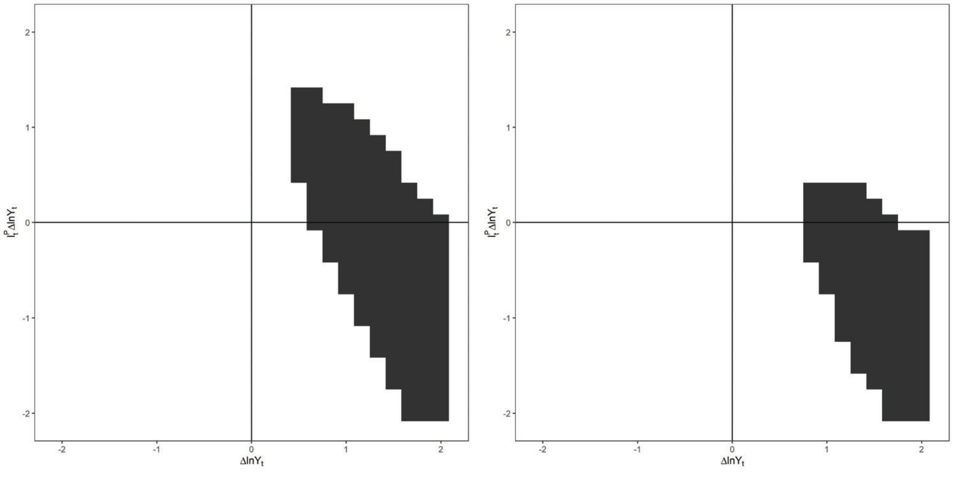
FIGURE 1.—Confidence Set for $I_t^P \Delta \ln Y_t$ and $I_t^N \Delta \ln Y_t$



(a) Including the interest rate (b) Excluding the interest rate

Note: 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 VII.

FIGURE 2.—Confidence Set for $I_t^P \Delta \ln Y_t$ and $I_t \Delta \ln Y_t$

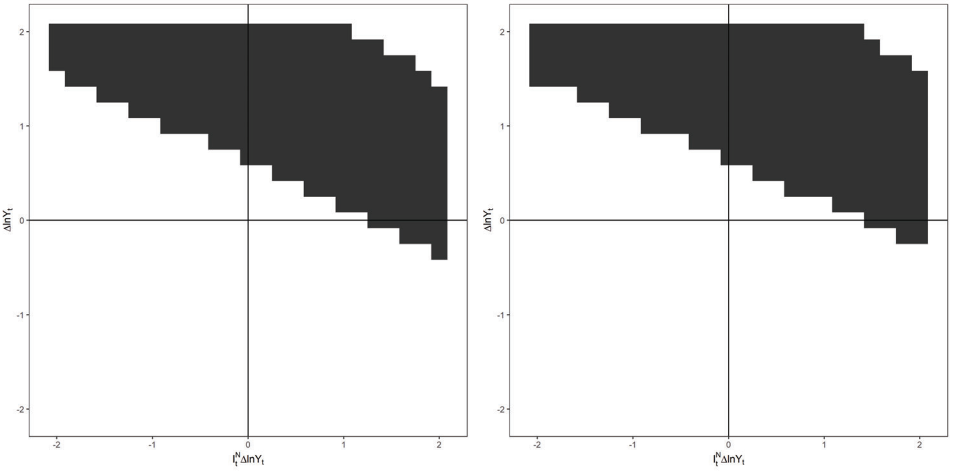


(a) Including the interest rate (b) Excluding the interest rate

Note: 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 VIII.

(1995a) approach, as in Gomes (2010) and Gomes and Paz (2010). The main difference between Shea (1995a) and our new approach is how the positive/negative income growth is calculated. While in Shea (1995a) $\hat{I}_t^P$ and $\hat{I}_t^N$ are calculated using $\widehat{\Delta \ln Y_t}$, in our new approach the indicator variables I_t^P and I_t^N are calculated using the realized value of $\Delta \ln Y_t$ and, after that, we estimate $E_t[I_t^P \Delta \ln Y_t]$ and/or $E_t[I_t^N \Delta \ln Y_t]$. Indeed, our approach allow us to both perform in-

FIGURE 3.—Confidence Set for $I_t^N \Delta \ln Y_t$ and $\Delta \ln Y_t$



(a) Including the interest rate (b) Excluding the interest rate

Note: 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 IX.

equality tests of interest and employ econometric tools developed to deal with weak instruments problem.

6. CONCLUSIONS

According to the LCH-PIH, predictable income changes should not affect the consumers' adjustment of the consumption. However, it's well documented in the literature its failure in aggregate data (see, for example, Campbell and Mankiw (1989; 1990)). In attempt to understand the reasons behind such a failure, Shea (1995a) tests two hypothesis: 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. Using Brazilian quarterly data, we found evidence that consumption growth responds more intensively to negative predictable income growth than to positive one. Those results are in line with the findings of Shea (1995a) using US data, but contrasts with the findings of Gomes (2010) and Gomes and Paz (2010) for the Brazilian case.

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APPENDIX: TSLS, GMM AND FULLER-K RESULTS

This Appendix presents the estimation of equations 8, 9 and 10 for other three estimators: two-stage least square (TSLS), continuously updating GMM (CUE-GMM) and Fuller-k.

CONSUMPTION (A)SYMMETRIC RESPONSE TO PREDICTABLE INCOME

TABLE A.X

TSLS ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.

TABLE A.XI

TSLS ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.

TABLE A.XII

TSLS ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.

TABLE A.XIII
CUE-GMM ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.

TABLE A.XIV

CUE-GMM ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.

TABLE A.XV

CUE-GMM ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.

TABLE A.XVI

FULLER-K ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.

TABLE A.XVII

FULLER-K ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.

TABLE A.XVIII

FULLER-K ESTIMATIONS BASED ON SPECIFICATION (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

Note: 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 IV.