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Abstract

Using monthly information on retail trade, we study the short-term dynamics of household consumption variations in Colombia. Based on a sample of retail trade excluding fuels and vehicles, we find that the growth of household consumption can be explained by lags in the Economy Monitoring Indicator (ISE), the interest rate, consumer credit, and consumer confidence. In a Granger sense, these four variables cause the growth of household consumption. Using instrumental variables, these variables remain as fundamental drivers of household consumption growth. Consumer confidence contains different information than the ISE. We associate this information with uncertainty due to a non-financial risk, possibly linked to unemployment according to our theoretical framework. Percentage annual variations of remittances and credit card limits are also determinant while the importance of labor market outcomes to explain the household consumption vanishes as long as the above variables are considered in the empirical models, or the consumption is modeled in annual percentage variations instead of monthly or quarterly.

***JEL* Classification:** *E*21, *E*27.

Keywords: *Retail trade indices, household consumption, labor market outcomes, consumer confidence, interest rates*.

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Consumo de los hogares en Colombia: ¿Qué nos dicen los índices de comercio al por menor?

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Resumen

Utilizando información mensual de comercio al por menor, estudiamos la dinámica de corto plazo del consumo de los hogares en Colombia. Basados en la muestra de comercio al por menor sin combustibles ni vehículos, encontramos que su crecimiento se explica mediante rezagos del ISE (Indicador de Seguimiento a la Economía), la tasa de interés, el crédito al consumo y la confianza del consumidor. En el sentido de Granger, estas cuatro variables causan el crecimiento del consumo de los hogares. Utilizando variables instrumentales, dichas variables permanecen como factores fundamentales en la explicación del crecimiento del consumo de los hogares. La confianza del consumidor contiene información diferente de la que contiene el ISE; dicha información la asociamos con incertidumbre, un riesgo no financiero, posiblemente vinculado con el desempleo según nuestro marco teórico. Las variaciones porcentuales anuales de las remesas y los cupos de las tarjetas de crédito también son determinantes, mientras que la importancia de las tasas nacional y urbana de desempleo y la tasa de ocupación en la explicación del consumo de los hogares desaparece siempre que las variables anteriores se incluyan en los modelos empíricos, o el consumo se modele en variaciones porcentuales anuales en lugar de variaciones mensuales o trimestrales.

Clasificación *JEL*: *E*21, *E*27

Palabras clave: *Índices de comercio al por menor, consumo de los hogares, mercado laboral, confianza de los consumidores, tasas de interés*.

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1. Introduction

In this paper, we aim to study the factors behind the consumption behavior of households in Colombia over the last two decades by using the retail trade indices published monthly by the National Administrative Department of Statistics (hereafter DANE, which is the acronym of its Spanish name). The motivation for using the retail trade indices is to exploit the monthly frequency not only of the indices but also of the explanatory variables in a period noted for the contraction of the economy during the first quarter of 2008 and the first quarter of 2009 (Alfonso et al., 2013), for the reduction of commodity prices in 2015 (International Monetary Fund, 2015) and for supply shocks linked to the deceleration of economic activity between 2015 and 2016 and to the COVID-19 pandemic. To the best of our knowledge, these retail trade indices have not been studied in depth previously.

The definition of household consumption that we use corresponds to that provided by DANE in its glossary of national accounts: that is, the final consumption of families, excluding the purchase of the home, which consists of the value of goods and services used for the direct satisfaction of individual human needs. For the retail commerce or retail trade indices that we use as proxies of household consumption, the definition provided by DANE (2002) is "the resale (sale without transformation) of new or used merchandise or products, available for view of the public, intended exclusively for personal or domestic consumption or use. For the purposes of retail trade investigations carried out by DANE, commercial activities in pawn shops, telemarketing, lottery outlets, mobile sales stands and in homes with economic activity are excluded; likewise, maintenance and repair activities associated with commerce are not part of the investigation, nor the sale of used merchandise."

Despite the quantitative importance of household consumption as a share of GDP (i.e. above 75%, as we show below), in Colombia there have been few studies that document the drivers of consumption in the medium term, or even in the short run. Important exceptions are the works of López (1993), Gaviria and Posada (1992), López and Ortega (1998), Posada (1999), Grupo de Estudios del Crecimiento Económico (2002), Murcia (2007), and Cortés and Pérez (2010).[1]

After the life cycle–permanent income hypothesis (LC–PIH),[2] the Euler equation approach has been utilized to test the behavior of consumption. The use of a concave utility function, time separable preferences, interest rate equal to the subjective discount, and no uncertainty about the wage profile made

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[1] Arango et al. (2021), Arango and Cardona-Sosa (2022), and Arango and Quevedo (2022) focus on consumer credit. Carranza and González (2014) study the determinants of the demand for new vehicles in Colombian households between 2001 and 2011.

[2] Note that this corresponds to the mix of two models: one set in a finite time horizon and the other in an infinite time horizon.

this model consistent with the desire for consumption smoothing over time. According to the life-cycle model, the reduction in income that happens after retirement induces households to accumulate wealth to smooth their consumption. This explanation for having a target wealth is fundamental although partial; such a target is best explained by the need to be prepared in case of an emergency, as noted by Carroll (1997). This uncertainty, key for saving, is the argument that we use below to introduce consumer confidence as a factor that partially explains the annual variation in consumption.

The use of quadratic preferences, rational expectations, separable preferences over time, and interest rate and subjective discount both equal to zero allowed Hall (1978) to obtain a closed-form solution, the random walk model, compatible with certainty equivalence. Regardless of this controversial result, the random walk turned into the benchmark model of consumption of households. Given the frequent deviations of household consumption from the model proposed by Hall (1978), other views emerged to explain the behavior of household consumption, including liquidity constraints (Flavin, 1981; Zeldes, 1989; Runkle, 1991; Ludvigson, 1999), habits (Deaton, 1987; Dynan, 2000), precautionary savings (Dreze and Modigliani, 1972; Kimball, 1990; Browning and Lusardi,1996; Carroll and Kimball, 1996), consumption relative to others (Abel, 1990), and so on.[3] Nevertheless, the main interest nowadays is to arrive at consumption functions that are heavily dependent on structural parameters linked to preferences and other unobserved phenomena.

This paper contributes to the understanding of household consumption behavior in the short run in Colombia from 2003 until December 2019 (before the COVID-19 pandemic) and up until 2021, including the pandemic period, by using univariate and multivariate approaches. With respect to the univariate approach, after rejecting the random walk behavior of consumption, proxied by retail trade indices, and observing that both the levels and its monthly, quarterly, and annual changes can be predicted, we check first the capacity of three labor market outcomes (i.e. urban and nationwide unemployment rates and urban occupation rate) to forecast the levels and changes of consumption (see Quah, 1990, who focused on labor income).

In fact, we present evidence of the capacity for such labor market outcomes to predict consumption; our results suggest that monthly variations of the urban occupation rate help to predict the log of the consumption level before the COVID-19 pandemic. This result holds when the analysis is carried out for monthly variations instead of levels. When the sample period is extended until July 2021, the three

[3] The arguments of excess sensitivity of consumption to disposable income (Flavin, 1981) and excess smoothness of consumption to permanent income (Deaton, 1992) became important implications of the analysis. According to Deaton (1992, chapter 3), there is no empirical evidence that supports the fact that permanent income is smoother than measured income.

variables of the labor market we are considering became significant in quarterly variations while in annual variations only the two unemployment rates (urban and nationwide) help to predict changes in consumption.

Nevertheless, we go further in the analysis by including some other variables, borrowed from theory, to find the factors behind the behavior of consumption. Once these variables are considered, the outcomes of the labor market no longer help to predict the annual percentage changes in consumption but do still help to predict quarterly variations, where the three variables are still significant.

Most empirical models we estimate are based on a combination of the approaches of Campbell and Mankiw (1990) and Carroll, Slacalek, and Sommer (2019) and aim to predict annual changes in consumption measured primarily by retail trade excluding fuels and vehicles; the reason for this selection is that, presumably, this measure is fairly close to the consumption of non-durable goods. However, in annual variations, similar models were estimated for trade excluding fuels and the Economy Monitoring Indicator (ISE) focused on domestic trade (ISE – commerce). In the univariate framework, the models are estimated by ordinary least squares (OLS), some of them after choosing the lag optimally; in these cases, the explanatory variables remain.[4]

The models were also estimated by instrumental variables. In this paper we claim that the variables that best help to predict the changes in consumption are the percentage variation of the ISE, as our proxy of income, the percentage change of consumer credit in real terms, the real interest rate (corresponding to consumer credit and the usury[5]), and the annual variation of the consumer confidence index. The latter variable, published on a monthly basis by Fedesarrollo,[6] plays an important role in our findings because, as we have said, it has a marginal capacity to predict the changes of consumption.[7] Our interpretation is that, in our empirical model, it represents, to some extent, a measure of uncertainty associated with the wealth target. Remittances from abroad as well as the change in the limit of credit cards also help to predict changes in consumption in some specifications.

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[4] Some models (not shown) were also chosen by using optimal lag criteria, such as the Akaike information criterion, the Bayesian information criterion, and the Hannan–Quinn information criterion; in this case, the criteria suggest the use of different lags of the dependent variable but only one lag for the explanatory variables. The results we discuss later essentially remain.

[5] The return of the Treasury Bonds denominated in real value units (RVUs) could not be used because we could not reject the null hypothesis of non-stationary variables.

[6] This is one of the most important think-tanks in Colombia. Information about the consumer confidence index can be found at https://www.repository.fedesarrollo.org.co/handle/11445/36.

[7] Bram and Ludvigson (1998), Easaw, Garratt, and Heravi (2005), and Dees and Brinca (2013) use consumer confidence indices for the study of consumption expenditure while Gric, Ehrenbergerova, and Hodula (2022) use them to research consumer credit.

The multivariate approach rests on a vector autoregressive (VAR) model constructed following Bram and Ludvigson (1998) and Dees and Brinca (2013). The aim of this approach is to look at the dynamic response of consumption to shocks linked to the variables mentioned above – but mainly to consumer confidence. The results show an intuitive dynamic response of consumption consistent with univariate models.

As we have explained, this paper is based on aggregate time series rather than microdata; in this sense, it is unable to provide an estimation and identification of structural parameters such as prudence, time preference, or intertemporal elasticity of substitution, which are necessary, in the context of consumption, for evaluating economic policy. Nevertheless, we consider that the paper helps to enrich the discussion of the short-run behavior of household consumption.

The paper proceeds as follows. In Section 2, we give some descriptive facts of consumption in Colombia. In Section 3, we review some key literature in the field, show some preliminary results based on some labor market outcomes, and set out the theoretical models that shed light on our empirical approaches. In Section 4, we briefly describe some of the main variables used in the paper. In Section 5, we present and discuss the results. Finally, in Section 6, we draw some preliminary lessons.

2. Some salient facts on consumption

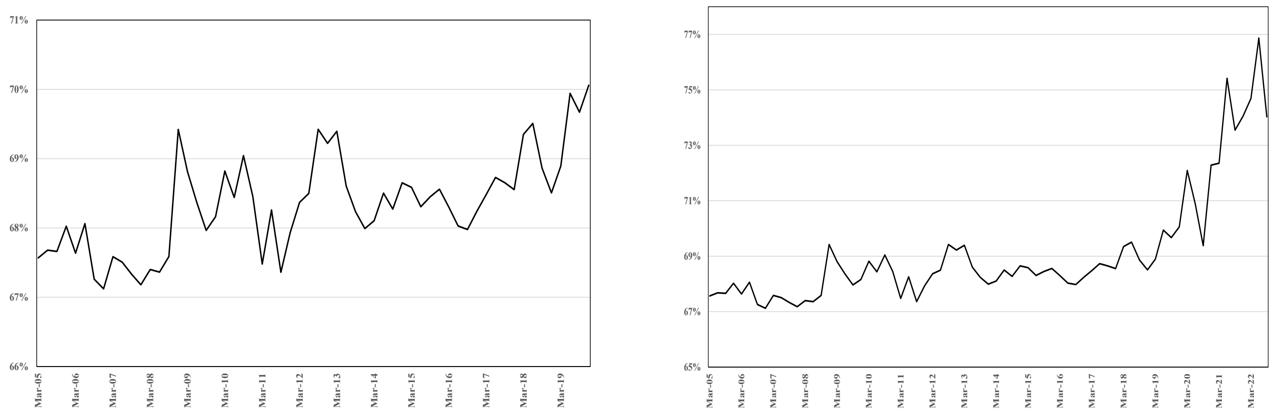
Between 2005 and 2022, household consumption in Colombia represented, on average, slightly less than 70% of GDP. As seen in Figure 1, until 2019 its share of GDP was somewhat stable, after which it increased, reaching levels of 76%. Figure 2 shows the annual variations in consumption on a quarterly basis between March 2005 and December 2019, and between March 2005 and September 2022. In the first subperiod, the average of the annual variations was 4.1% while over the entire period, including the time of the COVID-19 pandemic, it was 4.6%. Interestingly, during the same sample periods, the GDP had average annual variations of 3.9% and 4.4%, respectively, while the gross formation of fixed capital had average changes of 6.2% and 11.5%, respectively, in the same two sample periods.

However, this investigation of the drivers of the behavior of household consumption is not based on the national-account series of consumption. Although the latter includes not only goods (durable and non-durable) but also services, we focused on retail trade indicators published monthly by DANE with the aim of exploiting not only the higher frequency of data but also its informative content; to the best of our knowledge, these indicators have not been used before to explore in depth the behavior of consumption in Colombia.

Figure 3 shows the behavior of the three retail trade variables used in this work. Nevertheless, we focus on the results based on the variables excluding fuels and vehicles with the aim of capturing the dynamics of non-durable goods and its drivers. Some results using retail trade excluding fuels and ISE – commerce are presented in Appendix A.

Figure 1. Household consumption as a share of GDP, quarterly data

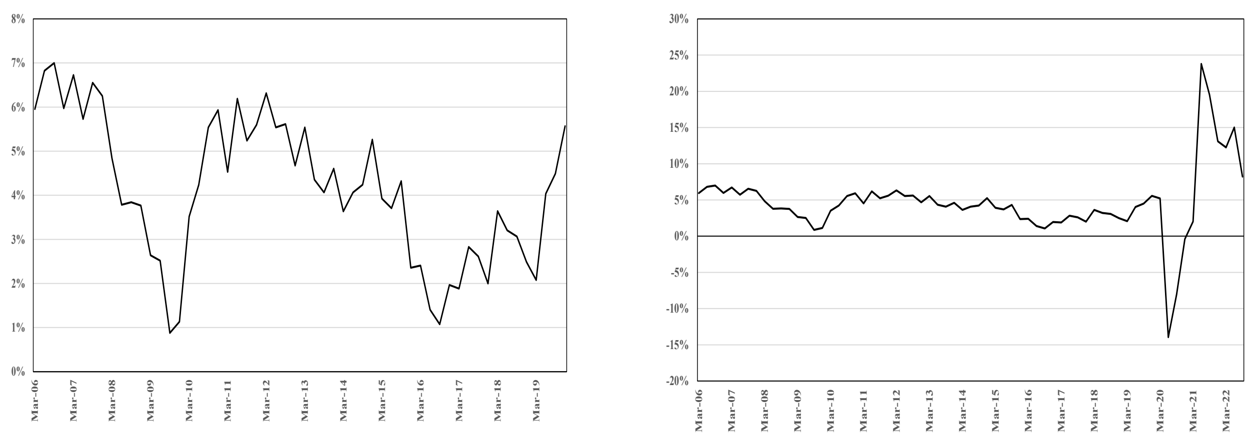
2005:01–2019:04 **2005:01–2022:03**



Source: DANE – national accounts. Chained volume series with reference year 2015. Data adjusted for seasonal and calendar effects. Authors' calculations.

Figure 2. Annual variation of household consumption

2006:01–2019:04 **2006:01–2022:03**

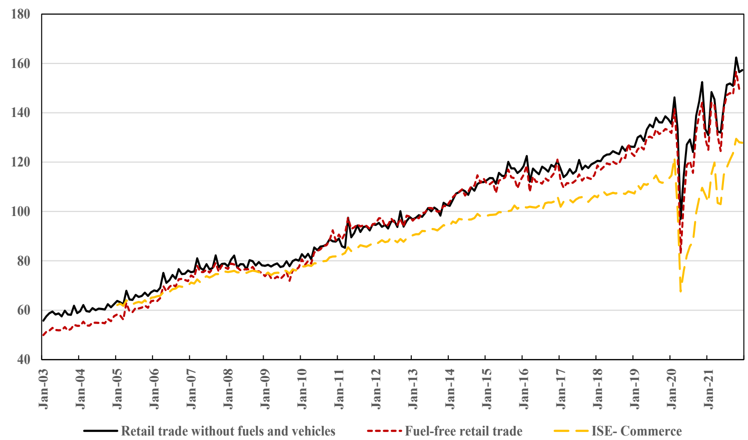


Source: DANE – national accounts. Chained volume series with reference year 2015. Data adjusted for seasonal and calendar effects. Authors' calculations.

Table 1 presents the evolution of weights in the consumer price index (CPI) basket of the different proxies of household consumption. Accordingly, the average weight of total retail trade excluding fuels was about 47.6% during the sample period (2003–2021); the average weight of retail trade excluding both fuels and vehicles was 44.1% in the CPI basket, while the average weight of ISE – commerce was 51.4%. According to these numbers, the mentioned variables include an important proportion of the goods and services of the CPI basket.

Importantly, in comparison with consumption in the national accounts, the annual variation of the three retail trade indicators is higher both until 2019 (before the COVID-19 pandemic) and 2021 (see Figure 4 and Table 2). Only ISE – commerce has a volatility that is similar to that of consumption in the national accounts, although the standard deviation of the former is higher. The other two indicators exhibit annual variations higher than those of consumption.

Figure 3. Retail trade indices, 2003:01–2021:12



Source: DANE.

Table 1. CPI weights of retail trade indices (percentages)

Components	**2000–2008 (1998 = 100)**	**2009–2018 (2008 = 100)**	**2019–2023 (2018 = 100)**
Total retail trade excluding fuels and vehicles	49.76	44.28	29.53
Total retail trade excluding fuels	52.92	48.95	32.46
Transport			
Public transport	5.34	6.80	5.52
Parking service	0.13	0.18	0.59
Mechanical service	1.72	0.42	0.50
Fuels	1.08	2.91	2.91
Total transport	**8.27**	**10.31**	**9.52**
Hotel, accommodation, and restaurant services			
Hotel and accommodation services	0.27	0.27	0.23
Restaurant and catering services	–	–	9.20
Total hotel, accommodation, and restaurant services	**0.27**	**0.27**	**9.43**
ISE — commerce	**61.46**	**59.53**	**51.41**

Source: DANE – authors' calculations.

Table 2. Average annual variation of different consumption variables

Consumption variables	**Average**		**Standard deviation**	
	2006–2021	**2006–2019**	**2006–2021**	**2006–2019**
Consumption including expenditure of NPISH with GKF	4.3%	4.1%	4.6%	1.6%
Retail trade excluding fuels and vehicles	5.6%	5.3%	5.4%	3.9%
Fuel-free retail trade	5.9%	5.8%	7.7%	5.9%
ISE – commerce	4.3%	4.2%	8.8%	2.5%

Source: DANE – national accounts. Authors' calculations.

Figure 4. Annual variation of household consumption, quarterly data

Source: DANE – national accounts. Chained volume series with reference year 2015. Data adjusted for seasonal and calendar effects. Authors' calculations.

3. Theoretical and empirical guidance

Household consumption is understood as a dynamic decision problem that should not be studied in isolation. Because such decisions correspond simultaneously to saving decisions that are mirrored in capital accumulation, consumers' attitudes to saving, risk-bearing, and uncertainty are crucial to understanding the behavior of capital markets (Attanasio, 1999). Since the 1950s, consumption behavior has been studied using the LC–PIH model (Modigliani and Brumberg, 1954; Friedman, 1957). In this model, the decisions are set as an intertemporal allocation problem, where prices and the available resources are important determinants of consumption. The concavity of the utility function implies the desire to smooth consumption over time. In this case, consumption increases with current income only if that increase corresponds to the permanent fraction of income.[8] With the introduction of the rational expectations hypothesis and uncertainty, time-separable preferences, equalization of the subjective discount rate to the interest rate, and a quadratic utility function, Hall (1978) established that consumption could be written as a random walk. Accordingly, the variation of consumption is unpredictable: $c_t = c_{t-1} + \varepsilon_t \Rightarrow \Delta c_t = \varepsilon_t$. This closed-form solution of the model was used to test simultaneously the LC–PIH under the above assumptions. By using aggregate data, Hall (1978) was able to reject the null hypothesis that past levels of real disposable income were useful to predict the level of consumption.

[8] Since this model was proposed, many authors have tried to test the PIH for the United States (Sargent, 1978; Flavin, 1981; Campell, 1987; Blundell and Preston, 1998). Some authors have found evidence of excess sensitivity of consumption to income (Flavin, 1981; Campell, 1987) and explicit borrowing constraints on consumption decisions (Tobin and Dolde, 1971; Flemming, 1973; Campbell and Mankiw, 1990; Meghir and Weber, 1996) as well as precautionary motive for savings (Dreze and Modigliani, 1972; Kimball, 1990; Browning and Lusardi,1996; Carroll and Kimball, 1996).

An alternative to the random walk specification, linked to the excess sensitivity of consumption to transitory fluctuations in income or liquidity constraints, was verified by Campbell and Mankiw (1990) who proposed an empirical model given by $\Delta c_t = \alpha + \lambda \Delta y_t + (1-\lambda)\varepsilon_t$, where λ represents the fraction of income corresponding to liquidity-constrained consumers while $(1-\lambda)$ corresponds to the proportion of agents that spend strictly according to the standard LF–PIH.[9]

Following an instrumental variable strategy, they find a consistent point estimate of λ equal to 0.5. Campbell and Mankiw (1989, 1990, 1991) also propose an alternative specification to estimate, in the tradition of the Euler equation, given by $\Delta c_t = \alpha + \theta r_t + \lambda \Delta y_t + \varepsilon_t$, where y_t represents the labor income and r_t the interest rate, and $\theta = (1-\lambda)\sigma$ where σ is the intertemporal elasticity of substitution. In this specification, the parameter λ should be zero while the residual term should be orthogonal to the information available at time t.[10,11]

3.1. Consumption and the labor market performance

Our first empirical step relies on the link between the labor market and consumption, as the simple theory suggests (see Figure 5).[12] That is, the first variables that we are going to use to predict both the levels and annual changes in consumption are labor market outcomes. This intuition is guided by the familiar graph used in labor economics to explain the participation decision of agents in a framework in which no involuntary unemployment is allowed. The vertical axis represents consumption, *C*, while the horizontal axis represents the hours of leisure, *L*, which have a limit of L^* hours. In the figure, the interplay between the budget restriction, where *W* is the hourly wage, and the indifference curve suggests that the optimal combination for the consumer is at point *E*.

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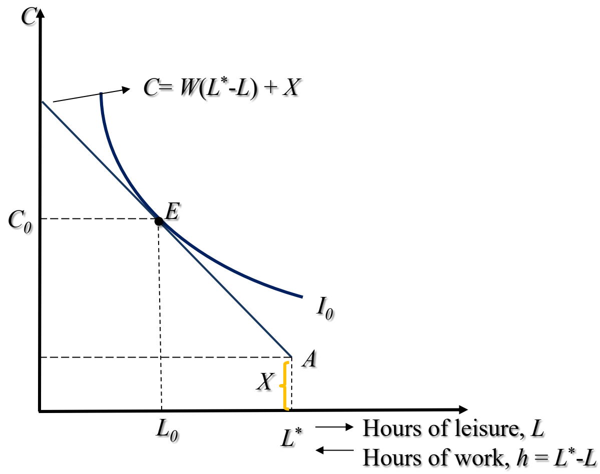
[9] According to Campbell and Mankiw (1989, p. 186), "[t]he strong connection between current income and consumption provides at least circumstantial evidence for 'rule-of-thumb' behavior on the part of some consumers." They also suggest that this model "will be hard to beat as a description of the aggregate data on consumption, income, and interest rates." However, Christiano (1989, p. 216) found it difficult to evaluate this statement based on the evidence provided in that paper. Carroll et al. (1994), given that the parameter λ can take values greater than 1, provide an alternative interpretation of it. They assert that "[…] the overall coefficient on contemporaneous changes in income is an increasing function of the durability of the consumption good" (Carroll et al., 1994, p. 1406).

[10] Campbell and Mankiw (1989) also estimate a fully fledged consumption function given by $c_t - y_t = (1-\lambda)E_t \sum_{j=1}^{\infty} \rho^j (\Delta y_{t+j} - \sigma r_{t+j}) - (1-\lambda)\rho\mu/(1-\rho)$. The estimates of λ range between 0.233 and 0.496 and R^2 does so between 0.302 and 0.792 for different definitions of consumption depending on the durability of goods.

[11] In the case of Colombia, Grupo de Estudios del Crecimiento Económico (2002, Chapter 5, Table 3) estimated the parameter λ to be between 0.464 and 0.796 for the period 1954–1995 (see also López and Ortega, 1998).

[12] After checking some other time-series properties of the retail trade excluding fuels and vehicles (see Appendix B), we conclude that this variable has a stationary trend, according to standard tests. In Appendix B, we show that all the variables we use are stationary during the different sample periods: 2004:01–2019:12, 2004:1–2021:07, and 2004:1–2021:12.

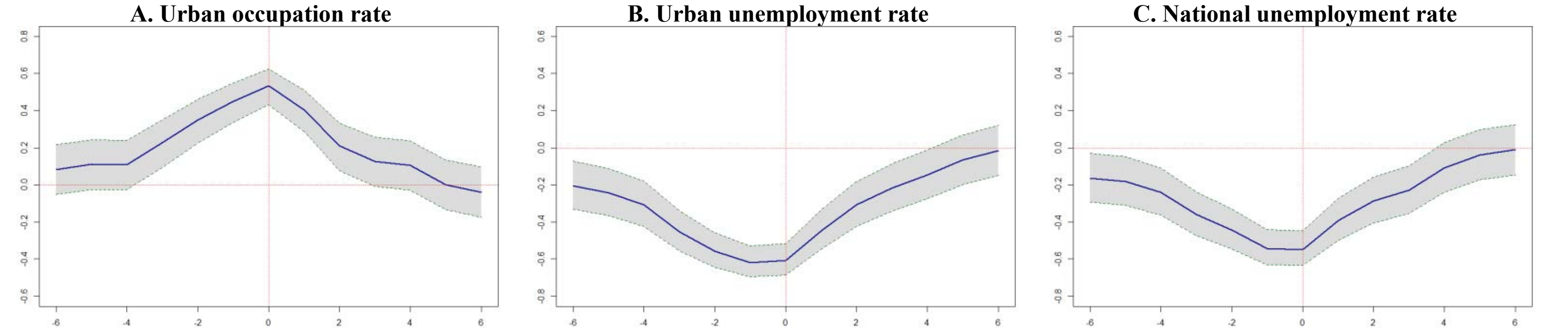
Figure 5. The participation decision



Source: Authors' own design.

In line with this argument, and allowing for involuntary unemployment, Figure 6 shows the cross-correlation between annual variations of consumption and three outcomes of the labor market: the urban occupation rate and the urban and nationwide unemployment rates. The highest values correspond to contemporaneous correlations, 0.534 in the case of the urban occupation rate, and −0.548 in the case of the nationwide unemployment rate. The highest correlation between consumption and the urban unemployment rate, −0.62, happens when consumption (see panel B of Figure 6) leads. However, the estimates are significant at several leads and lags.[13]

Figure 6. Cross-correlation between annual percentage variation in consumption and annual variations in labor market outcomes, 2004:01–2021:12



Note: The shadowed area corresponds to the 95% confidence interval.
Source: DANE – Authors calculations.

[13] Apart from individual observables linked to the labor market, Arango, Cardona-Sosa, and Pedraza-Jiménez (2021) show that the urban unemployment rate is a factor that explains the limit of credit cards for consumers and the probability of making a purchase.

To observe whether this intuition about the link between labor market and consumption is verified by the data, we run regressions first in levels and then in periodic variations in the spirit of Hall (1978). That is,

$$c_t = \alpha + \beta t + \mu c_{t-1} + \omega \Delta lmo_{t-1} + \varepsilon_t \qquad \text{(1a)}$$

where Δlmo corresponds to monthly variations of labor market outcomes (occupation and unemployment rates); thus, these variables are expressed in percentage points (pp). Table 3A presents the results of these regressions; columns (1) and (2) for the nationwide unemployment rate, columns (3) and (4) for the urban unemployment rate (13 areas), and columns (5) and (6) for the urban occupation rate. Two subperiods were considered; first, before the COVID-19 pandemic (2004:01–2019:12) and then up until 2021:07, because of the data availability at the beginning of this investigation. The inclusion of lagged variables avoids the consideration of endogeneity issues as discussed by Hall (1978). The autoregressive element in equation (1a) accounts for the fact that expenditure in consumption goods is made on a continuous basis while data are measured in time aggregates even if the goods are non-durable. This issue was addressed by Christiano, Eichenbaum, and Marshall (1991) who, based on a continuous-time model, recommended an IMA(1,1) process for the purchases. Mankiw (1982) suggested that the growth in spending on durable goods might be positively autocorrelated with an error term following an MA(1) process. In the case of Colombia, we choose MA(3) components in all cases. According to the results in these specifications in levels, only the occupation rate is significant before the COVID-19 pandemic.

Table 3A. Consumption goods, excluding fuels and vehicles, and labor market outcomes, equation (1a), OLS.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Nationwide unemployment rate ($t-1$)	−0.053	−0.006				
	(0.332)	(0.210)				
Urban unemployment rate ($t-1$)			−0.346	−0.010		
			(0.284)	(0.147)		
Urban occupation rate ($t-1$)					0.433**	0.165
					(0.198)	(0.128)
Consumer goods excluding fuels and	0.937***	0.723***	0.941***	0.722***	0.935***	0.711***
vehicles ($t-1$)	(0.031)	(0.037)	(0.029)	(0.039)	(0.030)	(0.035)
Constant	0.260**	1.133***	0.244**	1.136***	0.270**	1.179***
	(0.124)	(0.149)	(0.118)	(0.158)	(0.121)	(0.142)
MA(1) to MA(3) components	Yes	Yes	Yes	Yes	Yes	Yes
Dummy 2011:04	Yes	Yes	Yes	Yes	Yes	Yes
Dummy 2020:04	No	No	No	Yes	Yes	Yes
Sample period	2003:03–2019:12	2003:03–2021:07	2003:03–2019:12	2003:03–2021:07	2003:03–2019:12	2003:03–2021:07
Observations	202	221	202	221	202	221
Adjusted R^2	0.993	0.990	0.993	0.990	0.993	0.990
***F*-statistic (prob)**	0.000	0.000	0.000	0.000	0.000	0.000
Durbin–Watson	2.078	1.863	2.069	1.862	2.057	1.841

Note: The three labor market outcomes correspond to monthly variations. All models include an impulse dummy in 2011:04 and those of columns (4)–(6) include an additional impulse dummy in 2020:04. All the roots of the MA components fall inside the unit circle. *, **, and * mean that the estimated coefficients are significant at the 10%, 5% and 1% level of significance, respectively.**
Source: Authors' calculations.

As we can observe the models include autoregressive components and the coefficients are high enough that they can be considered to mirror some consumption-habit formation (Dynan, 2000). Dynan also mentions that, according to Deaton (1987), "[…] the autoregressive coefficient must be at least equal 0.78 to fully explain the 'excess smoothness' of aggregate consumption".[14] Notice that we are running regressions in levels for consumption and in differences for the labor market outcomes. According to Fuhrer (2000, p. 369), "[…] consumers wish to smooth both the level and the change in consumption. Thus, in response to shocks to interest rates or income, both the level and the change in consumption will respond gradually, leading to a hump-shaped response." We discuss this further in Section 5.3, when we analyze the VAR model.

The model was also specified in first, quarterly, and annual differences in percentage points;[15] that is,

$$\Delta c_t = \alpha + \mu \Delta c_{t-1} + \omega \Delta lmo_{t-1} + \varepsilon_t. \qquad (1b)$$

Table 3B presents the results of these regressions between 2003 and 2021.[16] Accordingly, the three labor market outcomes we consider, consistent with Figure 6, help to predict the changes in household consumption, mostly in quarterly variations. Nevertheless, when the variations are monthly and annual, such outcomes also contribute to predict the percentage changes in consumption. In all cases, irrespective of the significance of the estimates, the signs are as expected. The memory of the changes in consumption is also important; however, the interpretation in this case is different from the previous models as any habit is weaker but still significant. It is worth noting that, in the models of columns (1), (4), and (7) corresponding to monthly variations, the autoregressive component of the models is negative, suggesting a correction of the past variation in consumption. The best-fitting models are those set in quarterly and annual variations. In fact, R^2 is close to the values obtained by other authors (Campbell and Mankiw, 1989).

Although we believe that both the status of the individual in the labor market (i.e. employed, unemployed, etc., as verified in Arango, Cardona-Sosa, and Pedraza-Jiménez, 2021) and the aggregate outcomes of the labor market (Quah, 1991; Arango et al., 2021) are fundamental drivers of household consumption, there are other complementary mechanisms that, in a further step, affect the consumption of households and take information from the labor market. This is the case of the financial sector, which

[14] Constantinides (1990) and Carroll and Weil (1994) suggest that such a coefficient should be higher than 0.8 to explain the historical equity premium, or 0.95 to be compatible with the observed relationship between the growth of aggregate income and that of aggregate saving in subsequent periods. Carroll et al. (1994) suggest that habit formation implies sluggish responses of consumption to income shocks.

[15] The error terms are stationary.

[16] Results for the period before the COVID-19 pandemic are not shown for reasons of space but are available on request.

is in charge of mapping individual and aggregate labor market performance into the consumer credit supply and the interest rate, as well as the monetary authority and consumers themselves, with regards to their uncertainty about future income, and so on. Nevertheless, it is important to take into account that not all individuals are working all the time, in particular after retirement. Consequently, the coefficients in Tables 3A and 3B correspond to averages across individuals, fundamentally in the case of the occupation rate.

Table 3B. Periodic variations in percentage terms of consumption goods, excluding fuels and vehicles, and labor market outcomes, equation (1b), OLS.

Variables	Monthly (1)	Quarterly (2)	Annual (3)	Monthly (4)	Quarterly (5)	Annual (6)	Monthly (7)	Quarterly (8)	Annual (9)
Nationwide unemployment rate ($t-1$)	−0.033 (0.576)	−1.070*** (0.267)	−0.288* (0.165)						
Urban unemployment rate ($t-1$)				−0.242 (0.509)	−0.833*** (0.106)	−0.366*** (0.106)			
Urban occupation rate ($t-1$)							0.839* (0.502)	0.738*** (0.179)	0.171 (0.138)
Consumer goods, excluding fuels and vehicles ($t-1$)	−0.264** (0.114)	0.164*** (0.047)	0.496*** (0.082)	−0.260** (0.121)	0.153*** (0.036)	0.448*** (0.075)	−0.286*** (0.096)	0.105** (0.050)	0.500*** (0.073)
Constant	0.007*** (0.001)	0.011*** (0.002)	0.026*** (0.005)	0.007*** (0.001)	0.011*** (0.001)	0.028*** (0.005)	0.007*** (0.001)	0.012*** (0.001)	0.026*** (0.004)
Dummy 2011:04	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Dummy 2020:04	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummy 2020:05	Yes	No	No	Yes	No	No	Yes	No	No
Dummy 2020:07	No	Yes	No	No	Yes	No	No	Yes	No
Dummy 2021:04	No	No	Yes	No	No	Yes	No	No	Yes
Sample period	2003:03–2021:07	2003:05–2021:07	2004:02–2021:07	2003:03–2021:07	2003:05–2021:07	2004:02–2021:07	2003:03–2021:07	2003:05–2021:07	2004:02–2021:07
Observations	221	219	210	221	219	210	221	219	210
Adjusted R^2	0.389	0.530	0.606	0.390	0.535	0.618	0.422	0.536	0.604
***F*-statistic (prob)**	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durbin–Watson	2.323	1.978	2.098	2.340	2.041	2.023	2.351	1.943	2.087
Breusch–Godfrey autocorrelation test (prob)	0.000	0.417	0.201	0.000	0.147	0.668	0.000	0.779	0.239

Note: Newey–West standard errors. *, **, and * mean that the estimated coefficients are significant at the 10%, 5% and 1% level of significance, respectively.**
Source: Authors' calculations.

3.2. Other factors behind consumption

An argument used in this paper is related to the life-cycle model, a model where retirement is crucial as labor income disappears (or sometimes replaced by a pension) and, consequently, total income is reduced. This fact is an important motivation for saving. Eventually, households accumulate to reach a real or latent wealth target to cover not only the consumption of the household but also health contingencies, and so on.[17]

[17] This argument agrees closely with those of other researchers who have advocated the precautionary saving motive as an explanation of consumption behavior (see, among others, Carroll, 1994, 1997; Carroll and Jeanne, 2009; Carroll, Otsuka, and Slacalek, 2011; Mian, Rao and Sufi, 2013; Berger et al., 2018).

Carroll et al. (2019) present a model that explores three channels to explain consumption: the wealth effect, the availability of credit, and precautionary motives. The model captures the effects of a non-financial risk on intertemporal election; in essence, the risk consists of becoming unemployed. Their contribution is the use of a structural model of saving to construct such a quantitative decomposition. The intuition of the model is that, in the presence of income uncertainty, the optimizing households have a target ratio of wealth to permanent income that depends on time preference, prudence, the degree of labor income uncertainty, and the availability of credit.

This model builds on Carroll and Toche (2009), where a constant relative risk aversion (CRRA) utility function is assumed; the non-financial risk for a worker is the chance of losing their job, and once this happens the worker can never become employed again. This assumption allows a closed-form solution for the level of target wealth, which is defined as the point at which prudence becomes large enough to match impatience.

The model ends up with two equations, one for consumption, c_t^e, and the other for the market resources (i.e. financial wealth and current income, m_t^e), both when the representative agent is employed, e:

$$c_t^e = (1 - \mathcal{R}^{-1}) m_{t+1}^e + \mathcal{R}^{-1}; \tag{2}$$

$$m_{t+1}^e = (m_t^e - c_t^e)\mathcal{R} + 1 \, . \tag{3}$$

Here, $\mathcal{R}$ stands for the ratio of the rate of return conditional on the employment growth factor for individual labor income.

The solution of the model is obtained by solving the two equations in the steady state: $\Delta c_{t+1}^e = \Delta m_{t+1}^e = 0$. These two equations are represented in the phase diagram (Figure 7), where we can see that in steady state we obtain the level of target wealth, $\check{m}^e$. The decision to save or consume will depend on the gap between the target and the actual wealth of the individual.[18]

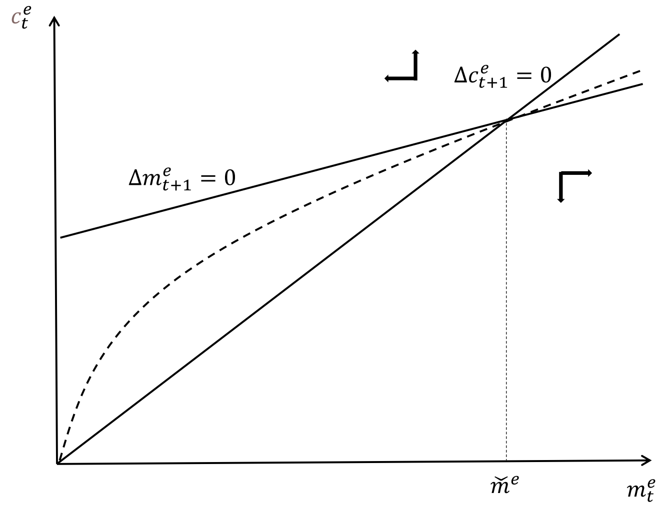
When the coefficient of relative risk aversion is equal to 1 ($\rho = 1$), the target level of market resources, $\check{m}^e$, is given by:

$$\check{m}^e \approx 1 + \left(\frac{1}{(\gamma - r) + \vartheta(1 + (\gamma + \vartheta - r)/\mho)}\right) \ , \tag{4}$$

[18] Solow (1970) also defines (one of) the determinants of the saving rate as the gap between the target wealth and the actual wealth of each individual.

where γ is log Γ, the conditional growth rate for labor income, r is log$R$, which is the rate of return, ϑ is the time preference rate corresponding to $-\log\beta$, which is the time preference factor, and $\mho$ is the probability of falling into permanent unemployment.

Figure 7. The phase diagram.



Source: Carrol and Toche (2019).

Accordingly, the human wealth effect of income growth is related to γ; thus, the higher the value of this parameter, the smaller the target level of wealth. Agents that foresee a high income for this reason will save less in the present, and the result will be reduced wealth. An increase in the interest rate will reduce the human wealth as the discounted value of future labor income will be lower. Higher values of time preference, ϑ, the discount rate of future utility, will imply a lower target level while higher values of unemployment risk, $\mho$, will drive the target wealth level upwards.[19]

Based on the structural theoretical model, Carroll et al. (2019) propose a simple reduced-form estimation for saving rate (s_t) defined as a proportion of disposable income:

$$s_t = \delta_1 + \delta_m m_t + \delta_{CEA} CEA_t + \delta_{Eu} \mathrm{E}_t u_{t+4} + \varepsilon_t. \tag{5}$$

Here, m_t is the measure of the household's normalized market resources as 1 plus the ratio of household net worth to disposable income; CEA measures the bank's willingness to make consumer

[19] In short, Carroll et al. (2019) show that employed consumers' target market resources $\check{m}^e$ will depend on a set of parameters given by $\check{m}^e = f(\mho, CEA(\varsigma), R, \Gamma, \sigma, \rho, \ldots)$, where the target wealth $\check{m}^e$ increases with unemployment risk $\mho$, as consumers build up large precautionary savings, and decreases with the Credit Easing Accumulated, $CEA(\varsigma)$, which depends on the unemployment insurance, ς, that allows the household more access to credit and therefore reduces the need to accumulate wealth for consumption smoothing. The target of market resources increases with a higher interest rate r, as the reward to holding wealth increases, reduces with a faster expected growth of labor income Γ, and increases with risk aversion σ, which increases the uncertainty, and finally increases with the consumer's patience ρ.

installment loans now as opposed to three months ago; finally, as a measure of $\mathrm{E}_t u_{t+4}$, Carroll et al. (2019) use the answers to the question about the expected change in unemployment in the University of Michigan Surveys of Consumers. From equation (5) we could arrive at a simple reduced form for consumption (as a proportion of the disposable income): $c_t = 1 - s_t$. Accordingly, we can add that: $\delta_m < 0$; $\delta_{CEA} < 0$; $\delta_{EU} > 0$.

According to Carroll and Toche (2009) and Carroll et al. (2019), r can have three effects on consumption, as follows: two negative effects are the traditional intertemporal substitution effect, and the effect that results from the increase in the desired wealth or wealth target (the higher r is, the greater $\check{m}^e$ will be, and then the lower consumption will be); the third effect, perhaps positive, results from a possible increase in effective wealth (current financial wealth) if the current loss of the value of bonds (and shares) is more than offset by the higher future financial income currently expected.

In the case of Colombia, there is not enough empirical evidence, during the last two decades, on the relevance of the variables in equation (5), in the short run, for consumption proxied by the retail trade indices.[20] Therefore, we will contribute to fill this gap, by combining the different mechanisms exposed by Carroll et al. (2019), which we briefly mentioned here, and Carrol and Toche (2009), such as the wealth effect, the availability of credit, and precautionary motives in an empirical equation similar to that of Campbell and Mankiw (1990).[21] Given that the properties of the variables are well preserved in monthly, quarterly, and annual variations in the empirical models, consequently the results are presented in such variations. Thus, we first set our empirical model as

$$\Delta c_t = \alpha + \sum_{i=1}^{J} \nu_i \Delta c_{t-i} + \lambda \Delta y_{t-1} + \pi \Delta CC_{t-1} + \theta r_{t-1} + \varphi \Delta CCI_{t-1} + \varepsilon_t, \qquad (6)$$

where, as before, Δc stands for the monthly, quarterly, or annual variation of consumption, r is the interest rate, y is income proxied here by the Economy Monitoring Indicator (ISE), CC is consumer credit in real terms, and CCI is the consumer confidence index, our proxy for uncertainty. The inclusion of CCI in the analysis is one of the main contributions of this paper.[22] The lag of the autoregressive component is chosen based on the significance of the coefficient. Most models include MA components; when this

[20] Some of the local literature has focused on testing the PIH during the period 1950–1997 (Carrasquilla, 1989; Clavijo and Fernández, 1989). Gaviria and Posada (1992) found evidence of an excess sensitivity of consumption to income, during the same period, rejecting the PIH.

[21] Clearly derived from another theoretical set-up.

[22] To close our connection to the prevalent literature on the field of household consumption with the topics we emphasize here, we make a simple reading of the titles of papers published in journals of economics and financial economics during the past decade and find no special emphasis in consumer confidence.

is not the case, Newey–West standard errors are computed. The optimal lags of the models in Table 7 are chosen based on the Hannan–Quinn criterion.

4. Data

The variables for consumption correspond to real retail sales indices, as these represent sales made directly to the final consumer. The data were obtained from various surveys conducted monthly by DANE on retail trade, primarily classified into two categories: merchandise lines and the International Standard Industrial Classification of All Economic Activities (ISIC). Over time, DANE has conducted different surveys with some modifications. We use the Monthly Sample of Retail Trade (hereafter MMCM, its acronym in Spanish), which began in 1989 but underwent a redesign in 2003, a year from which records are available. Subsequently, in 2013, DANE redesigned the survey, called the Monthly Survey of Retail Trade (EMCM, its acronym in Spanish). In 2019, the latest modification to date was presented, and the survey was renamed the Monthly Trade Survey (EMC, its acronym in Spanish), where the most significant change is the inclusion of retail and wholesale trade. However, for this study, only data from retail trade were considered.

Given the above, DANE provides two time cuts for the retail trade sales indices. The first sample spans from January 2003 up to December 2019, encompassing both the MMCM and the EMCM. This period includes 15 merchandise lines and ten classifications based on the fourth revision of the ISIC, with the base year set in 2013. The second sample cut refers to the period from January 2013 to June 2022, comprising 16 merchandise lines (including the fuels category, not previously included) and six ISIC categories based on 2019. Thus, to extend the MMCP series from 2019 to 2021, we use the growth rates of the MMCM.

Total real consumer credit corresponds to the series published by Banco de la República (the central bank of Colombia). This variable was deseasonalized and deflated by the consumer price index (CPI) before computing its percentage annual variation. The consumer credit interest rate refers to the series published by Banco de la República; the variable was converted to real terms by using the *ex ante* Fisher equation, assuming perfect foresight (i.e., expected inflation equal to actual inflation). The same treatment was carried out with the usury interest rate taken from the Financial Supervisory Authority. This corresponds to the maximum value of the remunerative or default interest that a financial institution can charge to the customers and is computed as 1.5 times the average current bank interest by type of credit, in this case, consumer credit.

The ISE corresponds to the series provided by DANE in real terms without the seasonal component, in a monthly frequency, since January 2005, using 2015 as the base year. To extend the ISE series before 2005, we use the growth rates from the previous series also published by DANE. Finally, the consumer confidence index is the series published by Fedesarrollo, which is available since 2001 on a monthly basis, and composed by the index of consumer expectations (IEC) and the index of economic conditions (ICE) both built based on 14 questions.

5. Results

5.1. Univariate approach

This set of results (see Table 4A) corresponds to the estimates of equation (6) including monthly percentage variations not only of consumption but also of the ISE, consumer credit (CC), and the consumer confidence index (CCI). Accordingly, these estimates can be read as elasticities while the estimate corresponding to the real interest rate can be interpreted as a semi-elasticity. Table 4A shows the results before the COVID-19 pandemic. In these cases, none of the labor market outcomes used in the previous section, introduced one at a time, was statistically significant; thus, these variables were not included in the estimation process.

Table 4A. Monthly variation in percentage terms of consumption goods excluding fuels and vehicles before the COVID-19 pandemic, equation (6), OLS

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ISE ($t-1$)	0.417***	0.422***	0.417***	0.417***	0.374***	0.394***
	(0.141)	(0.136)	(0.143)	(0.134)	(0.125)	(0.137)
Real consumer credit ($t-1$)	0.045***	0.043***	0.044***	0.043***	0.040***	0.044***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Real interest rate ($t-1$)	−0.026*	−0.029**	−0.026	−0.028**	−0.019	−0.033**
	(0.015)	(0.014)	(0.016)	(0.013)	(0.013)	(0.015)
Consumer confidence index ($t-1$)		0.044**		0.045**	0.057***	0.041**
		(0.019)		(0.019)	(0.017)	(0.020)
Remittances ($t-1$)					0.035***	
					(0.011)	
Credit card limit ($t-1$)						0.065
						(0.043)
Consumer goods excluding fuels and vehicles ($t-1$)			−0.036	0.044	0.107	−0.019
			(0.114)	(0.122)	(0.106)	(0.118)
Constant	0.006**	0.006***	0.006**	0.006**	0.004*	0.006**
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
MA(1) and MA(2) components	Yes	Yes	Yes	Yes	Yes	Yes
Sample period	2003:03–2019:12	2003:03–2019:12	2003:03–2019:12	2003:03–2019:12	2003:03–2019:12	2003:03–2019:12
Observations	202	202	202	202	202	202
Adjusted R^2	0.542	0.551	0.539	0.549	0.566	0.552
F-statistic (prob)	0.000	0.000	0.000	0.000	0.000	0.000
Durbin–Watson	1.956	1.946	1.956	1.945	1.933	1.972

Note: All models include impulse dummies in 2011:04. All the roots of the MA components fall inside the unit circle. *, **, and * mean that the estimated coefficients are significant at the 10%, 5% and 1% level of significance, respectively.**
Source: Authors' calculations.

The model in column (1) includes the first lags of ISE, y, real consumer credit, CC, and real interest rate, r; all variables are statistically significant at different levels and have the expected signs. In column (2), following the practice of Carroll, Fuhrer, and Wilcox (1994) and Ludvigson (2004), we introduce the CCI to observe the response of the adjusted R^2 and clarify our interpretation about this variable. As we observe, the model in column (2) has a better goodness of fit than that of column (1). Thus, the information content of the CCI is different from the ISE.

The models in columns (5) and (6) include two variables that go beyond our core framework; these are monthly variations of remittances to households from abroad, included as part of the market resources of households,[23] and the change in the aggregate limit of credit cards. Only the former became significant and with the expected sign. However, in this case, the real interest rate stops being statistically significant, suggesting that some collinearity between these two variables might be behind this result.

The models estimated in Table 4B include the urban occupation rate as it was the only labor market outcome to be systematically significant, which suggests that its monthly variations help to predict the percentage changes in consumption. In this case, the inclusion of the CCI instead of increasing the R^2 reduces it; see the models in columns (1) and (2). We obtain a marginal increase of the goodness of fit when the CCI is included but the lag of the consumption goods excluding fuels and vehicles is present in the model.

The inclusion of the urban occupation rate weakens the ISE in the model of monthly percentage changes of household consumption. Thus, the former also operates as an indicator of economic activity. It is also important that, when comparing the models of Tables 4A and 4B, the estimated coefficients of the CCI increase when the sample period is extended up until July 2021 as a symptom (evidence) of higher uncertainty. Although the models are not strictly comparable (given that those in Table 4B include the urban occupation rate and that the drivers included in the models should take into account most of the pandemic's economic environment), there are other reactions of the aggregate consumption that could come from sources other than those included up until now in the model (as presented in Tables 4A, 4B, and 5). In fact, in 2020 it was the first health crisis and the first lockdown with enormous losses of jobs and value assets that triggered the uncertainty. Thus, we have included dummies to control for this (see Table 6B).

[23] On average, between 2000 and 2022, the remittances were 2.01% of GDP, according to the figures from the Banco de la República.

Table 5 shows the results of the same models as in Table 4B (up until 2021), but the percentage variations are quarterly instead of monthly. In this case, the goodness of fit of the models is lower for the similar specifications. The capacity of the quarterly percentage variations of the *ISE* to predict the percentage changes of consumption is weakened, based on the statistical significance, while that of the *CC*, *r*, *CCI*, and the urban occupation rate remain. In this case, the quarterly percentage variations of remittances and credit card limits do not help to predict the quarterly variations of household consumption either.

Table 4B. Monthly variations of consumption goods excluding fuels and vehicles up until 2021, equation (6), OLS

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ISE ($t-1$)	0.298**	0.316**	0.223*	0.196	0.166	0.203*
	(0.119)	(0.131)	(0.130)	(0.119)	(0.105)	(0.121)
Real consumer credit ($t-1$)	0.040***	0.037***	0.041***	0.037***	0.034***	0.037***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)
Real interest rate ($t-1$)	−0.023	−0.026**	−0.020	−0.024	−0.018	−0.027*
	(0.016)	(0.011)	(0.016)	(0.015)	(0.016)	(0.015)
Consumer confidence index ($t-1$)		0.056**		0.053***	0.065***	0.051***
		(0.023)		(0.019)	(0.018)	(0.019)
Remittances ($t-1$)					0.037***	
					(0.013)	
Credit card limit ($t-1$)						0.037
						(0.044)
Occupation rate 13 areas ($t-1$)	0.705***	0.472**	0.616***	0.557***	0.564***	0.575***
	(0.162)	(0.184)	(0.178)	(0.173)	(0.159)	(0.177)
Consumer goods excluding fuels and vehicles ($t-1$)			0.096	0.101	0.104	0.087
			(0.088)	(0.086)	(0.076)	0.086)
Constant	0.005**	0.006***	0.005*	0.006**	0.004*	0.006**
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
MA(1) and MA(3) components	Yes	Yes	Yes	Yes	Yes	Yes
Sample period	2003:03–2021:07	2003:03–2021:07	2003:03–2021:07	2003:03–2021:07	2003:03–2021:07	2003:03–2021:07
Observations	221	221	221	221	221	221
Adjusted R^2	0.646	0.637	0.646	0.656	0.667	0.656
F-statistic (prob)	0.000	0.000	0.000	0.000	0.000	0.000
Durbin–Watson	1.977	2.052	1.991	1.988	1.987	1.997

Note: All models include impulse dummies in 2011:04, 2020:04, and 2020:05. All the roots of the MA components fall inside the unit circle. *, **, and * mean that the estimated coefficients are significant at the 10%, 5% and 1% level of significance, respectively.**
Source: Authors' calculations.

Tables 6A and 6B show the results of the models for annual variations of consumption and the explanatory variables up until 2019 and 2021, respectively, to point out differences in estimated parameters. In annual percentage variations, we obtain the highest fit of the models, and the best performance of the four drivers of changes in consumption in terms of statistical significance and the expected signs. It is worth noting that there is a reduction in the value of the coefficients between 2019 and 2021. Thus, while the estimated coefficients of ISE (y), CC, and r fall in absolute value, that of CCI increased in absolute terms.[24] The models in Table 6B include two impulse dummy variables in April

[24] These types of regression with all explanatory variables lagged one period were also run for the sample period from January 2008 to December 2019, and to July 2021, including the variation of the median hourly wage of salaried workers at the

2020 and 2021 to account for the pandemic period but this result is noticeable as well as the lack of significance of labor market outcomes.

Table 5. Quarterly percentage variation of consumption goods excluding fuels and vehicles up until 2021, equation (6), OLS.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
***ISE* (*t* − 1)**	0.225*	0.125	0.192	0.097	0.099	0.075
	(0.120)	(0.133)	(0.118)	(0.126)	(0.126)	(0.123)
Real consumer credit (*t* − 1)	0.026**	0.026**	0.023*	0.022*	0.021*	0.023*
	(0.013)	(0.012)	(0.013)	(0.012)	(0.012)	(0.012)
Real interest rate (*t* − 1)	−0.080*	−0.063	−0.091**	−0.074**	−0.059	−0.083**
	(0.044)	(0.038)	(0.041)	(0.036)	(0.037)	(0.034)
Consumer confidence index (*t* − 1)			0.055**	0.051**	0.060***	0.047**
			(0.021)	(0.020)	(0.021)	(0.019)
Remittances (*t* − 1)					0.022	
					(0.014)	
Credit card limit (*t* − 1)						0.063
						(0.045)
Occupation rate 13 areas (*t* − 1)	0.588***	0.480***	0.547***	0.431**	0.435***	0.419**
	(0.153)	(0.172)	(0.150)	(0.167)	(0.164)	(0.165)
Consumer goods excluding fuels and vehicles (*t* − 1)		0.148		0.153	0.126	0.176
		(0.112)		(0.107)	(0.105)	(0.108)
Constant	0.022***	0.018***	0.024***	0.020***	0.018***	0.020***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
MA(1) and MA(2) components	Yes	Yes	Yes	Yes	Yes	Yes
Sample period	2003:05–2021:07	2003:05–2021:07	2003:05–2021:07	2003:05–2021:07	2003:05–2021:07	2003:05–2021:07
Observations	219	219	219	219	219	219
Adjusted R^2	0.562	0.563	0.572	0.574	0.577	0.576
***F*-statistic (prob)**	0.000	0.000	0.000	0.000	0.000	0.000
Durbin–Watson	1.886	1.896	1.872	1.887	1.886	1.882

Note: All models include impulse dummies in 2020:04 and 2020:07. All the roots of the MA components fall inside the unit circle. *, **, and * mean that the estimated coefficients are significant at the 10%, 5% and 1% level of significance, respectively.**
Source: Authors' calculations.

In none of the models in columns (5) of Tables 6A and 6B are the remittances significant[25] while in both models in columns (6) the annual variation in credit card limits is statistically significant. However, we should recall that remittances were statistically significant when the variation was monthly (see Tables 4A and 5B). Finally, the model in column (7) of Table 6B includes the usury real interest rate as well as remittances and, as we can observe, both are significant. In this case, the semi-elasticity of the usury interest rate is lower in absolute value.

national level (results not shown but available on request). The four core variables remained significant in most models, but the median hourly wages were only significant when they appear along with remittances.

[25] This result resembles that of Medina and Cardona (2010). However, below we find a result showing that the remittances help to predict the annual changes in consumption.

Table 6A. Annual percentage variation of consumption goods excluding fuels and vehicles up until 2019, equation (6), OLS.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
$ISE\ (t-1)$	0.708***	0.535***	0.644***	0.501***	0.511***	0.425***
	(0.139)	(0.101)	(0.134)	(0.104)	(0.107)	(0.103)
Real consumer credit $(t-1)$	0.065***	0.058***	0.058***	0.053***	0.053***	0.052***
	(0.009)	(0.008)	(0.010)	(0.009)	(0.009)	(0.009)
Real interest rate $(t-1)$	−0.413***	−0.312***	−0.418***	−0.327***	−0.266***	−0.383***
	(0.065)	(0.061)	(0.072)	(0.068)	(0.088)	(0.075)
Consumer confidence index $(t-1)$			0.042**	0.034**	0.043***	0.026
			(0.018)	(0.016)	(0.016)	(0.016)
Remittances $(t-1)$					0.016	
					(0.010)	
Credit card limit $(t-1)$						0.060*
						(0.036)
Dummy 2011:04	0.117***	0.130***	0.118***	0.129***	0.131***	0.126***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Consumer goods excluding fuels and vehicles (t-1)		0.211***		0.188***	0.192***	0.153**
		(0.069)		(0.067)	(0.064)	(0.071)
Constant	0.079***	0.059***	0.083***	0.065***	0.055***	0.072***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.016)	(0.014)
Sample period	2004:02–2019:12	2004:02–2019:12	2004:02–2019:12	2004:02–2019:12	2004:02–2019:12	2004:02–2019:12
Observations	191	191	191	191	191	191
Adjusted R^2	0.583	0.606	0.597	0.614	0.617	0.618
F-statistic (prob)	0.000	0.000	0.000	0.000	0.000	0.000
Durbin–Watson	1.711	2.115	1.702	2.076	2.107	2.010
Breusch–Godfrey autocorrelation test (prob)	0.063	0.140	0.048	0.286	0.172	0.819

Note: All models include impulse dummy in 2011:04. Newey-West standard errors. *, **, and * mean that the estimated coefficients are significant at the 10%, 5% and 1% level of significance, respectively.**
Source: Authors' calculations.

Table 6B. Annual percentage variation of consumption goods excluding fuels and vehicles up until 2021, equation (6), OLS.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ISE\ (t-1)$	0.506***	0.302***	0.446***	0.288***	0.277***	0.285***	0.222**
	(0.076)	(0.082)	(0.074)	(0.085)	(0.086)	(0.096)	(0.093)
Real consumer credit $(t-1)$	0.033**	0.031**	0.027*	0.025*	0.025*	0.027**	0.025*
	(0.016)	(0.014)	(0.015)	(0.014)	(0.014)	(0.012)	(0.013)
Real interest rate $(t-1)$	−0.347***	−0.252***	−0.362***	−0.284***	−0.256***	−0.395***	
	(0.085)	(0.074)	(0.075)	(0.065)	(0.072)	(0.062)	
Usury real interest rate $(t-1)$							−0.250***
							(0.070)
Consumer confidence index $(t-1)$			0.073***	0.065***	0.070***	0.041**	0.062***
			(0.022)	(0.020)	(0.021)	(0.017)	(0.018)
Remittances $(t-1)$					0.009		0.024***
					(0.009)		(0.008)
Credit card limit $(t-1)$						0.121***	
						(0.040)	
Consumer goods excluding fuels and vehicles $(t-1)$		0.221***		0.177***	0.176***	0.121*	0.174**
		(0.067)		(0.064)	(0.063)	(0.067)	(0.075)
Constant	0.080***	0.062***	0.087***	0.071***	0.067***	0.077***	0.089***
	(0.012)	(0.010)	(0.010)	(0.009)	(0.011)	(0.009)	(0.018)
Sample period	2004:02–2021:07	2004:02–2021:07	2004:02–2021:07	2004:02–2021:07	2004:02–2021:07	2004:02–2021:07	2004:02–2021:07
Observations	210	210	210	210	210	210	210
Adjusted R^2	0.660	0.677	0.686	0.696	0.696	0.715	0.701
F-statistic (prob)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Durbin–Watson	1.371	1.799	1.463	1.806	1.809	1.810	1.835
Breusch–Godfrey autocorrelation test (prob)	0.000	0.015	0.000	0.014	0.016	0.016	0.040

Note: All models include impulse dummy in 2011:4, 2020:4, and 2021:4. Newey-West standard errors. *, **, and * mean that the estimated coefficients are significant at 10%, 5% and 1% level of significance, respectively. Source: Authors calculations.**

To predict the changes of retail trade excluding fuels and vehicles, we also estimated models with the number of lags chosen optimally by using criteria such as the Akaike information criterion, the Bayesian information criterion, and the Hannan–Quinn information criterion. In this case, we pay special attention to the latter. Thus, equation (6) is slightly modified and is written as

$$\Delta c_t = \alpha + \sum_{i=1}^{J} \nu_i \Delta c_{t-i} + \sum_{i=1}^{K} \lambda_i \Delta y_{t-i} + \sum_{i=1}^{K} \pi_i \Delta CC_{t-i} + \sum_{i=1}^{K} \theta_i r_{t-i} + \sum_{i=1}^{K} \varphi_i \Delta CCI_{t-i} + \varepsilon_t. \quad (7)$$

Importantly, as we can observe in Table 7, except for the model of column (4), the optimal lag of explanatory variables is one, as we have been doing until now. The core variables continue to be important factors behind the annual percentage changes in household consumption and with the expected signs; the lowest adjusted R^2 is 0.728, column (1), while the highest is 0.742, column (4). These values of the determination coefficient are higher than those of the models in Table 6B. Nevertheless, it is remarkable that when the usury interest rate is the variable used in the models, instead of the consumer credit interest rate, together with the remittances, the *ISE* is not statistically significant; this result is in stark contrast with the model of column (7) in Table 6B where both the *ISE* and remittances were statistically significant.[26]

Table 7. Consumer goods excluding fuels and vehicles, optimal lag, equation (7)[27]

Variables	(1)	(2)	(3)	(4)	(5)
***ISE* ($t-1$)**	0.292**	0.249*	0.283**	0.336*	0.206
	(0.137)	(0.144)	(0.121)	(0.192)	(0.131)
Real consumer credit ($t-1$)	0.047***	0.047***	0.042***	0.082***	0.044***
	(0.015)	(0.015)	(0.013)	(0.026)	(0.015)
Real interest rate ($t-1$)	−0.334***	−0.228*	−0.410***	−0.311***	
	(0.098)	(0.120)	(0.092)	(0.114)	
Usury real interest rate ($t-1$)					−0.259***
					(0.095)
Consumer confidence index ($t-1$)	0.093***	0.113***	0.067**		0.103***
	(0.028)	(0.032)	(0.027)		(0.031)
Remittances ($t-1$)		0.033			0.043***
		(0.020)			(0.017)
Credit card limit ($t-1$)			0.109**		
			(0.050)		
Constant	0.051***	0.041***	0.058***	0.039***	0.060***
	(0.012)	(0.013)	(0.012)	(0.013)	(0.017)
Lags of dependent variable	4	4	4	3	4
Lags of independent variables (*j*)	1	1	1	4	1
Sample period	2004:01–2021:07	2004:01–2021:07	2004:01–2021:07	2004:01–2021:07	2004:01–2021:07
Observations	207	207	207	207	207
Adjusted R^2	0.728	0.730	0.732	0.742	0.734
Prob (*F*-statistic)	0.000	0.000	0.000	0.000	0.000
Hannan–Quinn	−6.895	−6.893	−6.899	−6.873	−6.909
Durbin–Watson	1.893	1.907	1.892	1.909	1.928
Breusch–Godfrey autocorrelation test (prob)	0.213	0.291	0.189	0.302	0.436

Notes: All models include an impulse dummy in 2011:04. *, **, and * mean that the estimated coefficients are significant at 10%, 5% and 1% level of significance, respectively. The models are tested, using the Breusch–Godfrey autocorrelation test (prob), for MA (2) processes.**
Source: Authors' calculations.

[26] Consistent results are shown in Appendix A for consumption excluding fuels and ISE – commerce.
[27] The coefficients and the standard deviations were calculated using the Deltha method in the *R* software.

The empirical specifications presented so far are based on lags of the factors behind the growth of household consumption. However, it could be important to carry out the estimations using contemporary values of such factors. In this case, the potential endogeneity of ISE (y), consumer credit (CC), real interest rate (r), and consumer confidence index (CCI) emerges as an important problem to address. To overcome this difficulty, the models were also estimated by using instrumental variables, as we can observe in Table 8.

The models we estimated in this case consider two or three of the variables (y, r, CC, and CCI) as potentially endogenous while the remaining variables are lagged by one period.[28] The variables y (ISE) and r were instrumented in all models of Table 8. In such models, both were significant and with the expected sign. The variable CC, when instrumented, was also significant [see models in columns (3)–(5)] as well as the variation of the credit card limits. By contrast, the CCI was significant only in models of columns (1) and (2), those with the highest goodness of fit. As we can observe, according to the Sargan statistic, the Cragg–Donald, and the F-test, the models of Table 8 can be used to understand the behavior of household consumption.

5.2. Forecasting accuracy

It is natural to question the capacity of the models that we have shown so far to forecast the annual percentage changes of consumption. The models selected for this task are the model of column (6) in Table 6B (R^2 = 0.715) and the model in column (7) in which the real interest rate corresponds to the usury interest rate (R^2 = 0.701).[29] Both models, in annual variations, are estimated for the period 2003:01–2021:07. For this task, we also selected the five models in Table 7 with optimal lags to observe their forecasting performance. The sparring model is a simple AR(12).

Tables 8 and 9 show some measures used to evaluate the forecasting capacity of these models for different time horizons. These forecasting exercises are out-of-sample for the annual variation of consumption using the observed values of explanatory variables. That is, first, the models are estimated between 2004:01 and 2019:12 and then they are used to predict the annual variation of consumption one month, three months, and six months ahead. Next, we re-estimate the models including the observed value of consumption in January 2020 and make the predictions again, and so on. It is important to mention that all these models include the two dummies to account for the changes due the health crisis in addition to the 2011:04 dummy.

[28] It was difficult for us to instrument the four potentially endogenous variables at the same time.
[29] Not shown but available on request.

Table 8. Annual percentage variation of consumer goods excluding fuels and vehicles, instrumental variables

Variables	(1)	(2)	(3)	(4)	(5)
ISE	0.362***	0.346***	0.285*	0.287*	0.295*
	(0.125)	(0.125)	(0.168)	(0.168)	(0.159)
Real consumer credit			0.078**	0.077**	0.077**
			(0.038)	(0.037)	(0.036)
Real consumer credit (*t* − 1)	0.028***	0.027***			
	(0.008)	(0.008)			
Real interest rate	−0.329***	−0.326***	−0.329***	−0.326***	−0.340***
	(0.078)	(0.085)	(0.101)	(0.105)	(0.102)
Consumer confidence index	0.042*	0.042*		0.013	0.009
	(0.022)	(0.024)		(0.031)	(0.032)
Consumer confidence index (*t* − 1)			0.011		
			(0.027)		
Credit card limit		0.116**	0.129**	0.128*	0.141**
		(0.055)	(0.066)	(0.066)	(0.065)
Credit card limit (*t* − 1)	0.107***				
	(0.034)				
Consumer goods excluding fuels and vehicles (*t* − 1)	0.147**	0.152**	0.040	0.043	0.033
	(0.061)	(0.064)	(0.100)	(0.101)	(0.101)
Constant	0.065***	0.064***	0.062***	0.062***	0.063***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)
Sample period	2004:01 2021:07	2004:01 2021:07	2004:01 2021:07	2004:01 2021:07	2004:01 2021:07
Observations	205	207	206	206	206
Adjusted R^2	0.732	0.731	0.605	0.606	0.605
***F*-statistic (prob)**	0.000	0.000	0.000	0.000	0.000
Sargan statistic (prob)	0.136	0.438	0.318	0.213	0.454
Underidentification test Anderson canon (prob)	0.000	0.000	0.024	0.010	0.013
Cragg–Donald Wald (*F*-statistic)	24.791	16.107	1.616	1.673	1.630
Stock–Yogo weak ID test critical values					
5% maximal IV relative bias	12,20				
10% maximal IV relative bias	7,77				
20% maximal IV relative bias	5,35				
30% maximal IV relative bias	4,40				

Notes: Instruments for the model in column (1): the real interbank rate (TIB), annual inflation rate (*t* − 6), growth of ISE (*t* − 3), economic conditions index (ICE) (*t* − 3), change of urban unemployment rate (*t* − 1), change in country's expectations (*t* − 1). Instruments for the model in column (2): the real interbank rate (TIB), annual inflation rate (*t* − 1), growth of ISE (*t* − 3), economic conditions index (ICE) (*t* − 4), change of urban unemployment rate (*t* − 1), change in country's expectations (*t* − 1). Instruments for the models in columns (3) and (4): the real interbank rate (TIB), annual inflation rate (*t* − 4), growth of ISE (*t* − 1), economic conditions index (ICE) (*t* − 3), economic conditions index (ICE) (t − 4), economic conditions index (ICE) (*t* − 5), change in unemployment rate for the United States (*t* − 5), change in country's expectations (*t* − 1), Oceanic Niño Index (ONI) (*t* − 1). Instruments for the model in column (5): the real interbank rate (TIB), annual inflation rate (*t* − 2), annual inflation rate (*t* − 3), growth of ISE (*t* − 1), economic conditions index (ICE) (*t* − 3), economic conditions index (ICE) (*t* − 4), economic conditions index (ICE) (*t* − 5), change in unemployment rate for the United States (*t* − 5), change in country's expectations (*t* − 1), ONI (*t* − 1). All models include an impulse dummy in 2011:04, 2020:04, and 2021:04. *, **, and * mean that the estimated coefficients are significant at the 10%, 5% and 1% level of significance, respectively.**
Source: Authors' calculations.

Table 9 shows the results by using standard measures of some selected time horizons. Accordingly, the best performance in all time horizons corresponds to the model of column (6) of Table 6B, which, apart from the four main variables, also includes the annual variation of credit card limits. A similar table of forecast accuracy without including the dummies[30] was also built (not shown but available on request).

[30] In this case, the entire burden of the COVID-19 crisis in the models used to make the forecasts is left in the hands of the explanatory variables.

The model of column (4) in Table 7 presented the best results for one and six months ahead, when the criterion is the symmetric mean absolute percentage error (SMAPE) and the model of column (1) of the same table for the one-month ahead forecast under the mean absolute error (MAE) metric.

Table 9. Prediction accuracy of models in Tables 6B and 7 including dummies for the COVID-19 pandemic

Time horizon	MSE	RMSE	MAE	MAPE	SMAPE	Theil's U1	Theil's U2
				Model of column (6), Table 6B			
One month ahead	0.0039	0.0623	0.0549	1.2416	1.1175	0.2989	0.6407
Three months ahead	0.0034	0.0585	0.0476	1.1436	0.9929	0.2102	0.4349
Six months ahead	0.0070	0.0835	0.0710	1.1217	1.1778	0.2759	0.6371
				Model of column (7), Table 6B			
One month ahead	0.0045	0.0673	0.0591	1.3216	1.2013	0.3154	0.6925
Three months ahead	0.0046	0.0679	0.0540	1.2583	1.0585	0.2403	0.5047
Six months ahead	0.0076	0.0870	0.0734	1.3082	1.1755	0.2907	0.6638
				Model of column (1), Table 7			
One month ahead	0.0044	0.0664	0.0547	1.3786	1.0299	0.3173	0.6825
Three months ahead	0.0054	0.0736	0.0619	1.4434	1.0973	0.2595	0.5466
Six months ahead	0.0094	0.0971	0.0792	1.2940	1.0433	0.3080	0.7411
				Model of column (2), Table 7			
One month ahead	0.0045	0.0671	0.0555	1.3886	1.0342	0.3181	0.6898
Three months ahead	0.0055	0.0741	0.0628	1.4646	1.0976	0.2582	0.5506
Six months ahead	0.0099	0.0996	0.0814	1.3579	1.0422	0.3124	0.7601
				Model of column (3), Table 7			
One month ahead	0.0045	0.0671	0.0559	1.3698	1.0333	0.3194	0.6900
Three months ahead	0.0057	0.0752	0.0631	1.4616	1.0971	0.2643	0.5590
Six months ahead	0.0094	0.0969	0.0785	1.3144	1.0329	0.3098	0.7390
				Model of column (4), Table 7			
One month ahead	0.0045	0.0671	0.0560	1.4079	0.9969	0.3275	0.6899
Three months ahead	0.0054	0.0737	0.0626	1.5017	1.1109	0.2641	0.5474
Six months ahead	0.0093	0.0962	0.0749	1.2898	0.9602	0.3043	0.7341
				Model of column (5), Table 7			
One month ahead	0.0048	0.0690	0.0563	1.3979	1.0407	0.3273	0.7094
Three months ahead	0.0060	0.0775	0.0635	1.4688	1.1046	0.2754	0.5760
Six months ahead	0.0088	0.0938	0.0757	1.3806	0.9925	0.3094	0.7157
				Model AR(12)			
One month ahead	0.0068	0.0825	0.0706	1.6374	1.2064	0.4755	0.8479
Three months ahead	0.0136	0.1164	0.0945	2.0686	1.3875	0.4565	0.8650
Six months ahead	0.0148	0.1217	0.1078	1.8794	1.3590	0.3796	0.9286

Source: Authors' calculations.

Finally, we also implement a measure of forecasting accuracy using the Diebold and Mariano (1995) test for the models estimated for the sample period between 2004:1 and 2021:1. In this case, this test uses the MAE. In the R software program, we use the “greater” option for this test, where the hypotheses are “H_0 = the second model is not significantly better than the first model” and “H_1 = the second model is better than the first model”.[31]

Table 10. Diebold–Mariano tests for forecast accuracy using the final sample period.

First model versus second model	One month ahead		Three months ahead		Six months ahead	
	Statistic	***p*-value**	**Statistic**	***p*-value**	**Statistic**	***p*-value**
Column (1) of Table 7 versus AR12	−0.8580	0.7968	−0.9510	0.8205	−1.1949	0.8733
Column (1) of Table 7 versus Column (2) of Table 7	−1.8537	0.9567	−0.9344	0.8164	−1.9059	0.9605
Column (1) of Table 7 versus Column (3) of Table 7	−1.1551	0.8656	−0.7414	0.7642	0.1500	0.4415
Column (1) of Table 7 versus Column (4) of Table 7	−0.1455	0.5567	−0.0934	0.5365	2.8860	0.0064
Column (1) of Table 7 versus Column (5) of Table 7	−1.3086	0.8933	−0.3634	0.6389	0.2504	0.4031
Column (1) of Table 7 versus Column (6) of Table 6B	−0.0267	0.5105	2.8095	0.0074	1.1186	0.1418
Column (1) of Table 7 versus Column (7) of Table 6B	−0.5266	0.6963	2.3564	0.0174	0.6767	0.2552
Column (2) of Table 7 versus AR12	−0.8174	0.7858	−0.9082	0.8099	−1.1460	0.8638
Column (2) of Table 7 versus Column (3) of Table 7	−0.4618	0.6741	−0.1885	0.5733	0.6166	0.2741
Column (2) of Table 7 versus Column (4) of Table 7	−0.0566	0.5222	0.0324	0.4873	2.0546	0.0303
Column (2) of Table 7 versus Column (5) of Table 7	−0.6883	0.7483	−0.1543	0.5601	0.4237	0.3393
Column (2) of Table 7 versus Column (6) of Table 6B	0.0929	0.4637	3.0985	0.0042	1.2661	0.1138
Column (2) of Table 7 versus Column (7) of Table 6B	−0.4332	0.6640	2.5231	0.0127	1.1065	0.1443
Column (3) of Table 7 versus AR12	−0.8066	0.7828	−0.9028	0.8085	−1.3725	0.9034
Column (3) of Table 7 versus Column (4) of Table 7	−0.0122	0.5048	0.0587	0.4770	0.6037	0.2782
Column (3) of Table 7 versus Column (5) of Table 7	−0.3361	0.6289	−0.1168	0.5456	0.3121	0.3800
Column (3) of Table 7 versus Column (6) of Table 6B	0.1616	0.4371	2.4699	0.0141	0.9380	0.1827
Column (3) of Table 7 versus Column (7) of Table 6B	−0.4012	0.6526	4.5971	0.0003	0.5736	0.2880
Column (4) of Table 7 versus AR12	−1.0108	0.8347	−0.8510	0.7949	−1.1508	0.8647
Column (4) of Table 7 versus Column (5) of Table 7	−0.0360	0.5141	−0.0830	0.5324	−0.0554	0.5217
Column (4) of Table 7 versus Column (6) of Table 6B	0.1655	0.4355	5.5648	0.0000	0.3598	0.3624
Column (4) of Table 7 versus Column (7) of Table 6B	−0.3471	0.6330	0.8750	0.1987	0.1102	0.4570
Column (5) of Table 7 versus AR12	−0.7461	0.7656	−0.8379	0.7914	−1.4394	0.9132
Column (5) of Table 7 versus Column (6) of Table 6B	0.2065	0.4198	2.1112	0.0273	0.3512	0.3655
Column (5) of Table 7 versus Column (7) of Table 6B	−0.3042	0.6171	2.7009	0.0091	0.2579	0.4003
Column (6) of Table 6B versus AR12	−1.0253	0.8380	−1.3530	0.9004	−1.4174	0.9101
Column (6) of Table 6B versus Column (7) of Table 6B	−1.7077	0.9443	−0.9787	0.8272	−0.2077	0.5806
Column (7) of Table 6B versus AR12	−0.7401	0.7638	−1.2477	0.8829	−1.8664	0.9577

Source: Authors’ calculations.

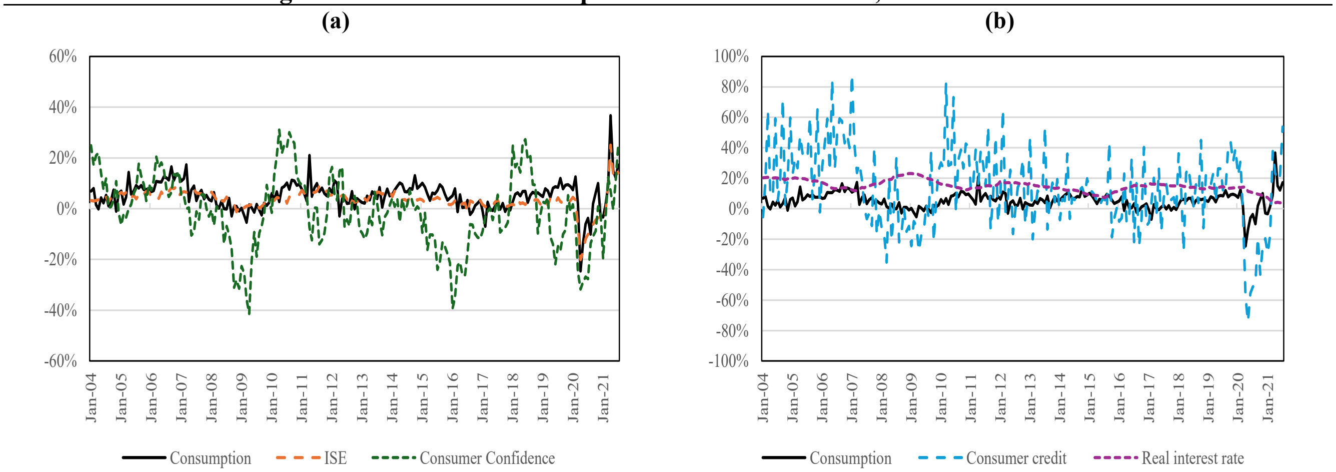
[31] According to the instructions: “This function implements the modified test proposed by Harvey, Leybourne and Newbold (1997). The null hypothesis is that the two methods have the same forecast accuracy. For the option “less”, the alternative hypothesis is that the second model is less accurate than the first model. For the “greater” option, the alternative hypothesis is that the second model is more accurate than the first model. Finally, for the “two-sided” option, the alternative hypothesis is that the first model and the second model have different levels of accuracy.”

According to the results, the models of columns (6) and (7) of Table 6B perform particularly well forecasting the annual variations of consumption three months ahead. In the other two time horizons, the models of Table 7 outperform the two models of Table 6B.

5.3. Multivariate approach: vector autoregression analysis

Figure 8 shows the behavior of percentage annual variations in consumption as well as the main factors behind the consumption behavior. Visually, it is not difficult to find some coherence between the consumption indicator and the *ISE* and consumer confidence (in panel a), and the real interest rate and real consumer credit (in panel b). In a Granger sense, these four variables cause the percentage variation of retail trade indices.

Figure 8. Household consumption and its main drivers, 2004:01–2021:07

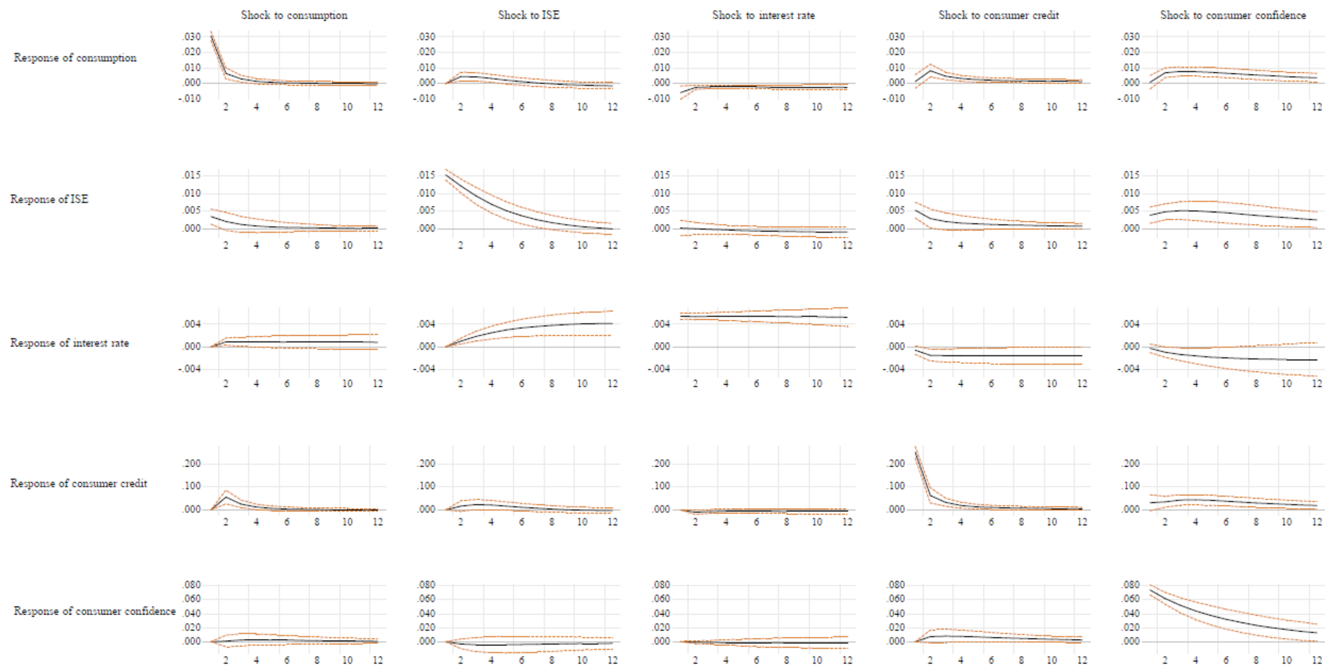


Source: Banco de la República, DANE, and Fedesarrollo; authors' calculations.

However, given that we have at hand several potentially endogenous variables, as we mentioned above, a multivariate approach is a natural step forward. Thus, following Bram and Ludvigson (1998) and Dees and Brinca (2013), we address the following question. What is the dynamic response of consumption to the shocks of the system variables including the consumer confidence? We ask this question because the inclusion of the ICC into the analysis of consumption is one of the main contributions of this work. To answer it, we follow a VAR analysis and, consequently, estimate a model consisting of five equations, one for each of the core variables used in the reduced-form regressions of the univariate approach of the previous section. With the aim of identification, the orthogonalization of the system is done via Cholesky factor decomposition of the variance-covariance matrix of the residuals. Thus, the restrictions are introduced at impact. Following Bram and Ludvigson (1998) and Dees and

Brinca (2013), the order of the variables is CCI, CC, r, C, and y, where y is the ISE; the lag of variables is equal to one as in the univariate approach (see Figure 9).

Figure 9. VAR analysis: responses of the variables



Source: Authors' calculations.

Variables such as C, y, and CC show intuitive dynamic responses given shocks to ICC and r, respectively. The responses of C have the same sign as those obtained in the univariate analysis; thus, we might claim that these variables content important information about the short-run dynamics of household consumption in Colombia. The dynamic responses of y to CC shocks and of r to y shocks are important predictions of the empirical multivariate model.

6. Some preliminary lessons

In this paper, we have studied the behavior of household consumption in the short term, over the two decades of this century, using the retail trade indices that DANE publishes monthly. To the best of our knowledge, these retail trade indices have not been carefully studied in the past. Given the properties of the data, we do not aim to obtain structural parameters, suitable for policy evaluation. We do not claim that we have identified causal relationships either. Instead, we provide evidence that sheds some light on the drivers of the dynamics of household consumption in Colombia, a country that is known for having an imperfect financial market, including liquidity constraints (see Arango and Quevedo, 2022) and other frictions that affect the behavior of household consumption.

To achieve this goal, we use an empirical approach that draws on the contributions of Hall (1978), Campbell and Mankiw (1990), Carroll and Toche (2009) and Carroll et al. (2019). The time series properties of the variables of household consumption allow us to reject the random walk hypothesis and to analyze the variables not only in levels but also in monthly, quarterly, and annual percentage variations. The empirical approaches are both univariate and multivariate. Thus, we estimate different types of models by OLS and instrumental variables, and report that labor market outcomes (nationwide and urban unemployment rates, and urban occupation rate) are highly important drivers of household consumption, mainly when this variable is set in log-levels, and monthly and quarterly percentage variations.[32] The importance of labor market outcomes vanishes as long as other variables, borrowed from the theory, are considered in the empirical models, or the consumption is modeled in annual percentage variations. This finding is very important as economists are always trying to connect the labor market outcomes with some other variables of the real sector, and the connection is diffuse.

Finally, we find that the short-run dynamics of household consumption depends on variations of *ISE*, the real interest rate, the real consumer credit, and consumer confidence, with some relevance of changes in credit card limits and remittances. All these variables explain more than 70% of the annual percentage variations of consumption in a period affected by the contraction of the economy during 2008 and the first quarter of 2009 (Alfonso et al., 2013), the reduction of commodity prices in 2015 (IMF, 2015), and the outbreak of the COVID-19 pandemic, apart from many other developments in the financial sector.

Importantly, the significance of consumer confidence would suggest the presence of some precautionary saving in consumer decisions, therefore, the presence of uncertainty (see Carroll et al., 1994). Thus, confidence helps to forecast future consumption. More precisely, in the model of Carroll et al. (2009), it represents a non-financial risk linked to the probability of being unemployed in the future, which motivates consumers to have a target for wealth that is linked to permanent income. According to our findings, based on consumption excluding fuels and vehicles, the coefficient of consumer confidence increased after the COVID-19 pandemic; nevertheless, this result does not hold for the other two consumption indicators used in this empirical work. Household consumption also responds to shocks to consumer confidence and consumer credit in a multivariate framework.

The evidence suggests that habit seems to be a characteristic of consumption with this data set when this variable is modeled in levels, but not when it is modeled in monthly, quarterly, and annual variations. In these cases, the significance of the autoregressive components of the models might be more associated

[32] In this sense, Arango et al. (2021), in the context of consumer-oriented credit cards, showed that the individual and aggregate labor market outcomes determine the limits and the probability of the use of credit cards but not the amount of purchases.

with the fact that expenditure in consumption goods is made on a continuous basis while data are measured in discrete time aggregates even if the goods are non-durable (Christiano et al., 1991). However, Mankiw (1982) suggested that the growth in spending might be positively autocorrelated because of the presence of durable goods.

Appendix A. Selected models for consumption goods excluding fuels and ISE – commerce

Table A.1. Models for annual variations of consumption goods excluding fuels: consumer credit and usury real interest rates, OLS, 2004:01–2021:07

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ISE $(t-1)$	0.5765***	0.6517***	0.6497***	0.6597***	0.7681***	0.6880***	0.2515**	0.2119*
	(0.1693)	(0.1587)	(0.1566)	(0.1491)	(0.1524)	(0.1489)	(0.1172)	(0.1131)
Real consumer credit $(t-1)$	0.0107	0.0119	0.0048	0.0080	0.0121	0.0078	0.0208**	0.0183*
	(0.0156)	(0.0147)	(0.0144)	(0.0139)	(0.0139)	(0.0139)	(0.0100)	(0.0100)
Real interest rate $(t-1)$	−0.3871***		−0.5073***		−0.8676***		−0.4875***	
	(0.1145)		(0.1074)		(0.1319)		(0.0990)	
Usury real interest rate $(t-1)$		−0.6895***		−0.6746***		−0.7287***		−0.4260***
		(0.1175)		(0.1104)		(0.1121)		(0.0832)
Consumer confidence index $(t-1)$			0.1844***	0.1534***	0.1275***	0.1416***	0.1055***	0.1131***
			(0.0304)	(0.0289)	(0.0318)	(0.317)	(0.0230)	(0.0228)
Credit card limit $(t-1)$					0.1438**	−0.0890*	0.1660***	0.0334***
					(0.0589)	(0.0538)	(0.0427)	(0.0398)
Remittances $(t-1)$					−0.0680***	−0.0336**	−0.0231*	−0.0041
					(0.0185)	(0.0170)	(0.0138)	(0.0124)
Dummy 2011:04							0.1136***	0.1150***
							(0.0361)	(0.0359)
Dummy 2020:04							−0.3150***	−0.3159***
							(0.0388)	(0.0385)
Dummy 2021:04							0.4393***	0.4409***
							(0.0388)	(0.0382)
Constant	0.0721***	0.1840***	0.1033***	0.1910***	0.1452***	0.2119***	0.0860***	0.1277***
	(0.0183)	(0.0296)	(0.0176)	(0.0278)	(0.0194)	(0.0294)	(0.0146)	(0.0219)
Lags of dependent variable	2	2	2	2	2	2	2	2
Sample period	2004:01–2021:07	2004:01–2021:07	2004:01–2021:07	2004:01–2021:07	2004:01–2021:07	2004:01–2021:07	2004:01–2021:07	2004:01–2021:07
Observations	209	209	209	209	209	209	209	209
Adjusted R^2	0.5165	0.5633	0.5890	0.6148	0.6224	0.6208	0.8040	0.8058
F-statistic (prob)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Durbin–Watson	1.8833	0.8730	1.8323	1.8491	1.7969	1.8229	1.8316	1.8449
Jarque–Bera (prob)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0022	0.0603
Breusch–Godfrey autocorrelation test (prob)	0.0000	0.0001	0.0016	0.0071	0.0005	0.0013	0.1753	0.2123

Note: *, **, and *** mean that the estimated coefficients are significant at the 10%, 5% and 1% level of significance, respectively.
Source: Authors' calculations.

Table A.2. Annual variation of ISE – commerce: consumer credit and usury real interest rates, OLS

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ISE ($t-1$)	0.5849**	0.2677*	0.5175**	0.2297	0.7704***	0.3049*	0.1777	0.4236*	−0.0320
	(0.2311)	(0.1468)	(0.2354)	(0.1494)	(0.2527)	(0.1659)	(0.1772)	(0.2350)	(0.1479)
Real consumer credit ($t-1$)	−0.0024	0.0143	−0.0048	0.0127	−0.0019	0.0130**	0.0196***	−0.0066	0.0207**
	(0.0140)	(0.0088)	(0.0140)	(0.0088)	(0.0139)	(0.0054)	(0.0095)	(0.0137)	(0.0086)
Real interest rate ($t-1$)	−0.2837***	−0.1679***	−0.2631***	−0.1596***	−0.3695***	−0.1630**	−0.2107***		
	(0.0987)	(0.0619)	(0.0975)	(0.0612)	(0.1110)	(0.0721)	(0.0757)		
Usury real interest rate ($t-1$)								−0.1866**	−0.2100***
								(0.0942)	(0.0581)
Consumer confidence index ($t-1$)			0.0383	0.0199	0.0258	0.0230	0.0133	0.03581	0.0068
			(0.0256)	(0.0159)	(0.0286)	(0.0182)	(0.0188)	(0.0265)	(0.0164)
Credit card limit ($t-1$)					−0.1196**	−0.0398	−0.0207		
					(0.0543)	(0.0350)	(0.0361)		
Remittances ($t-1$)					−0.0411**	−0.0033	−0.0072		
					(0.0168)	(0.0109)	(0.0110)		
Unemployment rate ($t-1$)							−0.5170*	0.0754	−0.8180***
							(0.2691)	(0.4168)	(0.2638)
Dummy 2020:04		−0.3600***		−0.3585***		−0.3537***	−0.3563***		−0.3624***
		(0.0299)		(0.0297)		(0.0305)	(0.0303)		(0.0298)
Dummy 2021:04		0.4007***		0.3991***		0.3938***	0.4077***		0.4271***
		(0.0306)		(0.0304)		(0.0189)	(0.0318)		(0.0312)
Constant	0.0394	0.0278***	0.0398***	0.0283	0.0629***	0.0062	0.0435***	0.00469*	0.0670***
	(0.0146)	(0.0092)	(0.0145)	(0.0091)	(0.0163)	(0.0067)	(0.0124)	(0.0262)	(0.0162)
Lags of dependent variable	3	3	2	2	3	3	3	2	2
Sample period	2006:01–2021:07	2006:01–2021:07	2006:01–2021:07	2006:01–2021:07	2006:01–2021:07	2006:01–2021:07	2006:01–2021:07	2006:01–2021:12	2006:01–2021:12
Observations	184	184	185	185	184	184	184	190	190
Adjusted R^2	0.7343	0.8978	0.7368	0.8986	0.74805	0.8976	0.9637	0.7625	0.9097
F-statistic (prob)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Durbin–Watson	1.9715	2.1006	1.9239	2.0838	1.8917	2.0802	2.2159	1.9304	2.0558
Jarque–Bera (prob)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Breusch–Godfrey autocorrelation test (prob)	0.4825	0.0000	0.0391	0.0002	0.0065	0.0001	0.0045	0.0267	0.1788

Note: *, **, and * mean that the estimated coefficients are significant at the 10%, 5% and 1% level of significance, respectively.**
Source: Authors' calculations.

Appendix B. Stationary tests of variables

ADF tests were carried out with the help of the Akaike criterion in the *R* software and some additional tests in EViews with the Schwartz criterion, for more than 100 variables at different periodicities.

Table B.1. Main variables of the models

Variables	**2003:01 – 2019:12**	**2003:01– 2021:07**	**2003:01– 2021:12**	**2004:01– 2019:12**	**2004:01– 2021:07**	**2004:01– 2021:12**
Main variables in log-levels[33]						
Total retail trade excluding fuels	†	†	✓			
Total retail trade excluding fuels and vehicles	†	✓	✓			
Real consumption interest rate	✓	✓	X			
Usury real interest rate	✓	✓	✓			
Main variables in monthly variations						
Total retail trade excluding fuels				†/✓	✓	✓
Total retail trade excluding fuels and vehicles				†/✓	✓	✓
ISE				✓	✓	✓
Real consumer credit				✓	✓	✓
Consumer confidence index				✓	✓	✓
Remittances				✓	✓	✓
Credit card limits				✓	✓	✓
Main variables in quarterly variations						
Total retail trade excluding fuels				✓	✓	✓
Total retail trade excluding fuels and vehicles				✓	✓	✓
ISE				✓	✓	✓
Real consumer credit				✓	✓	✓
Consumer confidence index				✓	✓	✓
Remittances				✓	✓	✓
Credit card limits				✓	✓	✓
Main variables in annual variations						
Total retail trade excluding fuels				✓	✓	✓
Total retail trade excluding fuels and vehicles				✓	✓	✓
ISE				✓	✓	✓
Real consumer credit				✓	✓	✓
Consumer confidence index				✓	✓	✓
Remittances				✓	✓	✓
Credit card limits				†	✓	✓

Notes: ✓ (†) mean that we can (cannot) reject the null hypothesis that the variable has a unit root. X means that the series is not available for that (complete) period.
Source: Banco de la República, DANE, and Fedesarrollo; authors' calculations.

[33] The ADF test was carried out under the Schwartz criterion for the lag selection.

References

Abel, A. (1990), Asset prices under habit formation and catching up with the Joneses, *American Economic Review*, 80 (2), 38–42.

Alfonso, V., Arango, L. E., Arias, F., Cangrejo, G. & Pulido, J. D. (2013), Ciclos de negocios en Colombia: 1975–2011, *Lecturas de Economía*, 78, 115–149.

Arango, L. E. & Cardona-Sosa, L. (2022), Consumer credit in an emerging economy: demand, supply, and liquidity restrictions, *Emerging Markets Review*, 54, 100949, https://doi.org/10.1016/j.ememar.2022.100949.

Arango, L. E. & Quevedo, I. K. (2022), Credit constraints in Colombia: evidence from the use of credit cards among low- and middle-income individuals, *International Journal of Emerging Markets*, forthcoming, https://doi.org/10.1108/IJOEM-08-2021-1241.

Arango, L. E., Cardona-Sosa, L. & Pedraza-Jiménez, N. A. (2021), The use of credit cards among low- and middle-income individuals in Colombia and the channels of monetary policy, *Economic Modelling*, 94, 150–169, https://doi.org/10.1016/j.econmod.2020.09.018.

Attanasio, O. P. (1999), Consumption, in J. B. Taylor and M. Woodford (eds), *Handbook of Macroeconomics*, Vol. 1B, Amsterdam: Elsevier, 741–812.

Berger, D., Guerrieri, V., Lorenzoni, G. & Vavra, J. (2018), House prices and consumer spending, *Review of Economic Studies*, 85, 1502–1542.

Blundell, R. & Preston, I. (1998). Consumption inequality and income uncertainty, *Quarterly Journal of Economics*, 113, 603–640.

Bram, J. & Ludvigson, S. (1998), Does consumer confidence forecast household expenditure? A sentiment index horse race, *Economic Policy Review*, 4 (2), https://www.newyorkfed.org/medialibrary/media/research/epr/98v04n2/9806bram.pdf.

Browning, M. & Lusardi, A. (1996), Household saving: micro theories and micro facts, *Journal of Economic Literature*, 34, 1797–1855.

Campbell, J. Y. (1987), Does saving anticipate declining labor income? An alternative test of the permanent income hypothesis, *Econometrica*, 55, 1249–1273.

Campbell, J. Y. & Mankiw, N. G. (1989), Consumption, income, and interest rates: reinterpreting the time series evidence, in M. Eichenbaum, E. Hurst, and V. Ramey (eds), *NBER Macroeconomics Annual*, Vol. 4, Cambridge, MA: MIT Press, 185–216.

Campbell, J. Y. & Mankiw, N. G. (1990), Permanent income, current income, and consumption, *Journal of Business & Economics Statistics*, 8, 265–279.

Campbell, J. Y. & Mankiw, N. G. (1991), The response of consumption to income: a cross-country investigation, *European Economic Review*, 35, 723–756.

Carranza, J. E. & González, X. (2014), Estimación de la demanda de vehículos nuevos de los hogares colombianos entre 2001 y 2011, *Borradores de Economía*, 824, Banco de la República.

Carrasquilla, A. (1989), La asignación intertemporal del consumo en Colombia, *Revista ESPE - Ensayos Sobre Política Económica, Banco de la República*, 8 (16), 67–82.

Carroll, C. D. (1994), How does future income affect current consumption?, *Quarterly Journal of Economics*, 109, 111–148.

Carroll, C. D. (1997), Buffer-stock saving and the life cycle/permanent income hypothesis, *Quarterly Journal of Economics*, 112, 1–55.

Carroll, C. D. and Jeanne, O. (2009), A tractable model of precautionary reserves, net foreign assets, or sovereign wealth funds, NBER Working Paper 15228.

Carroll, C. D. & Kimball, M. S. (1996), On the concavity of the consumption function. *Econometrica*, 64, 981–992.

Carroll, C. D. & Toche, P. (2009), A tractable model of buffer stock saving, NBER Working Paper 15265.

Carroll, C. D. & Weil, D. N. (1994), Saving and growth: a reinterpretation, *Carnegie-Rochester Conference Series on Public Policy*, 40, 133–192.

Carroll, C., Fuhrer, J. C. & Wilcox, D. W. (1994), Does consumer sentiment forecast household spending? If so, why?, *American Economic Review*, 84 (5), 1397–1408.

Carroll, C. D., Otsuka, M. & Slacalek, J. (2011), How large are housing and financial wealth effects? A new approach, *Journal of Money, Credit and Banking*, 43, 55–79.

Carroll, C. D., Slacalek, J. & Sommer, M. (2019), Dissecting saving dynamics: measuring wealth, precautionary, and credit effects, NBER Working Paper 26131.

Christiano, L. (1989), Comment on “Consumption, income, and interest rates: reinterpreting the time series evidence”, in M. Eichenbaum, E. Hurst, and V. Ramey (eds), *NBER Macroeconomics Annual*, Vol. 4, Cambridge, MA: MIT Press, 216–233.

Christiano, L. J., Eichenbaum, M. & Marshall, D. (1991), The permanent income hypothesis revisited, *Econometrica*, 59, 397–423.

Clavijo, S. & Fernández, J. (1989), Consumo privado e ingreso permanente: nueva evidencia para Colombia, *Revista ESPE - Ensayos Sobre Política Económica, Banco de la República*, 8 (16), 3–44.

Constantinides, G. M. (1990), Habit formation: a resolution of the equity premium puzzle, *Journal of Political Economy*, 98, 519–543.

Cortés, D. & Pérez, J. E. (2010), The consumption of Colombian Households, 2006–2007: estimation of demand systems, *Desarrollo y Sociedad*, 66, 7–44.

DANE (2002), Glosario de términos MMCM.

Deaton, A. (1992), *Understanding Consumption*, Oxford: Oxford University Press.

Deaton, A.S. (1987), Life-cycle models of consumption: is the evidence consistent with the theory? in T. F. Bewley (ed.), *Advances in Econometrics*, Fifth World Congress, Vol. 2, Cambridge: Cambridge University Press, 121–148.

Dees, S. & Brinca, P. S. (2013), Consumer confidence as a predictor of consumption spending: evidence for the United States and the Euroarea, *International Economics*, 134, 1–14.

Diebold, F. X. & Mariano, R. S. (1995), Comparing predictive accuracy, *Journal of Business and Economic Statistics*, 13, 253–263.

Dreze, J. H. & Modigliani, F. (1972), Consumption decisions under uncertainty, *Journal of Economic Theory*, 5, 308–335.

Dynan, K. E. (2000), Habit formation in consumer preferences: evidence from panel data, *American Economic Review*, 90 (3), 391–406.

Easaw, J. Z., Garratt, D. & Heravi, S. M. (2005), Does consumer sentiment accurately forecast UK household consumption? Are there any comparisons to be made with the US? *Journal of Macroeconomics*, 27, 517–532.

Flavin, M. A. (1981), The adjustment of consumption to changing expectations about future income, *Journal of Political Economy*, 89, 974–1009.

Flemming, J. S. (1973), The consumption function when capital markets are imperfect: the permanent income hypothesis reconsidered, *Oxford Economic Papers*, 25, 160–172.

Friedman, M. (1957), *Theory of the Consumption Function*, Princeton, NJ: Princeton University Press.

Fuhrer, J. C. (2000), Habit formation in consumption and its implications for monetary-policy, *American Economic Review*, 90 (3), 367–390.

Gaviria, A. & Posada, C. E. (1992), El consumo en Colombia: revisión de la evidencia empírica. *Coyuntura Económica*, 22, 137–149.

Gric, Z., Ehrenbergerova, D. & Hodula, M. (2022), The power of sentiment: irrational beliefs of households and consumer loan dynamics, *Journal of Financial Stability*, 59, 100973, https://doi.org/10.1016/j.jfs.2022.100973.

Grupo de Estudios del Crecimiento Económico (2002), El crecimiento económico colombiano en el siglo XX, *Fondo de Cultura Económica*, Banco de la República, Bogotá.

Hall, R. E. (1978), Stochastic implications of the life cycle-permanent income hypothesis: theory and evidence. *Journal of Political Economy*, 86, 971–987.

Harvey, D., Leybourne, S., & Newbold, P., (1997), Testing the equality of prediction mean squared errors, *International Journal of Forecasting*, 13, 2, 1997, 281-291.

International Monetary Fund (2015), The commodity price bust: fiscal and external implications for Latin America, in *Regional Economic Outlook*, *Western Hemisphere*, Chapter 3, April, 43–53.

Kimball, M. S. (1990), Precautionary saving in the small and in the large, *Econometrica*, 58, 53–73.

López, A. (1993), La función de consumo: una revisión de la literatura reciente, *Revista ESPE*, 24, 137–189.

López, A. & Ortega, J. R. (1998), Private saving in Colombia, IMF Working Paper 171.

Ludvigson, S. (1999), Consumption and credit: a model of time-varying liquidity constraints, *Review of Economics & Statistics*, 81, 434–447.

Ludvigson, S. C. (2004), Consumer confidence and consumer spending, *Journal of Economic Perspectives*, 18 (2), 29–50.

Mankiw, N. G. (1982), Hall's consumption hypothesis and durable goods, *Journal of Monetary Economics*, 10, 417–425.

Medina, C. & Cardona, L. (2010), El efecto de las remesas en Colombia sobre el consumo de los hogares, la asistencia escolar y el nivel de vida, *Lecturas de Economía*, 72, 11–43.

Meghir, C. & Weber, G. (1996), Intertemporal nonseparability or borrowing restrictions? A disaggregate analysis using a US consumption panel, *Econometrica*, 64, 1151–1181.

Mian, A., Rao, K. & Sufi, A. (2013), Household balance sheets, consumption, and the economic slump, *Quarterly Journal of Economics*, 128, 1687–1726.

Modigliani, F. & Brumberg, R. (1954), Utility analysis and the consumption function: an interpretation of cross-section data, *The Collected Papers of Franco Modigliani*, Vol. 6, Cambridge, MA: MIT Press, https://doi.org/10.7551/mitpress/1923.003.0004.

Murcia, A. (2007), Determinantes del acceso al crédito de los hogares colombianos, *Ensayos sobre Política Económica*, 25 (55), 40–83.

Posada, C. E. (1999), Tasa de cambio real y consumo: teoría, evidencia y estudios del caso colombiano (1950–1997), *Lecturas de Economía*, 51, 9–46.

Quah, D. (1990), Permanent and transitory movements in labor income: an explanation for "excess smoothness" in consumption, *Journal of Political Economy*, 98, 449–475.

Runkle, D. E. (1991), Liquidity constraints and the permanent-income hypothesis: evidence from panel data, *Journal of Monetary Economics*, 27, 73–98.

Sargent, T. J. (1978), Rational expectations, econometric exogeneity, and consumption, *Journal of Political Economy*, 86, 673–700.

Solow, R. M. (1970), *Growth Theory: An Exposition*, Oxford: Clarendon Press.

Tobin, J. & Dolde, W. C. (1971), Wealth, liquidity, and consumption, Reserve Bank of Boston, Monetary Conference Series 5.

Zeldes, S. P. (1989), Consumption and liquidity constraints: an empirical analysis, *Journal of Political Economy*, 97, 305–346.