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Bhatt, Vipul and Kishor, Kundan and Marfatia, Hardik

James Madison University, Harrisonburg, VA 22807, University of Wisconsin-Milwaukee, Milwaukee, WI 53201, Northeastern Illinois University, Chicago, IL 60625

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Estimating Excess Sensitivity and Habit Persistence in Consumption Using Greenbook Forecast as an Instrument

Vipul Bhatt* N. Kundan Kishor† Hardik Marfatia‡

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Abstract

In this paper, we revisit the issue of excess sensitivity of consumption to income and address the weak instrument problem that is well documented in this literature. Using quarterly data for the U.S. economy, we first highlight the weak instrument problem by showing that the use of conventional instruments tends to overestimate the share of rule-of-thumb consumers. To address this weak instrument problem, we propose a new instrument for endogenous disposable income growth in the consumption function, namely, the Greenbook forecast of real disposable income growth. We show that this instrument encompasses the information contained in the conventional set of instruments, and is a superior predictor of income growth. We find that using our proposed instrument ameliorates the weak instrument problem and provides a much smaller estimate for the rule-of-thumb consumers. We also extend our empirical framework to allow for habit persistence and provide an estimate for this important parameter of the consumption function. Finally, we use a time-varying specification of consumption function that allows for endogenous regressors, and document a decline in the share of rule-of-thumb consumers and a rise in the habit-persistence parameter in the U.S. over our sample period. We find that an increase in credit growth and supplementary income benefits are negatively correlated with share of rule-of-thumb consumers, whereas they are positively correlated with habit persistence parameter.

JEL Classifications: E21, C22, C26, C53.

Keywords: Consumption, Greenbook Forecast, Rule-of-Thumb, Weak Identification, Time-Varying Parameter Model.

*421, Bluestone Dr., MSC 0204, Department of Economics, James Madison University, Harrisonburg, VA 22807. Email: bhattvx@jmu.edu.

†Department of Economics, University of Wisconsin-Milwaukee,Bolton Hall, Milwaukee, WI 53201. Email: Kishor@uwm.edu.

‡Department of Economics, Northeastern Illinois University, 5500 N St Louis Ave, BBH 344G, Chicago, IL 60625, USA. E-mail: h-marfatia@neiu.edu.

1 Introduction

The standard intertemporal consumption model of the household predicts that the changes in marginal utility from consumption cannot be predicted based on past information (Hall, 1978). There is a large literature on empirically testing this property of the standard model using aggregate as well as household level consumption data.[1] Campbell and Mankiw (1989) provided a framework that extends the standard model of consumption by incorporating consumers who use a fraction of their current income for consumption as a *rule-of-thumb*. Their framework allows for testing the excess sensitivity of consumption to current income changes by estimating the economic and statistical significance of the estimated fraction of rule-of-thumb consumers. An important methodological constraint imposed in the implementation of this framework is the availability of instruments for the potentially endogenous income growth variable in the consumption function. Many studies have implemented the framework of Campbell and Mankiw (1989) and have used lagged values of income growth, consumption growth, interest rates, inflation, stock returns, etc as instruments.[2]

A valid instrument must be both exogenous and relevant. Although the literature in this area has paid substantial attention to the issue of exogeneity, the issue of weak instruments remains a key problem (Kiley, 2010; Weber, 2000). Given very noisy feature of quarterly disposable income growth, it is often difficult to predict this variable, and hence most of the instruments used in the existing literature suffer from the weak instrument problem (Weber, 2000; Kiley, 2010). An important contribution of our paper is to provide an instrument that is both exogenous as well as strongly correlated with income growth.

In this paper, we propose to use the Greenbook (GB, henceforth) forecast of real disposable income growth as an instrument for income growth. GB forecast of disposable income growth is a natural candidate as it is both exogenous, and more importantly, it is directly relevant in terms of predicting contemporaneous disposable income growth. First, the exogeneity is ensured by the fact that these forecasts are performed in the past.[3] Because these forecasts are made in the past, any unanticipated shock to contemporaneous consumption growth will be uncorrelated with the GB forecast. More importantly, these forecasts have strong predictive power for future income growth, as they are based on a richer information set and possibly based on information not available to private forecasters (Sims, 2002). Many studies in the forecasting literature have documented the usefulness of these forecasts in terms of providing valuable information about the

[1] See Jappelli and Pistaferri (2010) and Attanasio and Weber (2010) for an excellent survey of theoretical as well as empirical contributions to the issue of consumption response to income changes.

[2] Weber (2000) provides an excellent survey of empirical studies that provide an estimate of the fraction of rule-of-thumb consumers.

[3] The data on GB forecasts are available at:`https://www.philadelphiafed.org/research-and-data/real-time-center/greenbook-data/pdf-data-set`.

future movements in important macroeconomic variables (for example, see Romer and Romer (2000), Sims (2002), and Faust and Wright (2009), among others). We find that the one-period ahead GB forecast of real disposable income growth is a strong predictor of the disposable income growth. Further, we find that the GB forecast encompasses the information contained in the conventional set of instruments used in the existing literature, and in this sense provides a superior forecast of income growth.

Given the dynamic nature of the U.S. economy over the last few decades, one would expect that the relative importance of rule-of-thumb behavior has changed over time, and therefore, a fixed coefficient approach may mask some of the interesting dynamics in this parameter over time. Our paper also contributes to the literature by providing time-varying estimates of the parameters of the consumption function. The existing literature in this area also suffers from the weak instrument problem as stated above (see Bacchetta and Gerlach (1997), McKiernan (1996), and Everaert et al. (2016), among others).

There are several findings of interest. First, using the quarterly data for the U.S. from 1978Q1-2010Q4, we highlight the weak instrument problem in estimating the aggregate consumption function using the conventional set of instruments.[4] Using the framework of Stock and Yogo (2005) and Olea and Pflueger (2013), we formally define a set of instruments to be weak based on two criteria, namely, relative bias and size of the Wald test for statistical significance. Accordingly, an instrument is considered weak if it results in a relative bias or size above a certain threshold. Based on both of these criteria, we find that the conventional set of instruments are weak. For instance, even when we consider a maximum relative bias of 30% for the instrumental variable estimator when compared to the OLS estimator, we are not able to reject the hypothesis of weak instruments for the conventional set of instruments. In contrast, we find that the lagged one-period ahead GB forecast for income growth is a strong instrument based on both aforementioned criteria. Second, we provide evidence on the superiority of the GB forecast variable in predicting future income growth. For this purpose, we use the least absolute shrinkage and selection operator (LASSO, henceforth) approach to determine the relative usefulness of different instruments in the first stage regression. We find that the dominance of the GB forecast as an instrument is robust to this shrinkage method. Third, using our proposed instrument, we provide an estimate for the excess sensitivity of consumption to income which we believe is more robust to the bias caused by weak instruments.

We find that the use of GB forecast as an instrument yields a much smaller estimate of rule-of-thumb consumers for the full sample period. The estimated fraction of rule-of-thumb consumers is 0.7 for the con-

[4]Based on our review of the existing literature, the list of variables in the conventional set of instruments include lagged values of income growth, consumption growth, real interest rates, lagged consumption-income ratio, stock price return, inflation, and consumer sentiments.

ventional set of instruments, whereas the corresponding estimate is 0.24 for GB forecast as an instrument. Not surprisingly, this share exhibits variation over time. For instance, using the two sub-samples of 1978Q1-1999Q4 and 2000Q1-2010Q4, we find that the fraction of rule-of-thumb consumers is much smaller in the latter sub-sample. Fifth, we extend the benchmark model to account for habit persistence in consumption behavior. We find that between 1978Q1-1999Q4, the rule-of-thumb consumption behavior was both economically and statistically more significant when compared to habit persistence. However, during the latter period of 2000Q1-2010Q4, habit persistence component has a much larger impact on consumption growth. Sixth, we formally address the observed time variation in the fraction of rule-of-thumb consumers as well as habit persistence by estimating a time-varying parameter specification for the Campbell and Mankiw (1989) regression. In the benchmark case of no habit persistence, we find substantial time variation in the fraction of rule-of-thumb consumers and document a strong declining trend in this fraction between 1981-2010. When we add habit persistence to the model, we find a rising trend in the habit persistence parameter implying strengthening of habit during the same time period.

Finally, to provide an interpretation of main findings of our time-varying parameter model, we conduct an exploratory analysis to identify factors that are associated with the observed time variation in rule-of-thumb consumption and habit persistence. We find that these patterns have economically meaningful and statistically significant relationship with aggregate credit growth, a measure of risk in the economy, and a measure of supplementary income program. In particular, we find that an increase in the credit growth and supplementary income benefits tend to reduce the rule-of-thumb consumption and increase habit persistence parameter. This suggests that easier availability of credit helps in consumption smoothing and therefore, is associated with lower sensitivity of consumption to current income. Similarly, supplementary income benefits are associated with higher degree of persistence in consumption presumably due to increased capacity of consumers to maintain habit-based consumption in the presence of supplementary income benefits.

The remainder of the paper is organized as follows. Section 2 provides a brief review of the related literature. In Section 3, we discuss the data utilized in our empirical analysis. Section 4 presents the conceptual framework and highlights the weak instrument problem in estimating the consumption-income relationship. Section 5 presents formal tests of weak instruments and provide evidence for the superiority of the GB income forecast in predicting income growth for the U.S.. In Section 6, we present and discuss findings from the instrumental variable estimation. Section 7 presents the results of our time-varying model and discuss potential explanations for the observed time variation in consumption behavior in the U.S.. Section 8 concludes.

2 Related Literature

In this section, we provide a brief review of the related literature. The empirical framework we employ in this paper is based on Campbell and Mankiw (1989). Campbell and Mankiw (1989) extended the framework of Hall (1978) by allowing for deviation from random walk consumption behavior. Using quarterly data for the U.S. between 1953-1986 and based on different set of instrumental variables, they report an estimated value of 0.5 for the fraction of consumers who consume out of their current income. They also find that after incorporating the rule-of-thumb consumption behavior, there is no evidence that ex-ante real interest rate is associated with consumption growth. See Weber (2000) for a comprehensive survey on different estimates of rule-of-thumb consumption behavior.

One of the criticisms of the earlier literature on this modified consumption function was that it does not produce the hump-shaped behavior in response to a shock. The literature on habit persistence in consumption explores the implications of a utility function that should be expected to produce more sluggish responses because it allows for slowly-changing habit formation among consumers (Fuhrer, 2000; Dynan, 2000). In addition to solving the slow response of consumption to income, it can also explain the puzzle in the growth literature. For instance, Carroll and Weil (1994) find that the periods of high aggregate income growth are followed by the periods of high aggregate saving. In addition, because habits increase the disutility associated with large declines in consumption, they may provide a partial solution to the equity premium puzzle. It is important to note here a logical distinction between rule-of-thumb behavior and habit formation in consumption. Rule-of-thumb consumers respond immediately and one-for-one to the shock in current income as well as to the predictable component of current income. Consumers with a habit formation utility function will delay some of the response to an income shock, smoothing the change in consumption. Thus, these two consumption motives are empirically distinct. Fuhrer (2000) incorporates habit persistence in the consumption model and finds an important role for rule-of-thumb behavior even in the extended framework. Weber (2000) argues that it is important to distinguish between risk aversion and the elasticity of intertemporal substitution when testing the prevalence of rule-of-thumb consumers. Using the generalized method of moments and post-war data for the U.S. economy, he found no evidence for the rule-of-thumb consumption behavior. Kiley (2010) uses the generalized method of moments and incorporates rule-of-thumb behavior, habit persistence, and non-separability between leisure and consumption. He first illustrates the weak instrument problem that affects the estimation of the consumption-income relationship. Second, using weak instrument with robust standard errors he finds support for both rule-of-thumb behavior and habit persistence, but no evidence for the non-separability between leisure and consumption. Our paper

contributes to this literature by proposing an instrumental variable that does not suffer from the weak instrument problem and hence can improve upon the existing estimates of the rule-of-thumb behavior for the U.S..

Our paper is also related to the literature on the weak identification problem in macroeconomics. Mavroeidis (2004, 2005) and Kleibergen and Mavroeidis (2009) show that the single equation generalized method of moment (GMM) approach that exploits the rational expectation property of the macroeconomic models are subject to the weak identification problem because the percentage of predictable variation in the future movement in the forward-looking variable is very small as compared to the unpredictable component. We also show that the similar critique applies to consumption equation that contains endogenous disposable income growth as an explanatory variable on the right-hand side, as the conventional instruments predict a very small fraction of the next quarter's movement in disposable income growth.

We also contribute to the literature that investigates the time variation in excess sensitivity of consumption to income. McKiernan (1996) shows that there is significant time-variation in the fraction of rule-of-thumb consumers. She reports that the time-varying fraction is related to several measures of liquidity constraints and finds that the episodes of credit crunch are associated with the higher share of rule-of-thumb consumers. Kim (2006) argues that the conventional estimation of the time-varying parameter (TVP) with endogeneity in a 2-SLS framework suffers from generated regressor problem. Therefore, he proposed using Heckman two-step procedure to estimate the TVP model with endogeneity. Kim and Kim (2011) apply this two-step estimation of TVP model with endogeneity and find that the share of rule-of-thumb consumers have been declining. Our paper contributes to this strand of literature on two fronts. First, Kim and Kim (2011) use the same set of instruments that we illustrate in our analysis to suffer from the weak instrument problem. Hence, using our proposed instrument will provide a more robust measure of the time-varying fraction of rule-of-thumb consumers. Second, our approach also augments the consumption function and estimates the time-varying shares for both the rule-of-thumb and habit persistence consumers.

3 Data

3.1 Aggregate Consumption, Income, and Relevant Economic Indicators

Our measure of consumption is the real per capita consumption expenditure on non-durable goods and services. Income is defined as real per capita personal disposable income growth. In addition, we use 3-month Treasury bill rate, consumer sentiments, S&P 500 return, and consumer price index inflation. We

use quarterly data from 1978 through 2010. All data series have been obtained from the Federal Reserve Economic Data (FRED®) maintained by the Federal Reserve Bank of St. Louis.

3.2 Greenbook Forecast of Real Personal Disposable Income Growth

Our proposed instrument for the endogenous income growth in the consumption function is the lagged one-period ahead GB forecast of real personal disposable income growth. GB forecasts are presented to the Federal Open Market Committee (FOMC) before each meeting. There are eight regular meetings of the FOMC in a calendar year implying that we can obtain a new set of forecasts every 1.5 months. Note that these forecasts are made available to the public with a lag of five years.[5] Hence, our sample only includes data from 1978 through 2010. The data on GBs are available from the Federal Reserve Bank of Philadelphia.[6]

In order to obtain forecasts at a quarterly frequency, we use forecasts made at the end of each quarter for our sample period. Note that for each quarter, we have two set of forecasts, namely, one made in the first half of the quarter and the other one made in the second half of the quarter. In each case, the forecast is made for the current quarter as well as for multiple quarters into the future. To ensure exogeneity of our proposed instrument, we need a forecast of real personal disposable income growth that is uncorrelated with the error term at time t. Therefore, we use the one-period ahead forecast that was made at the end of time period t-1. For example, for the fourth quarter of 2010, we use the forecast of real disposable income growth that was made at the end of third quarter of 2010.[7] Use of this timeline serves two purposes. On the one hand, it utilizes as much information as possible for making a reasonable forecast of the next quarter's income growth. More importantly, theoretically, this lagged one-period ahead forecast of real disposable income growth should be uncorrelated with the error term in the consumption growth equation since any unexpected shock to consumption growth at time t should be unknown to the forecaster at time t-1 (see equation (1) in section 4). For robustness check, we also use lagged two-period ahead forecast in our empirical analysis.[8]

[5] For example, the GB forecast of 2016 will only be made available in 2021.

[6] See `https://www.philadelphiafed.org/research-and-data/real-time-center/greenbook-data/pdf-data-set`

[7] In the appendix, we provide a detailed description of the each quarter and the corresponding GB forecasts months that we utilized in construction our instrumental variable.

[8] Note that there is also a large literature on real-time data in macroeconomics and finance. Our forecast is real-time, but the other data used in our exercise is based on current-vintage. For instrument validity purposes, the use of current vintage data and the real-time GB forecast data does not create a problem. For details on real-time data, see Croushore and Stark (2001) and Croushore (2011), among others.

4 Conceptual Framework

In this section, we provide a discussion of the weak instrument problem that plagues the estimation of the consumption-income relationship. For this purpose, we use the framework of Campbell and Mankiw (1989) as the benchmark. There are two types of consumers: the forward-looking consumers who consume out of their permanent income and the rule-of-thumb consumers who consume a fraction of their current income every time period. Formally,

$$\Delta C_t = \alpha + \lambda \Delta Y_t + \epsilon_t \tag{1}$$

where ΔC_t and ΔY_t represent the change in log consumption and change in log disposable income, respectively. The parameter λ represents the percentage of consumers who are liquidity constrained and consumes a portion of their current income, often known as *the rule-of-thumb* consumers. As discussed by Campbell and Mankiw (1989), given the potential endogeneity of ΔY_t in (1), we must use the instrumental variable (IV, henceforth) estimation to obtain a consistent estimator of λ.[9]

A large number of studies have estimated some version of equation (1) using different sets of instruments for income growth.[10] Some of the variables used to instrument income growth include lags of income growth, consumption growth, consumption-income ratio, stock returns, inflation, consumer sentiments, real interest rate, etc. The focus of these studies has almost exclusively been on the exogeneity of the instruments utilized in the estimation. However, a valid instrument must also be *relevant*, i.e., strongly correlated with the endogenous variable in the regression model. This problem is known as the *weak instrument* problem in the literature.

Kiley (2010) illustrates that the different instruments employed in estimating the consumption-income relationship suffer from the weak instrument problem. This is partially due to the persistence in the income data making its growth close to a white noise and hence very difficult to predict. As a result, most of the instruments used in the existing literature, although exogenous, only weakly identify the parameter of interest, λ (Kiley, 2010).

[9] As shown by Campbell and Mankiw (1991), the model in the logarithmic form can be derived from the first-order log-linear approximation of the consumption Euler equation under power utility. An important consequence of using logs is that the parameter λ cannot be precisely interpreted as the fraction of rule-of-thumb consumers. However, if one uses first differenced variables in the consumption function specified in (1) then the λ parameter can be interpreted as the share of rule-of-thumb consumers (Weber, 2000). In this paper, to ensure comparability of our estimates with those reported in other studies in the literature, we follow the convention and estimate equation (1) using the logarithmic transformation for all variables. However, our main results are robust to using first differenced variables in estimating equation (1). For brevity, we do not report these results here but they are available upon request. For the remainder of the paper we interpret λ as the share of rule-of-thumb parameter as is the convention on this literature.

[10] See Weber (2000) and Kiley (2010) for an excellent survey of this literature.

The literature on weak instrument shows that inference based on IV estimation is misleading as the IV estimate is strongly biased in the same direction as ordinary least squares (OLS) and the estimated standard error is too small, the result being that the true null hypothesis is rejected too often (see, for example, Nelson and Startz (1990b,a), Staiger and Stock (1997), and Zivot et al. (1998), among others). Staiger and Stock (1997) show that the 2-stage least square (2SLS) estimator under weak identification is not consistent. Moreover, the weak instrument asymptotic distribution of the 2SLS estimator depends on the nuisance parameters that cannot be consistently estimated from the data.

In this paper, we address the issue of weak instruments that plague the empirical estimation of the consumption-income relationship. The discussion below is based on Stock and Yogo (2005) who provide a framework for testing for the weakness of instruments. Formally, consider the following reduced form equation for the endogenous income growth in equation (1) above:

$$\Delta Y_t = Z_t \Gamma + \nu_t \tag{2}$$

where Z_t denotes a $1 \times K$ vector of excluded instrumental variables and Γ represents a $K \times 1$ vector of coefficients. The problem of weak instruments can be investigated by focusing on the F-statistic associated with testing the null hypothesis that $\Gamma = 0$, also known as the *first-stage F-statistic* in the IV estimation literature.

Stock and Yogo (2005) provide two alternative formal definitions of weak instruments. The first definition is based on the idea of limiting the relative bias of the IV estimator with respect to an OLS estimator to a certain level. Accordingly, they define a group of instruments to be weak if the bias of the IV estimator based on this group relative to the bias of the OLS estimator is above a certain threshold. The procedure developed by Stock and Yogo (2005) assumes homoscedastic error structure. In an extension of their framework, Olea and Pflueger (2013) provide a version of the relative bias test that is robust to heteroscedasticity and serial correlation. In this paper, we use the test statistic and critical values provided by Olea and Pflueger (2013) when testing the relative bias of the IV estimation. The second definition considers a group of instruments to be weak if the Wald test based on IV estimators has a size that exceeds a certain threshold. Based on these definitions, Stock and Yogo (2005) provide a formal test of the null hypothesis that a group of instruments is weak based on Cragg-Donald statistic (Cragg and Donald, 1993) and provide critical values for this test. In our case, because we only have one endogenous regressor the Cragg-Donald statistic is the first-stage F-statistic.[11] Formally, the two tests are given by:

[11] Staiger and Stock (1997) provide an informal rule that if the first stage F-statistic is less than 10 then we have weak

1. Test based on relative bias:

$$H_0 : Z \in \Omega_{bias}$$

$$H_0 : Z \notin \Omega_{bias}$$

where Z denotes the group of exogenous instruments used in the IV estimation. Ω_{bias} refers to the set of weak instruments based on the relative bias criteria Stock and Yogo (2005).

2. Test based on the size of the Wald test based on the IV estimator:

$$H_0 : Z \in \Omega_{size}$$

$$H_0 : Z \notin \Omega_{size}$$

where Ω_{size} refers to the size-based weak instruments set Stock and Yogo (2005).

5 A New Instrument for Endogenous Income Growth

An important contribution of our paper is to suggest a new instrument for estimating the consumption-income relationship. Our proposed instrument for the endogenous income growth in equation (1) is the lagged one-period ahead GB forecast for real personal disposable income growth. In this section, we first provide evidence on this variable being a strong instrument. We accomplish this by formally testing the two hypotheses outlined in Section 4 for the GB forecast as well as the conventional set of instruments commonly employed in the estimation of consumption-income relationship. This is followed by a discussion on why the GB forecast variable outperforms the other predictors of future income growth.

5.1 Strength of the Greenbook Forecast as an Instrument

Table 1 provides the results of the two weak instrument tests outlined in Section 4. In the first column, we provide results for the set of instruments used by Campbell and Mankiw (1989). These include lags 2 through 4 of income growth, consumption growth, and 3-month treasury bill growth, and the second lag of logarithm of consumption-income ratio. In the second column, we provide results for the set of instruments where we

instruments. The procedure developed by Stock and Yogo (2005) allow us to formally compare the first stage F-statistic to the appropriate critical values, and hence can be seen as an improvement in the identification of weak instruments. Olea and Pflueger (2013) show that the well-known rule of thumb of F-statistic greater than one is neither necessary nor sufficient for the instrument to be strong in the presence of heteroscedasticity and autocorrelation.

add second lag of consumer sentiments, real S&P 500 returns, and inflation to those used by Campbell and Mankiw (1989). Finally, in the last column, we provide results when we use the lagged one-period ahead GB forecast of the real disposable income growth as an instrument.[12] We observe that the conventional set of instruments used in estimating the consumption-income relationship suffer from the weak instrument problem, based on both definitions of weak instruments. For instance, from column (1) and (2) we can conclude that both sets of instruments are weak even when we consider the case of the maximum relative bias of at least 30% and the maximal IV size of 20%. In contrast, we find that the lagged one-period ahead GB forecast for income growth is a strong instrument as the null hypotheses for both relative bias and size are rejected at the 5% level of significance. Although not reported in the paper, we find similar result using the two-period lagged value of the two-period ahead GB forecast.

5.2 The Superiority of the Greenbook Forecast of Disposable Income Growth

One interpretation of the results presented in Table 1 is that the GB forecast of real disposable income growth has valuable information in predicting the future disposable income growth. There is a substantial literature on the comparison of GB forecast with the private sector professional forecasts, and the consensus seems to be that the GB forecasts tend to dominate private sector forecasts at short- and medium-horizons. For example, using data until 1991, Romer and Romer (2000) show that the GB forecasts of inflation and real GDP are statistically unbiased and dominate private sector forecasts. Their findings suggest that the Federal Reserve has considerable information about inflation beyond what is known to the private sector. Sims (2002) extends the analysis of Romer and Romer (2000) and finds that the Federal Reserve Board staff forecasts outperform those from the Survey of Professional forecasters. Similarly, Faust and Wright (2009) reaffirm the dominance of the GB forecasts over private sector forecasts for inflation and output growth. Sims (2002) provides a rationale for the superior performance of the GB forecasts over private sector forecasts. He conjectures that the Federal Reserve Bank (Fed) has an advantage in assessing the current state of the economy at the time of making the forecast and also has superior information about its own future policy actions. Using a Vector Autoregression framework he finds evidence for this hypothesis. Faust and Wright (2009) find support for the view that the Fed simply has better information about the recent past or current state of the economy when comparing the output growth forecasts of the private sector and the GB.

In this section, we examine the relative predictive power of the GB forecast with other conventional

[12]Note that an alternative approach would be to replace the disposable income growth with the GB forecast of disposable income growth in equation (1). This will, however, create a problem of measurement error in the explanatory variable and the measurement error may be correlated with the error term, rendering the estimated coefficient inconsistent.

instruments in two ways. First, we follow the recommendation of Ng and Bai (2009) that in the presence of multiple instruments the information from them should be aggregated using the principal components of different components. We examine whether aggregating the information in the form of principal components has some marginal information beyond what is already present in the GB forecasts. Our set of instruments includes lagged disposable income growth, consumption growth, changes in Treasury bill yield, and consumer sentiments. We obtain the principal components of these instruments and conduct a forecast encompassing exercise where we regress the actual disposable income growth on 1-period ahead GB forecast and different principal components. The results of this exercise are presented in Table 2. We observe that coefficients on lags of different principal components are statistically insignificant and hence provide evidence for the hypothesis that the GB forecast encompasses the information present in different instruments commonly used in the estimating the consumption-income relationship.

Second, we use the least absolute shrinkage and selection operator (LASSO) approach to assess the relative usefulness of various instruments in predicting the income growth. LASSO is a shrinkage method that has been widely used in machine learning and statistics. It performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the estimated model. The LASSO shrinkage provides us relative usefulness of different instruments in the first stage regression of real income growth. For this purpose, we include the GB forecast and 15 conventional instruments as explanatory variables.

The results of this exercise are reported in Figure 1. The graph depicts the evolution of the coefficients for different values of the tuning parameter, ν. The parameter ν controls the degree of shrinkage. When ν=0, the LASSO model simply gives the OLS fit, and when ν becomes sufficiently large, the LASSO gives the null model in which all the coefficient estimates equal zero. We observe that as the tuning parameter, ν increases, all the coefficients are shrunk to zero. However, the dominance of GB forecast is substantially more than other variables as evidenced by the fact that it's coefficient shrinkage from the OLS coefficient estimate does not start even after the coefficients of all other variables have already shrunk to zero. The value of ν at which the coefficient on the GB forecast is shrunk to zero is much higher than 0.14, which is the optimal value of ν chosen by the 10-fold cross-validation.

6 IV Estimation Results

The above discussion establishes the superiority of our newly proposed instrument over the conventional instruments used in estimating the consumption-income relationship. In this section, we discuss the IV

estimates of the consumption function using the GB forecast of real personal disposable income growth as an instrument under two separate cases - without and with habit formation in consumer's behavior.

6.1 Benchmark Consumption Function Without Habit Formation

Table 3 presents the results from estimating equation (1) using the instrumental variable approach. For comparing the results obtained from the GB forecast as an instrument, in this table, we also present the estimates obtained by using the conventional instruments. Accordingly, following Campbell and Mankiw (1991) in Column (1), we use lags 2 through 4 of income growth, consumption growth, and 3-month Treasury bill growth, and second lag of consumption-income ratio as instruments for the endogenous income growth in equation (1). In Column (2), we add second lag of consumer sentiments, real S&P 500 return, and inflation to the list of instruments used for Column (1) specification.[13] Finally, Column (3) uses our proposed instrument, namely, lagged one-period ahead GB forecast of real disposable income growth. Furthermore, in the same table, we also present the results by splitting the sample into two periods: 1978Q1-1999Q4 and 2000Q1-2010Q4. Although this sample split may appear rather ad-hoc, our purpose is only to highlight the importance of time variation in the consumption-income behavior and use these results to motivate our time-varying specification presented in Section 7.

For the full sample period, we find that using the GB forecasts as an instrument leads to an estimated λ coefficient of 0.24 which is economically meaningful in terms of magnitude and is also statistically significant. This implies that about 25% of consumers consume out of their current income and hence follow a *rule-of-thumb* spending behavior in the 1978-2010 period. In contrast, when we use the conventional set of instruments, the estimated λ coefficient is much larger. Given our discussion on the weakness of these instruments, this suggests that the use of conventional instruments markedly overestimates the rule-of-thumb consumption behavior in our sample.

These differences become even starker when one looks into the sub-sample results. We find the estimated λ coefficient varies significantly in the two sub-sample periods. For the 1978-1999 period, we find that the GB forecast instrumented specification imply that 61% of consumers were consuming out of their current income. In contrast, in other two specifications that use conventional instruments, we get a coefficient on current income of greater than one which is theoretically non-intuitive and hard to explain.

In cases where real stock returns and consumer sentiments are used as instruments, λ is statistically

[13] We also test other instruments such the lagged spread between 10-year Treasury bond and 3-month Treasury bills, lagged income and consumption. Our main findings remain robust to these and for brevity, we do not present the results of this exercise.

significant but the value exceeds one. Thus, when the alternative set of instruments are used we find rather non-intuitive results. For the 2000-2010 period, we find that there is a sharp decline in the magnitude of the estimated λ coefficient and it is also statistically insignificant in all three specifications.

There are at least three overall insights gained from these results. First, the results indicate that after accounting for the weak instrument problem, our estimate of the rule-of-thumb consumption is much smaller when compared to the one we obtain from using the conventional set of instruments. Second, there is suggestive evidence that the consumption-income relationship has not remained constant for the sample period. Third, the sub-sample results indicate that the rule-of-thumb consumption has declined over time in the U.S. In Section 7 we formally address this issue by estimating a time-varying parameter model that allows for endogenous regressors.

6.2 Consumption Function With Habit Formation

The literature on consumption behavior has also emphasized the role played by habit formation that can introduce persistence in consumption growth. For example, Fuhrer (2000) estimates a specification that allows for both rule-of-thumb consumption and habit formation. He finds that both motivations play an important role and the inclusion of habit formation allows a more realistic hump-shaped response of real spending to monetary policy shocks. Similarly, Kiley (2010) finds empirical evidence in favor of habit persistence in consumption behavior. Habit persistence also plays an important role in explaining various stylized facts in macroeconomics and finance. For instance, incorporating habit formation can help resolve the equity premium puzzle and can also be used to explain important asset pricing facts such as predictability of excess equity return at longer horizon and countercyclicality of stock market volatility (Constantinides, 1990; Campbell and Cochrane, 1999). Similarly, in the dynamic stochastic general equilibrium model, a common finding is that the inclusion of habit persistence is important for a delayed hump-shaped response of macro variables to policy shocks, making their quantitative predictions more consistent with the observed dynamics of output (Bouakez et al., 2005; Del Negro et al., 2007).

In order to accommodate habit persistence on the part of the consumer, we estimate the following modified version of equation (1):

$$\Delta C_t = \alpha + \lambda \Delta Y_t + \theta \Delta C_{t-1} + \epsilon_t \tag{3}$$

By adding lagged consumption growth (ΔC_{t-1}) as an independent variable, the above equation captures

the role of habit persistence on consumption growth. The parameter θ measures the persistence in the consumption growth process and can be interpreted as capturing the effect of habit formation in consumption behavior.

Table 4 presents the results of this exercise. Focusing on Column (3) which reports the estimates using the proposed instrument for endogenous income growth, we observe that for the entire sample, habit persistence component has a relatively bigger effect on consumption growth when compared to the rule-of-thumb consumption, both in terms of economic and statistical significance. However, as before, there seems to be clear evidence of substantial time variation in the relative importance of rule-of-thumb consumption behavior and habit persistence. During 1978Q1-1999Q4, the rule-of-thumb consumption behavior dominated the habit persistence component, whereas during 2000Q1-2010Q4 there is little evidence for such behavior. In the next section, we estimate a time-varying parameter specification that formally models the time variation in both of these components and also accounts for the endogeneity of income growth.

7 Modeling Time Variation with an Endogenous Regressor

7.1 Model Specification

We extend the specification in equation (2) to model time variation in the coefficients of both rule-of-thumb behavior and habit persistence. This modification allow us to accommodate one of the important characteristics of the U.S. economy, namely, the ever changing credit market and economic conditions. These conditions are often cited as the source of the sensitivity of consumption to current income McKiernan (1996). For example, easy access to credit will allow consumers to maintain their consumption habits and also relaxing the liquidity constraint may reduce the sensitivity of consumption to income. Thus, changes over time in the credit market may induce changes in the relationship between consumption and income, and the degree of habit persistence overtime. To formally model such time-variation, we allow for a gradual evolution in the impact of current income and habit persistence on the consumption. Hence, we estimate the following time-varying version of equation (1),

$$\Delta C_t = \alpha + \lambda_t \Delta Y_t + \theta_t \Delta C_{t-1} + e_t \tag{4}$$

Assume $\beta_t = (\lambda_t \;\; \theta_t)'$.

$$\beta_t = \beta_{t-1} + u_t \qquad u_t \sim N(0, \sigma^2) \tag{5}$$

As stated before, ΔY_t is correlated with the disturbance term leading to the problem of endogeneity. As a result, the maximum likelihood estimation of the model in equations (4)-(5) via the conventional Kalman filter would result in invalid inferences. For a consistent and efficient estimation of the model in the presence of endogeneity, we adopt the approach proposed by Kim (2006) and Kim and Nelson (2006).[14] The basic idea of this procedure involves a Heckman-type two-step procedure. In step 1, ΔY_t is regressed on a set of instruments, and standardized residuals are obtained for ΔY_t. Kim and Nelson (2006) have shown that an equivalent way of writing the error term in equation 4 is:

$$e_t = \rho\sigma_{e,t}v_t^* + \omega_t \qquad \omega_t \sim N(0, (1-\rho^2)\sigma_{e,t}^2) \tag{6}$$

Here, the idea is to decompose the error term in the consumption function (equation (4)) into a component that is correlated with the explanatory variable ($\mathrm{E}[e_t|\psi_t] = \rho\sigma_{e,t}v_t^*$) and the uncorrelated component (ω_t $=e_t-\mathrm{E}[e_t|\psi_t]$). If there is no endogeneity in equation 4, the coefficient ρ should be insignificant.

Step 2 involves substituting equation (6) in equation (4) and estimate the following equation:

$$\Delta C_t = \alpha + \lambda_t \Delta Y_t + \theta_t \Delta C_{t-1} + \rho\sigma_{e,t}v_t^* + \omega_t \qquad \omega_t \sim N(0, (1-\rho^2)\sigma_{e,t}^2) \tag{7}$$

The augmentation of the consumption function with the standardized bias error correction term (equation (7)) resolves the endogeneity problem in equation (4). We use the lagged one-period ahead GB forecast of real personal disposable income as instruments to correct for endogeneity.

7.2 Estimation Results

The hyperparameters of the time-varying specification in (4) are presented in Table 5. The statistical significance of the correlation coefficient ρ indicates the presence of endogeneity and therefore justifies the use of the 2-step Heckman procedure.

For ease of presentation, we use a graphical illustration of our main findings from this estimation. In Figure 2 we plot estimated λ_t in panel (a) and θ_t in panel (b). From panel (a) of this figure, we observe that the impact of current income on consumption has varied significantly over time, though overall it has been on a declining path. The panel (a) of Figure 2 reveals that the sensitiveness of consumption to income declined during the 1983-1987 period, but steadily increased for the most part of the 1990s. In the pre-2000 period, the coefficient was mostly above 0.3. This trend reversed since the 2001 recession, and the estimated

[14] This approach has also been applied by Kishor (2012) in context of estimating the time-varying Taylor rule.

λ_t was as low as 0.1 in 2002 and was nearly at the same level in 2010. More importantly, in the post-2000 period, this coefficient remained below 0.3.[15]

In panel (b) of Figure 2, we plot the evolution of the habit persistence parameter, θ_t, that captures the impact of lagged consumption on the current consumption. We find that the effect of past consumption has grown steadily over time with a more pronounced increase in the periods of economic downturns. This is consistent with the pattern of declining importance of rule-of-thumb consumption presented in panel (a) as such a decline implies an increase in the permanent income consumers. Consuming out of permanent income indicates greater consumption smoothening on the part of consumers, and hence, increased the role of the past consumption on the current consumption.

The increase in the role of habit persistence coupled with a decline in the share of rule-of-thumb consumers imply that the hump-shaped response of consumption to a shock. The dramatic increase in the habit persistence component during the great recession suggests that the consumers responded slowly to the big decline in permanent income and the response was slower than the average. It is important to note that rule-of-thumb behavior and habit formation in consumption are two distinct issues. Rule-of-thumb consumers respond immediately and one-for-one to the shock in current income, as well as to the predictable component of current income.

One potential factor for this time variation could be the gradual liberalization of the financial sector that improved access to credit which, in theory, can serve to reduce the liquidity constraints faced by many consumers. Such a development may serve to reduce the excess sensitivity of consumption to current income changes. Another important factor affecting such behavior is the state of the economy. The sample period in the present study covers four recessions and comparing the behavior of consumers in these four recessions also provide interesting insights. In all the episodes of economic downturns, we find that the rule-of-thumb coefficient is declining. The rationale for such a behavior could be that during recessions the loss of employment causes the current income to decline. Consequently, the degree of consumption smoothing tends to increase in the downturns and we see that more and more consumers begin to consume out of permanent income during that period. Also, economic downturns are typically characterized by an increase in supplementary income program disbursements, which can also play a role in consumption behavior especially of low-income households. Finally, though the 2008 economic crisis was far more severe compared to the other three recessions, the share of rule-of-thumb consumers declined much more significantly in 2001

[15]For robustness, we also estimated a time-varying specification without habit persistence. We find that this exclusion does not affect the broad trend observed in the rule-of-thumb consumption behavior in Panel (a) of Figure 2. These results are not presented here for brevity and are available upon request.

recession. This big drop can be explained by the housing market boom during that time period in the U.S..

There is a large literature on wealth effect that has suggested that consumption did not decline as much during the 2001 recession even in the presence of big stock market collapse because the housing market's wealth effect is higher than the stock market wealth effect.[16] Therefore, the impact on consumption because of a decline in income and stock market wealth was neutralized by the boom in the housing market wealth. There is also some evidence on the changing wealth effect and that the wealth effect has increased over time in the U.S. (see, for example, Bhatt and Kishor (2014)).

7.3 Interpreting the Time-Variation in Rule-of-Thumb and Habit Persistence Parameters

Our findings show that the proportion of consumers who consume out of current income has gone down over time. Alternatively, the proportion of consumers who behave as per the permanent income hypothesis has increased over time. We also find substantial variation in the habit persistence parameter over our sample period, with a rising trend in the recent times. In this section, we attempt to provide the economic rationale of these patterns. Our objective is to document interesting associations that can be attached to the economic interpretations of the results. We do not aim to tease out the causal mechanisms and we believe such analysis is an important avenue for future research.

We now provide a discussion on the potential explanations for the observed declining pattern in the share of consumers consuming out of their current income (λ_t) during our sample period. In order to empirically examine the factors that may have played a role in driving such variation, we estimate a regression model where the estimated time-varying λ_t is the dependent variable. As explanatory variables, we follow McKiernan (1996) and include variables that can serve as a proxy for credit market conditions. These include credit-income ratio, the difference between bank-lending rate and deposit rate (Wedge), TED spread, and VIX volatility index. In addition, we also include Supplemental Nutrition Assistance Program (SNAP) - income ratio and a lagged dependent variable that captures persistence in rule-of-thumb behavior.[17] We hypothesize that the rule-of-thumb consumption will be negatively associated with the ease with which one can obtain credit (credit-income ratio), availability of supplementary income (SNAP-Income ratio), and

[16] For example, see Case et al. (2005) and Kishor (2007), among others.

[17] Credit-Income Ratio is the natural log of the ratio of total consumer credit outstanding to personal disposable income. Wedge is the difference between the Prime lending rate and 3-month Certificate of deposits rate. SNAP-Income Ratio is the natural log of the ratio of SNAP expenditure to personal disposable income. TED spread is the difference between the 3-month LIBOR based on US dollars and 3-month Treasury Bill rate. VIX SP100 is the CBOE S&P 100 Volatility Index. With the exception of SNAP, data on other variables are sourced from Fred Stat: `https://fred.stlouisfed.org/`. SNAP data is obtained from Food and Nutrition website: `https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap`.

greater uncertainty in the economy. In contrast, it will be positively related to Wedge and TED spread, as an increase in both signal tighter credit conditions in the economy.

The results of this exercise are reported in Table 5. We find that all estimated coefficients are consistent with economic intuition, have an economically significant effect, and with the exception of Wedge, are also statistically significant at varying levels of significance. The finding that λ_{t-1} has the largest coefficient indicates a substantial degree of persistence in the rule-of-thumb consumption. The next biggest effect is that of the credit-income ratio where a 1% increase in this ratio lowers the fraction of rule-of-thumb consumer and this reduction is both economically and statistically significant. Similarly, greater TED spread indicating increased credit risk, significantly lowers the rule-of-thumb consumption. Finally, an increase of 1% in the SNAP-income ratio lowers the rule-of-thumb consumption significantly. Note that since SNAP expenditure tends to increase during economic downturns, this association can also explain the observed decline in λ_t in each of the four recessions in our sample period.

In order to examine the time variation in the habit persistence parameter, we use the same set of explanatory variables. The results are reported in Table 5, and we find associations that are consistent with economic theory. For example, greater access to credit should make it easier to maintain consumption habit. Accordingly, we find that increase in credit-income ratio by 1% increases the habit persistence coefficient and this effect is both economically and statistically significant. Similarly, availability of supplementary income should favor habit persistence and our regression results confirm this. Finally, the coefficient of lagged dependent variable is bigger indicating greater persistence for habit when compared with the rule of thumb consumption.

8 Conclusion

One of the recurring issues in the estimation of consumption function that includes some form of rule-of-thumb consumption behavior is the absence of strong instruments for potentially endogenous disposable income growth. In this paper, we propose a new instrument that is both exogenous and is also a strong predictor of disposable income growth. We show that the lagged one-period ahead GB forecast of real disposable income growth is a strong instrument and this property is due to its superiority in predicting future income growth when compared to the conventional set of instruments used in the empirical literature on the consumption-income relationship.

The results from our IV estimation indicate that the use of conventional instruments tends to overesti-

mate the importance of rule-of-thumb consumption behavior. Use of our proposed instrument suggests an estimated coefficient of 0.25 for income in the consumption function for our sample period of 1978-2010. We also find that including habit persistence further reduces the relative importance of the rule-of-thumb behavior over this period. Using a time-varying parameter model with endogenous regressors, we document a declining trend in the rule-of-thumb consumption parameter and rising trend in the habit persistence parameter over time. We find that such time variation in these two types of consumption variable is related to the growth of credit and the state of the economy. For example, we find that the degree of habit persistence tends to increase during the recessions and is positively related to credit growth and supplementary income benefits.

Our paper shows the value of using a forecast that in principle aggregates the information about an endogenous variable. It is perfectly plausible to use GB forecast of other variables as an instrument in a different context. In addition, the findings presented in this paper has important implications for both our understanding of consumption dynamics as well as the existing theoretical frameworks for assessing the impact of policy shocks on the real sector. For instance, using our proposed instrument results in a much smaller parameter estimate for rule-of-thumb consumption and in more recent years, there seem to be a shift in consumption behavior with habit persistence assuming a more important role than rule-of-thumb consumption. The results overall are consistent with the view that financial liberalization and the state of economy plays a significant role in consumption behavior of households.

Similarly, our finding that habit persistence parameter has increased over time also has implications for the theoretical dynamic general equilibrium models that typically assume a constant parameter for habit persistence when analyzing the effect of monetary policy and other shocks to the real sector of the economy (Bouakez et al., 2005; Fuhrer, 2000; Del Negro et al., 2007). For instance, Havranek et al. (2017) show that the size of the habit persistence parameter plays an important role for the accuracy of quantitative predictions of these models in terms of the dynamic response of macro variables after a policy shock. Specifically, a large value for this parameter generates a more pronounced hump-shaped response to a monetary policy shock (Havranek et al., 2017). Our findings of increasing habit persistence parameter has two implications for this literature. First, the effect of habit persistence on the hump-shaped dynamics of macro variables in response to policy shocks in DSGE models will be more pronounced in recent years. Second, given that we find substantial time variation in this parameter and find that such variation strongly correlates with the state of the economy as well as credit growth, the existing theoretical models with constant habit persistence parameter may not be sufficient to fully incorporate consumption dynamics in the general equilibrium frame-

work. We believe our findings can provide an empirical motivation for developing the DSGE models with time-varying habit persistence parameter and studying the dynamics of macro variables to policy shocks in such an environment is an important area for future research.

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Table 1A: Weak Instrument Test Results (1978Q2-2010Q4)

	(1)	(2)	(3)
A) Olea-Pflueger's Effective F-Statistic	3.14	3.29	37.56
5% Critical Values for the worst-case bias:			
$\tau = 10\%$	16.691	17.341	23.109
$\tau = 20\%$	10.227	10.675	15.062
$\tau = 30\%$	7.896	8.262	12.039
B) First-Stage F-Statistic	4.04	8.34	37.56
Stock and Yogo (2005) 5% Critical Values for the Maximal IV Size:			
Maximal Size=10%	38.54	45.64	16.38
Maximal Size=15%	20.88	24.42	8.96
Maximal Size=20%	14.78	17.14	5.53

*** p<0.01, ** p<0.05, * p<0.1

1. Columns (1) presents results using lags 2-4 for income growth, consumption growth, 3-month Treasury bill growth, and second lag of consumption-income ratio. Column 2 adds the second lag of consumer sentiments, real S&P 500 return, and inflation to the list of instruments in Column 1. Column 3 uses GB forecast of income growth as an instrument.

2. We report the relative bias test results using Olea and Pflueger (2013) that accounts for heteroscedasticity and serial correlation.

Table 1B: Weak Instrument Test Results (1978Q2-1999Q4)

	(1)	(2)	(3)
A) Olea-Pflueger's Effective F-Statistic	2.624	2.555	35.65
5% Critical Values for the worst-case bias:			
$\tau = 10\%$	18.298	17.868	23.109
$\tau = 20\%$	11.404	11.064	15.062
$\tau = 30\%$	8.889	8.591	12.039
B) First-Stage F-Statistic	12.82	13.45	35.65
Stock and Yogo (2005) 5% Critical Values for the Maximal IV Size:			
Maximal Size=10%	38.54	45.64	16.38
Maximal Size=15%	20.88	24.42	8.96
Maximal Size=20%	14.78	17.14	6.66

*** p<0.01, ** p<0.05, * p<0.1

1. Columns (1) presents results using lags 2-4 for income growth, consumption growth, 3 month Treasury bill growth, and second lag of consumption-income ratio. Column 2 adds the second lag of consumer sentiments, real S&P 500 return, and inflation to the list of instruments in Column 1. Column 3 uses GB forecast of income growth as an instrument.

2. We report the relative bias test results using Olea and Pflueger (2013) that accounts for heteroscedasticity and serial correlation.

Table 1C: Weak Instrument Test Results (2000Q1-2010Q4)

	(1)	(2)	(3)
A) Olea-Pflueger's Effective F-Statistic	1.709	1.092	25.19
5% Critical Values for the worst-case bias:			
$\tau = 10\%$	17.418	16.775	23.109
$\tau = 20\%$	10.747	10.248	15.062
$\tau = 30\%$	8.331	7.897530	12.039
B) First-Stage F-Statistic	7.01	5.18	25.19
Stock and Yogo (2005) 5% Critical Values for the Maximal IV Size:			
Maximal Size=10%	38.54	45.64	16.38
Maximal Size=15%	20.88	24.42	8.96
Maximal Size=20%	14.78	17.14	5.53

*** p<0.01, ** p<0.05, * p<0.1

1. Columns (1) presents results using lags 2-4 for income growth, consumption growth, 3 month Treasury bill growth, and second lag of consumption-income ratio. Column 2 adds the second lag of consumer sentiments, real S&P 500 return, and inflation to the list of instruments in Column 1. Column 3 uses GB forecast of income growth as an instrument.

2. We report the relative bias test results using Olea and Pflueger (2013) that accounts for heteroscedasticity and serial correlation.

Table 2: Forecast Encompassing Exercise

Explanatory Variable	Model 1	Model 2	Model 3	Model 4
1-step ahead GB Forecast	0.599	0.596	0.591	0.572
	(0.00)	(0.00)	(0.00)	(0.00)
PC1	-	-0.147	-0.162	-0.115
	-	(0.47)	(0.47)	(0.66)
PC2	-	-	-0.066	-0.139
	-	-	(0.81)	(0.60)
PC3	-	-	-	-0.298
	-	-	-	(0.24)
R^2	0.359	0.362	0.362	0.372

P-values are in parentheses.
The dependent variable is real disposable income growth.
PC1 is first principal component for conventional set of instruments that include real disposable income growth, consumption growth, changes in treasury bill yield and consumer sentiment. PC2 is the second principal component and PC3 is the third principal component.
All right hand side variables are lagged one period.

Table 3: Results of IV Estimation: Rule-of-Thumb Consumption

$$\Delta C_t = \alpha + \lambda \Delta Y_t + \epsilon_t$$

Full Sample: 1978Q2-2010Q4			
	(1)	(2)	(3)
Income Growth	0.690**	0.712**	0.244
	(2.68)	(3.03)	(1.65)
Constant	0.717	0.642	1.473**
	(1.53)	(1.47)	(2.86)
Observations	131	130	130
Sub-Sample: 1978Q2-1999Q4			
	(1)	(2)	(3)
Income Growth	1.061***	1.094***	0.610***
	(6.28)	(6.56)	(3.63)
Constant	0.314	0.209	1.090
	(0.70)	(0.52)	(1.92)
Observations	87	86	86
Sub-Sample: 2000Q1-2010Q4			
	(1)	(2)	(3)
Income Growth	0.0860	-0.0516	0.115
	(0.59)	(-0.33)	(0.70)
Constant	1.181	1.412**	1.132
	(1.74)	(3.03)	(1.38)
Observations	44	44	44

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Columns 1 presents results using lags 2-4 for income growth, consumption growth, 3 month Treasury bill growth, and second lag of consumption-income ratio. Column 2 adds the second lag of consumer sentiments, real S&P 500 return, and inflation to the list of instruments in Column 1. Column 3 uses the GB forecast of income growth as an instrument.

Table 4: Results of IV Estimation: Rule-of-thumb Consumption and Habit Persistence

$$\Delta C_t = \alpha + \lambda \Delta Y_t + \gamma \Delta C_{t-1} + \epsilon_t$$

	Full Sample: 1978Q2-2010Q4		
	(1)	(2)	(3)
Income Growth	0.456	0.422	0.163
	(1.24)	(1.24)	(1.09)
Lagged Consumption Growth	0.241	0.251	0.305**
	(1.32)	(1.49)	(2.73)
Constant	0.669	0.671	1.025*
	(1.70)	(1.52)	(2.09)
Observations	131	130	130
	Sub-Sample: 1978Q2-1999Q4		
	(1)	(2)	(3)
Income Growth	0.964***	1.016***	0.543***
	(6.30)	(6.51)	(3.67)
Lagged Consumption Growth	-0.00335	-0.0103	0.100
	(-0.03)	(-0.08)	(1.32)
Constant	0.498	0.373	0.987
	(1.00)	(0.74)	(1.72)
Observations	87	86	86
	Sub-Sample: 2000Q1-2010Q4		
	(1)	(2)	(3)
Income Growth	-0.183*	-0.215**	0.0455
	(-2.20)	(-2.93)	(0.25)
Lagged Consumption Growth	0.616***	0.620***	0.586***
	(7.01)	(7.48)	(6.11)
Constant	0.796	0.844*	0.454
	(1.89)	(2.14)	(0.72)
Observations	44	44	44

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Columns 1 presents results using lags 2-4 for income growth, consumption growth, 3 month Treasury bill growth, and second lag of consumption-income ratio. Column 2 adds the second lag of consumer sentiments, real S&P 500 return, and inflation to the list of instruments in Column 1. Column 3 uses the GB forecast of income growth as an instrument.

Table 5: Parameter Estimates of the TVP Model

Hyperparameters	Estimate	S.E.
c	1.104	0.273
ρ	0.168	0.097
σ_e	2.138	0.149
σ_1	0.197	0.118
σ_2	0.025	0.021
Likelihood Value	-265.81	

Note: The table provides the maximum likelihood estimates of the TVP consumption function using the GB forecasts as the instruments.

Table 6: Economic Interpretation of Time-varying Rule-of-Thumb and Habit Persistence Parameters

Explanatory Variables	Dependent Variable: λ_t	Dependent Variable: θ_t
Credit-Income Ratio	-0.151***	0.155**
	(0.049)	(0.062)
Wedge	0.022	-0.009
	(0.014)	(0.009)
SNAP-Income Ratio	-0.032*	0.045**
	(0.019)	(0.018)
TED Spread	0.031*	-0.002
	(0.017)	(0.011)
VIX SP100	-0.0009*	0.001**
	(0.0004)	(0.0005)
Lagged Dependent Variable	0.759***	0.826***
	(0.067)	(0.068)
Constant	-0.488**	0.652***
	(0.215)	(0.267)
Sample	1986Q1-2010Q4	1986-2010Q4
Observations	100	100
R-squared	0.838	0.960

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

[i] Newey-West Heteroscedasticity and Autocorrelation Consistent standard errors are reported in the parenthesis.

[ii] Variable Definitions:

- Credit-Income Ratio is the natural log of the ratio of total consumer credit outstanding to personal disposable income.
- Wedge is the difference between the Prime lending rate and 3 month Certificate of deposits rate.
- SNAP-Income Ratio is the natural log of the ratio of SNAP expenditure to personal disposable income.
- TED spread is the difference between the 3-Month LIBOR based on US dollars and 3-Month Treasury Bill rate.
- VIX SP100 is the CBOE S&P 100 Volatility Index.

[iii] With the exception of SNAP, data on other variables are sourced from Fred Stat: `https://fred.stlouisfed.org/`. SNAP data is obtained from Food and Nutrition Website: `https://www.fns.usda.gov/pd/supplemental-nutrition-assistance-program-snap`.

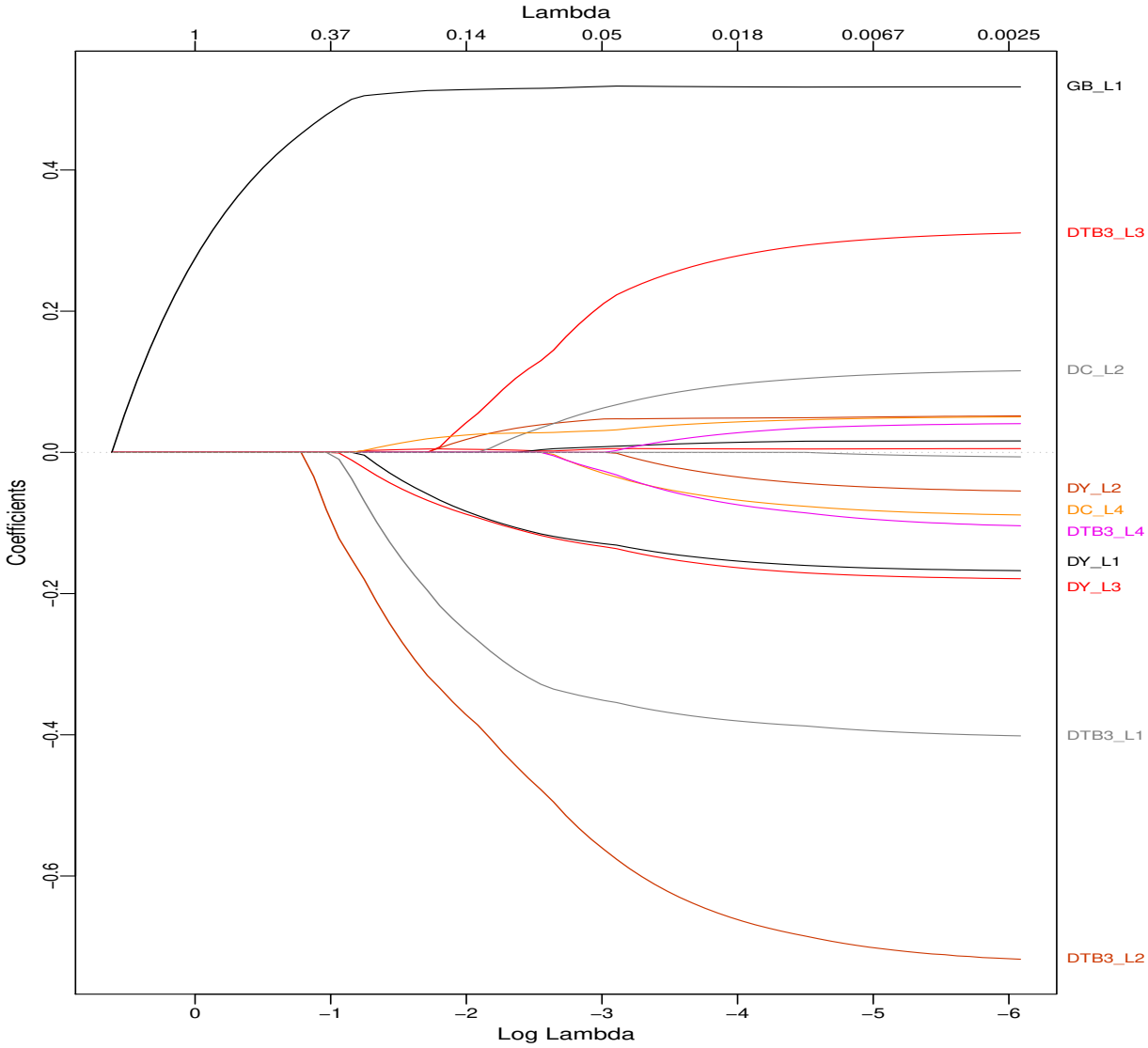

Figure 1: LASSO Plot

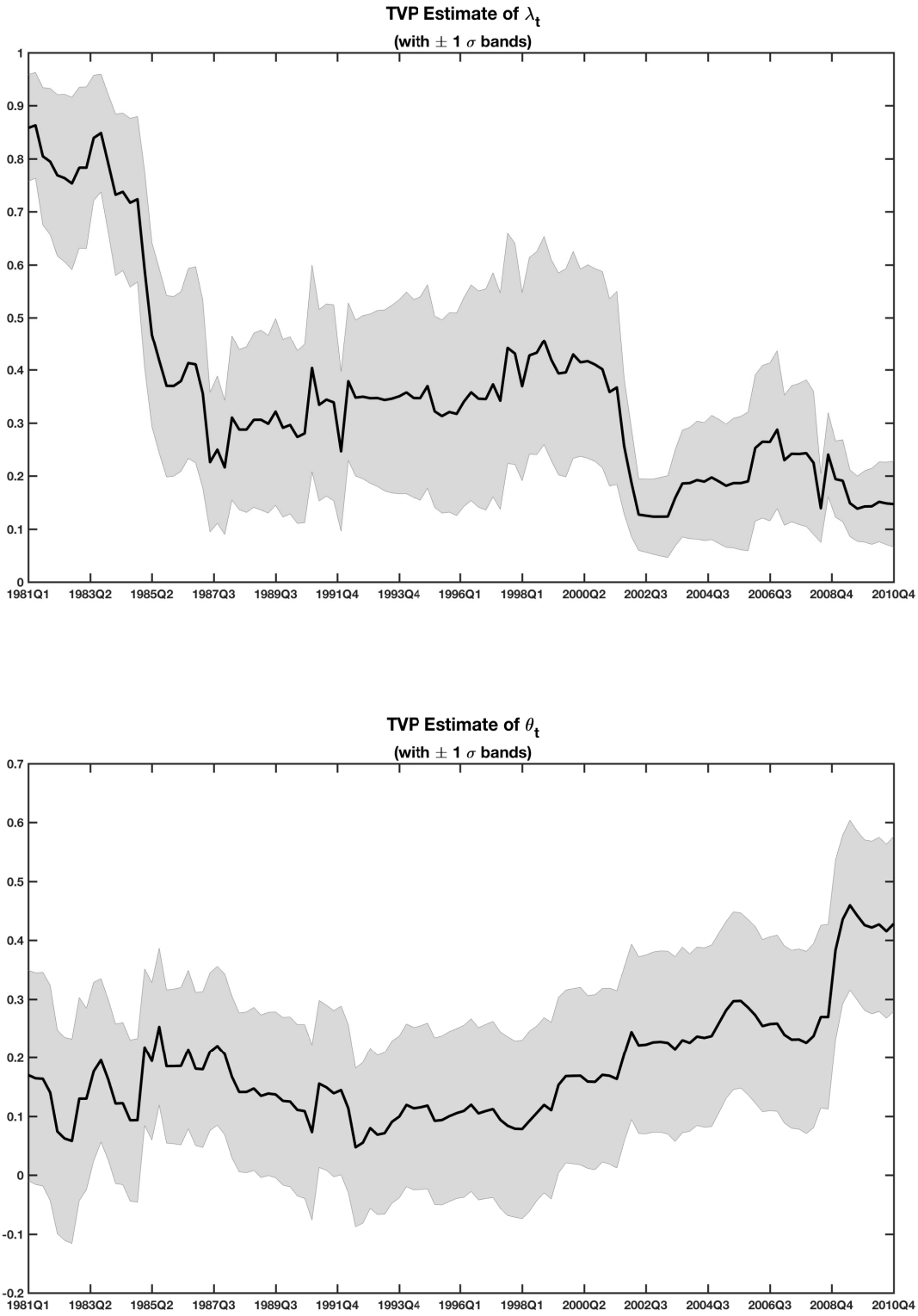

Figure 2: TVP Model with Habit Persistence

Appendix: Relevant GB Forecast Month

The Quarter and Corresponding GB Forecast Month

Quarter	GB Forecast	Quarter	GB Forecast	Quarter	GB Forecast	Quarter	GB Forecast
1978Q1	Mar-78	1981Q1	Mar-81	1991Q1	Mar-91	2001Q1	Mar-01
1978Q2	Jun-78	1981Q2	May-81	1991Q2	Jun-91	2001Q2	Jun-01
1978Q3	Sep-78	1981Q3	Sep-81	1991Q3	Sep-91	2001Q3	Oct-01
1978Q4	Dec-78	1981Q4	Dec-81	1991Q4	Dec-91	2001Q4	Dec-01
1979Q1	Mar-79	1982Q1	Mar-82	1992Q1	Mar-92	2002Q1	Mar-02
1979Q2	May-79	1982Q2	Jun-82	1992Q2	Jun-92	2002Q2	Jun-02
1979Q3	Sep-79	1982Q3	Sep-82	1992Q3	Sep-92	2002Q3	Sep-02
1979Q4	Nov-79	1982Q4	Dec-82	1992Q4	Dec-92	2002Q4	Dec-02
1980Q1	Mar-80	1983Q1	Mar-83	1993Q1	Mar-93	2003Q1	Mar-03
1980Q2	May-80	1983Q2	May-83	1993Q2	Jun-93	2003Q2	Jun-03
1980Q3	Sep-80	1983Q3	Sep-83	1993Q3	Sep-93	2003Q3	Sep-03
1980Q4	Dec-80	1983Q4	Dec-83	1993Q4	Dec-93	2003Q4	Dec-03
		1984Q1	Mar-84	1994Q1	Mar-94	2004Q1	Mar-04
		1984Q2	May-84	1994Q2	Jun-94	2004Q2	Jun-04
		1984Q3	Sep-84	1994Q3	Sep-94	2004Q3	Sep-04
		1984Q4	Dec-84	1994Q4	Dec-94	2004Q4	Dec-04
		1985Q1	Mar-85	1995Q1	Mar-95	2005Q1	Mar-05
		1985Q2	May-85	1995Q2	Jun-95	2005Q2	Jun-05
		1985Q3	Sep-85	1995Q3	Sep-95	2005Q3	Sep-05
		1985Q4	Dec-85	1995Q4	Dec-95	2005Q4	Dec-05
		1986Q1	Mar-86	1996Q1	Mar-96	2006Q1	Mar-06
		1986Q2	May-86	1996Q2	Jun-96	2006Q2	Jun-06
		1986Q3	Sep-86	1996Q3	Sep-96	2006Q3	Sep-06
		1986Q4	Dec-86	1996Q4	Dec-96	2006Q4	Dec-06
		1987Q1	Mar-87	1997Q1	Mar-97	2007Q1	Mar-07
		1987Q2	May-87	1997Q2	Jun-97	2007Q2	Jun-07
		1987Q3	Sep-87	1997Q3	Sep-97	2007Q3	Sep-07
		1987Q4	Dec-87	1997Q4	Dec-97	2007Q4	Dec-07
		1988Q1	Mar-88	1998Q1	Mar-98	2008Q1	Mar-08
		1988Q2	Jun-88	1998Q2	Jul-98	2008Q2	Jun-08
		1988Q3	Sep-88	1998Q3	Sep-98	2008Q3	Sep-08
		1988Q4	Dec-88	1998Q4	Dec-98	2008Q4	Dec-08
		1989Q1	Mar-89	1999Q1	Mar-99	2009Q1	Mar-09
		1989Q2	Jun-89	1999Q2	Jun-99	2009Q2	Jun-09
		1989Q3	Sep-89	1999Q3	Oct-99	2009Q3	Sep-09
		1989Q4	Dec-89	1999Q4	Dec-99	2009Q4	Dec-09
		1990Q1	Mar-90	2000Q1	Mar-00	2010Q1	Mar-10
		1990Q2	Jun-90	2000Q2	Jun-00	2010Q2	Jun-10
		1990Q3	Sep-90	2000Q3	Oct-00	2010Q3	Sep-10
		1990Q4	Dec-90	2000Q4	Dec-00	2010Q4	Dec-10

The table shows for each quarter the instrument used, that is, the 1-quarter ahead GB forecasts made in the given month.