Household Savings & The Macroeconomy

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August 2, 2021

Abstract

In this paper, we document some key relationships between micro-level household behavior and macro-level aggregates for the Indian economy. Using the CMIE's Consumer Pyramids Survey, we show that for the period 2014-19, the household-level savings rate around the median of the income distribution correlates strongly with, and has predictive power for, macro-aggregate variables such as the Wholesale Price Index and its rate of change, the Prime Lending Rate, the growth rate of bank credit for personal loans, the growth rate of industry-sector GDP, and the growth rate of bank credit to the household sector. Equally, we also document as a puzzle the absence of any strong relationship between the household-level savings rate and RBI-surveyed indices that are meant to capture citizens' expectations about the future. We uncover these results at business cycle frequencies, i.e., monthly and quarterly, and we detrend all variables so that what we document are cyclical co-movements (or lack thereof). We conjecture that this mode of analysis can be a fruitful way of relating the micro to the macro for the Indian economy, and can offer avenues for uncovering meaningful empirical relationships that warrant proper theoretical explanations. Our primary goal in this paper is to uncover these relationships, and not to explain them. We also offer some conjectures about the meaning of the relationships, or lack thereof, that we document.

Keywords: Household Savings, Macroeconomic cycles.

JEL Codes: E32, D14, G51

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1 Introduction & Literature Review

The relation between individual economic behavior and macro-aggregate variables has always been a topic of deep interest for economists. In the 1970s, the economics discipline began to explicitly incorporate so-called "micro-foundations" into macroeconomic analysis. Since then, the practice has become second nature to macroeconomists, who have typically presumed individual economic behavior to be "representative" of aggregate economic behavior. Yet, through all the decades of its influence, this methodological innovation has remained confined to the world of theory. There has been no empirical confirmation that individual economic behavior and macro-aggregate variables do indeed correlate, if not mirror each other. Our paper is a first step in this direction. In it, we establish for the Indian economy, correlations over the cycle between household-*level* economic behavior, specifically the household savings rate, and various macro-aggregate variables such as Gross Domestic Product (GDP) growth, the aggregate price level and its rate of change, credit growth, and the like. For our analysis, we use data drawn from disparate sources, but compiled at very different levels of resolution. The data on household-level economic behavior is constructed "ground-up", as it were, from a large-scale household-level panel survey. On the other hand, the data on macro-aggregates is obtained from standard sources such as official publications that also aggregate up from more disaggregated origins but do not start at the highest level of resolution possible or indeed warranted in an economy, which we take to be the household.

For household-level economic behavior, we confine our attention to the savings rate for good reasons. We define the savings rate as the surplus of household income over household expenditures, divided by household income, where expenditures include interest payments on outstanding debt. The savings rate, thus calculated, is a key flow indicator of a household's financial and economic well-being, and a key determinant of a household's credit worthiness. Therefore, it seems to make good sense to explore the relationship between the household savings rate and macro-aggregate variables which have implications for economic health at the level of the entire country. As we will show below, in our literature review, this is also the direction pursued by some of the more recent empirical literature in macroeconomics, although admittedly, there, the focus has always been on household-level indebtedness and not household savings per se. But the implication of that literature, or the inference one can safely draw from it, is that household savings could well be an important driver of business cycles. This is what we also hope to draw attention to, with our work. We do not prove that household savings *drive* the cycle, but we do show that savings *at the household level* fluctuate over the cycle in tandem with macro-aggregate variables.

Given its focus on savings and the macroeconomy, and also given its methodological orientation of working with datasets at different levels of resolution, our paper can be properly situated, we think, at the intersection of three different strands of literature without fitting neatly into any one of them. The first strand of literature is the role of savings in macro-aggregate contexts. Here, the literature divides into two sub-strands. One of them addresses the older, classic, question of what role savings plays in fueling long-run economic growth. Beginning with the analyses of Harrod (1939) and Domar (1946), continuing with the landmark contribution of Solow (1955), and culminating in a spate of important research papers in the 1980s and early 1990s (Feldstein & Horioka, 1979; Romer, 1986 & 1989; Lucas, 1988; Mankiw, Romer, & Weil, 1992), this literature has evolved over time but remained always anchored to a notion of the savings rate that is the aggregate, macro, or national savings rate, rather than any version of a household savings rate. The outlook here is typically long-run, covering 4-5 decades of time length, and where there is any empirical work, it has mostly used macro-aggregate data at the annual frequency. Furthermore, the savings rate in this literature is typically assumed to be constant, or if it changes, it does so discontinuously at best. This is also the context for Mohan (2008), who in considering the role of the savings in fuelling long-term economic growth in India, makes a surprising call (that is relevant to us) for micro-level savings data, presumably to validate the macro-aggregate data that is typically used for empirical work in this area. Where the savings rate is allowed to change continuously, the focus shifts away from long-run economic growth and towards empirical work, mixing time-series and panel data approaches, to uncover long-run demographic and socioeconomic determinants of the savings rate (Deaton, 1989; Collins, 2009; Attanasio et al., 2000; Chamon & Prasad, 2008; Samantaraya & Patra, 2014). In much of this empirical literature, some form of lifetime consumption smoothing model (at the level of the individual, not household) is the main theoretical scaffolding, either implicitly or explicitly.

A second sub-strand of the macro-aggregate analysis of savings studies the relation between aggregate savings and inflation. Here, the empirical modelling spans 2-3 decades, the data is quarterly in frequency, and household or more properly private savings are backed out from macro-aggregate national income accounts. The method is time-series analysis, incorporating some kind of dynamic causality from inflation expectations or inflation uncertainty to savings behavior. Therefore, this too is a literature about the determinants of the savings rate, but unlike in the previous set of papers, here the focus is on understanding medium-run rather than long-run determinants, and so the attention is not towards demographics and socioeconomic factors (which change very slowly, and therefore belong properly in long-run analysis) but rather to inflation, interest rates, and such (which change over the medium-run).[1] Campbell & Lovati (1979) and Davidson & MacKinnon (1983) are illustrative of this approach.

[1] Here, we are using the term "medium-run" to describe a time span of 2-3 decades, so as to contrast it with a time span of 4-5 decades, which we are calling the "long-run". We note, however, that these terms are also used in the context of business cycle analysis, where they denote much shorter time spans.

The second set of papers to which our work bears some correspondence is the rapidly growing literature on the composition of household finances. Here, too, there are two sub-strands to be considered. The first has to do with household finances in developed or advanced economies, and is nicely reviewed in Gomes, Haliassos, & Ramadorai (2020). This literature has complied extensive empirical evidence on households' choice of assets and liabilities, trading behavior, peer effects, financial literacy, etc. Even though it calls itself household finance, the literature has typically worked with data collected at the level of the individual decision maker. Likewise, where there is any theoretical modelling, it is usually of individual optimizing behavior. Savings behavior at the level of either the individual or the household is not systematically studied in this literature. The second sub-strand has to do with household finances in developing or emerging economies, and in particular, India. Badarinza, Balasubramaniam, & Ramadorai (2019) survey the composition of household finances in emerging markets and review the relevant literature, bringing to it a similar principle of organization as does the Gomes et al. (2020) paper. The one important difference, though, is that in the case of developing and emerging economies, the data is actually collected at the level of the household. Badarinza et al. (2019) find a lot of literature for developing and emerging economies on the extensive margin of finance (access to finance) but not enough on the intensive margin (ownership or usage of particular assets and liabilities). Also, there do not appear to be any systematic studies of individual or household savings behavior (its dynamics, its determinants, etc.). An earlier paper in the same vein by the same authors, Badarinza, Balasubramaniam, & Ramadorai (2016), analyzes the composition of household finances in India using household-level data (drawn from the All India Debt and Investment Surveys, or AIDIS), but not savings behavior. Certain aspects of the household balance sheet (such as allocations to gold or retirement assets, and the incidence of informal debt) but not the size of the balance sheet itself (or savings) are related to state-level macro factors such as the inflation rate, public sector employment, etc.. The approach here is not dynamic or time-series but cross-sectional.

The third strand of literature that provides relevant context for our work is a set of papers that study the relationship between household finances (specifically household debt) and macro-aggregate cycles. In its most recent vintage, this literature really begins with the unfolding of the 2008 crisis, and the necessity of thinking about credit cycles. There is an earlier vintage of models about credit cycles dating back to the 1980s, and owing their inspiration primarily to Minsky's classic analysis of credit-fuelled booms and subsequent busts (Minsky, 1982), but that literature was largely ignored by the mainstream and only recognized to be useful after the 2008 crisis. The post-2008 or more recent vintage begins with Mian & Sufi (2009) and Glick et al. (2010). The first of these papers performs a dynamic analysis with quarterly data for the US economy, and establishes a causal effect from increases in household leverage during 2002-2006 to decreases in consumption expenditure during and after 2006. The causal effect is uncovered via a comparison of dynamics across counties, and so the data is collected at the county level. In particular, the data on household leverage is obtained at the zip code level (i.e., not at the household level) from credit bureaus and then aggregated up to the county level. Glick et al. (2010) uncover a similar result at the country level using OECD quarterly data for a group of advanced economies. They go even further back in time to measure the build-up of leverage (1997-2007). The IMF's World Economic Outlook (2012, April, Ch. 3) reports similar findings from panel regressions for advanced economies over a 30-year period (1980-2010). The data appears to be quarterly and mostly from OECD countries. The build-up of household leverage is shown to amplify downturns and weaken recoveries. Qualitative case studies of the US (1930s, Great Depression), Colombia (1990s), and Scandinavian countries (1990s) are also presented in support of the regression results.

The outpouring of empirical work after 2008 on this topic has also motivated theoretical attempts to model the interaction between household leverage and aggregate output. Guerrieri & Lorenzoni (2017) and Martin & Philippon (2017) are exemplary of this new and emerging tradition. Here, the approach is usually to write up a dynamic stochastic general equilibrium model subject to credit-crunch shocks or "sudden stops". The demand side of these models anchors to representative agent foundations, even if there is some heterogeneity among agents. The approach is therefore atomistic and individual rather than group or household (even if the rhetoric is one of "households"). There is some consideration in these models about how individual savings responds to shocks and behaves over the cycle. Donaldson, Piacentino, & Thakor (2019) is an interesting take on theoretical approaches as it also models the labor market and shows how "household' leverage and employment interact over the cycle.

Alongside the advent of theoretical modelling, empirical work has continued to explore the interactions between household leverage (and in some cases, household net worth) and macro-cyclical phenomena (see Mian, Sufi, & Verner, 2016; Mian & Sufi, 2018; Bernstein, McQuade, & Townsend, 2018; Alter, Feng, & Valckx, 2018). Much of this literature seeks to establish that household leverage (the Bernstein et al. paper looks at household wealth, in particular housing wealth) is an important driver of cycles, rising on the upturn and falling on the downturn, often acting as an amplification mechanism for the booms and busts. The data is typically macro-aggregate data, not aggregated up from household-level surveys but via data from the reporting of financial institutions, as with Mian & Sufi (2009). Alter et al. (2018) do use some survey data, but only for a couple of years and for a small group of countries. The use of systematically collected household-survey data is usually missing in all of the empirical work that has been surveyed under this third strand, although that is not to say that such a literature does not at all exist. An empirical paper that studies the relationship between income-expenditure gaps and indebtedness at the household-level using household-survey data is Shraberman (2018) for Israel, and he finds that financially weaker households often tide over excesses of expenditure over income with informal credit from family and friends. The role of such informal networks is absent in theoretical models of household leverage, and hidden in aggregate data that is typically sourced from the formal sector. Yet such networks and the patterns of savings and dis-savings they facilitate surely also have implications for macro-aggregate cycles. Shraberman (2018), however, does not study these implications.

Our paper is closest to Shraberman (2018), but takes up the question that that paper does not - is there a connection between household-level decision making and outcomes at the macro-aggregate level? We answer this question by documenting robust positive correlations between the household-level savings rate and the aggregate price level, its rate of change (inflation rate), and the prime lending rate, and robust negative correlations between the household-level savings rate and the growth rates of GDP and aggregate credit (personal loans). Our results indicate, broadly, clear gains from studying household-level economic behavior for understanding macroeconomic cycles in India. A number of caveats are also in order. To the best of our knowledge, this is the first study of its kind, at least for India. Badarinza et al. (2016) is possibly the only precedent, but when looking at the aggregate picture, they stop at state-level aggregates, and then too, they focus on inflation rates but not the full array of standard macro-aggregate variables such as the price level, GDP growth, etc. Given the pioneering nature of our effort, we adopt an atheoretical or theory-agnostic approach. We are interested in only uncovering correlations and describing them, but not necessarily in explaining them and certainly not in establishing dynamic structural relationships between household-level decision making and the macroeconomy. That is, we focus on contemporaneous correlations and not on time-series relationships. We find that the data exhibits interesting correlations in the contemporaneous sense and we believe that these correlations are worth documenting. We leave the explanation of these correlations to future work. Indeed, we believe that a consensus-view about what kind of structural model best describes the Indian macroeconomy simply, does not exist, and so methodologically, our approach is to go to the data first.

The remainder of the paper is organized as follows. Section 2 presents the data and summary statistics, Section 3 presents the empirical methodology, Section 4 the results, and Section 5 concludes with suggestions for further work.

2 Data

We work with two sets of time series data to examine the correlations between macro-aggregate variables and the household-level savings rate. The first set, comprising data on the former type of variables, is collected from public and private sources, as described below. The second set, comprising data on the household-level savings rate, is extracted from the Center for Monitoring the Indian Economy (CMIE)'s Consumer Pyramids Households Survey (CPHS). Our analysis spans the period from 2014 to 2019 with data arranged to monthly and quarterly frequencies depending on the frequency at which macro-aggregate data is available.

The macro-aggregate variables of primary interest are price level, inflation rate, unemployment rate, GDP growth, lending rate, and credit growth. The Database on Indian Economy (DBIE) of the Reserve Bank of India (RBI) provides data on the Consumer Price Index (CPI) and Wholesale Price Index (WPI), both of which we use as stand-ins for the aggregate price level in our analysis. From monthly data on these price indices, we also compute year-on-year inflation rates for each month. Further, one other important price, namely the interest rate, is compiled at a monthly frequency, but we use several different versions of this price. The Weighted Average Lending Rate (WALR) of the RBI and several series of interest rates such as the Prime Lending Rate (PLR), Discount Rate, Interbank Interest Rate, 10-year Government of India (GoI) Bond Yield etc., are sourced from the St. Louis Fed's Federal Reserve Economic Data (FRED). From the CMIE's Unemployment Survey that reports the state of the labor market at the national level as well as the urban and rural regional levels, we obtain monthly unemployment rates.[2] Another variable that is available at a monthly frequency is the Index of Industrial Production (IIP), which may be considered as a rough proxy for monthly economic activity (GDP is only available at a quarterly frequency). Accordingly, we obtained IIP data from the Ministry of Statistics and Program Implementation (MOSPI) and computed its year-on-year growth rate for each month.[3] The RBI Monthly Bulletin publishes nominal data on bank credit and credit by use, such as food, non-food, and personal loans. These data are reported by Scheduled Commercial Banks to the RBI periodically under Section 42 returns.[4] From this data, and by applying the WPI-based inflation rate to back out real growth rates, we compute the year-on-year monthly growth rates of bank credit (overall), food credit, non-food credit, and personal loans.

At a quarterly frequency, we compute the year-on-year (real) GDP growth rate from the RBI's DBIE. We do this for overall and sector-wise GDP growth rates. From the Bank of International Settlements (BIS), we source a quarterly series for credit to households as a percentage of GDP. Importantly, this variable is not built up from the household-level but sourced from banks and other financial institutions reporting household credit outstanding on their balance sheets to the RBI, and the RBI then reporting the aggregate household credit figure to the BIS. For our analysis, we use both the ratio (household

[2] This is the only macro-aggregate variable that is actually built up from household-level data, since it comes from the CMIE's household-level unemployment survey.

[3] IIP series are available under several heads depending on the nature of the goods produced. These goods are categorized as primary, capital, intermediate, construction/infrastructure, consumer durables and consumer non-durables.

[4] See here: https://rbi.org.in/scripts/BS_ViewBulletin.aspx?Id=20338

credit as a share of GDP) and also compute a year-on-year quarterly (real) growth rate for aggregate household credit. Next, the Inflation Expectations Survey of the RBI, conducted on a sample of about 5000-6000 households across 18 cities, provides the current, 3-month ahead and 1-year ahead household expectations for the inflation rate, and we assemble a quarterly dataset for these expectations.[5] Finally, we also consider two other quarterly indices published by the RBI that capture the state of consumer confidence, namely the Current Situation Index and the Future Expectations Index.[6]

Next, we turn to the household-level data, which is entirely sourced from the CMIE CPHS, which is a set of large-scale panel surveys of Indian households conducted thrice a year in waves since 2014. We use monthly data from the period January 2014 to December 2019 (72 months or 6 years). There are about 150,000 households and over 440 variables, collected across multiple surveys. The People of India survey data comprise demographic variables such as age, education level and occupation, as well as financial market participation variables such as presence of bank accounts, credit cards etc. The Income and Consumption surveys contain monthly data on total income and expenditure of households. The income data is available at a granular level that differentiates the sources of income such as wages, pensions, dividends, interest, rent, sale of assets, and private and government transfers. Similarly, the consumption data covers different expenditure heads including food, clothing, appliances, power, fuel, transport, communication, education, health and instalment payments. The Aspirational India survey provides wave-level participation data on assets and liabilities (i.e. these are categorical variables documenting the ownership by a household of certain kinds of assets and liabilities). Household borrowings from formal and informal sources, savings and the intent to save are also recorded.

Each household in the CMIE surveys is provided a frequency weight. The weight can be used to replicate the household in the CMIE sample so as to arrive at its multiple mirror images in the population. In the event that the survey is missing data on certain households in any particular month due to a lack of response, we use a corrective non-responsive factor as a multiplier on household weights. By applying this procedure, we are able to go from the sample of about 150,000 households to a population of about 250-300 million households per month, which is practically the entire country. When going from the sample to the population, the breakup between urban and rural is reversed, 30% rural in the sample but 70% rural in the population, which is further confirmation that

[5] The survey was conducted quarterly until 2016 and bi-monthly from 2017 onwards. Households are asked if the prices of various categories of goods/services (General, Food, Non-food, HH Durables, Housing and Cost of Services) are expected to increase, decrease, or not change, and if they are expected to increase, then whether the expected increase is at the current rate, lesser or more than current rate, for 3 months ahead and 1 year ahead. The expected inflation rate is computed from the answers to these questions and is presented in Table 4 here: https://www.rbi.org.in/Scripts/PublicationsView.aspx?id=17389

[6] For the April 2021 calculations of these indices, see here: https://www.rbi.org.in/Scripts/PublicationsView.aspx?id=20351

the 250-300 million households in our population are indeed the entirety of the Indian population.

Although the CMIE dataset is exhaustive and deep, it does come with certain limitations. The most consequential of these is that although the survey identifies 400 variables, the dataset has been populated across households for a small fraction of them. We therefore avoid working with sparsely populated variables and incorporate only those with statistically robust responses. Additionally, many of the variables (such as household borrowings) are recorded as categorical variables and not continuous, quantitative variables. While we have limited our use of data in this paper to only continuous, quantitative variables, our intent is to utilize the categorical variables in a meaningful way in future work.

Before we move on to describe our methodology, we should clarify that the CMIE CPHS is not the only household-level survey dataset available for household balance sheets in India. Badarinza et al. (2016) use the AIDIS dataset for their work, but that dataset is available only once a decade, for 1992, 2003 and 2013. It covers a larger group of households (about 300,000) but the same households are not surveyed each time and weights are not available to go from the sample to the population. Assets and liabilities are recorded for surveyed households, but not their incomes or expenses. High frequency panel data at the household-level covering balance sheet, cashflows and household characteristics is only available through the CMIE CPHS and therefore it is this dataset that we use for our analysis of household economic behavior over the cycle.

3 Methodology

Recall that we are working with the population dataset. The household-level savings rate is computed for each household in this dataset for each of the 72 months. We compute this rate for each household each month by subtracting total expenditure from total income and dividing by total income. We then perform two separate aggregation exercises in order to arrive at two separate household-level savings rates for each month.

In the first method, we construct income deciles. The first (and poorest) income decile comprises of all households in the income quantile interval $q \in [0, 0.1]$. Likewise, the median decile corresponds to the quantile interval $q \in (0.4, 0.5]$ and is denoted by d_5. We label the deciles as $d_1, d_2, d_3, \ldots, d_{10}$, where d_1 is the poorest income decile and d_{10} the richest. For each income decile and each month, we compute the mean value of household-level savings rate over all households in that decile. This yields a 10×72 matrix of average household-level savings rates, a 72-month time series for the average household-level savings rate for each of 10 deciles.

In the second method, we adopt a state-space approach. We construct 9 household states labelled $s_1, s_2, \ldots, s_9$ and bin each household in the population into one of these states based on its level of income and expenditure. We split the total income distribution into 3 quantiles with intervals $q \in [0, 0.334]$, $(0.334, 0.667]$ and $(0.667, 1.0]$ corresponding to low, middle and high income groups respectively. A similar three-quantile split of the total expenditure distribution is also made. Those households having low incomes and low expenditures are defined to be in state s_1; those having low incomes and middle expenditures are defined to be in state s_2; and those having low incomes but high expenditures are defined to be in state s_3. Similarly, states s_4, s_5 and s_6 group households having middle incomes and low, middle and high expenditures respectively. Finally, states s_7, s_8 and s_9 group households having high incomes and low, middle and high expenditures respectively. We refer to s_1, s_2 and s_3 collectively as the low income states, s_4, s_5 and s_6 as the mid income states, and states s_7, s_8 and s_9 as the high income states. For each state thus defined and each month, we compute the mean value of the household-level savings rate over all households in that state. This yields a 9×72 matrix of average household-level savings rates, a 72-month time series for the average household-level savings rate for each of 9 states.

Since some of our macro-aggregate variables are only available at a quarterly frequency, the 72-month time series of the household-level savings rate for each decile and each state is converted into a 24-quarter time series of the household-level savings rate for each decile and each state by simple averaging over 3 months at a time. All the time series, of both macro-aggregate variables and the household-level savings rate, are passed through the Hodrick-Prescott (HP) filter which decomposes any time series into its trend and cyclical components. It is suggested in Ravn & Uhlig (2002), that a penalty of $\lambda = 1600$ for quarterly time series and $\lambda = 129600$ for monthly time series be applied, and so we use these values for our filtering process. We confirm that all the HP-filtered cyclical components are stationary. We then check for correlations between the cyclical component of the household-level savings rate and with the cyclical component of each of the macro-aggregate variables. We do this by regressing each of the latter variables in turn on the former variable and a constant term, and in each case, reporting the *R-squared* value from the regression.

4 Results

Before we present the correlations, it is worthwhile to get a sense of the profiles of monthly income, monthly expenditure, and the monthly savings rate for the different deciles and states. These summary statistics (obtained by averaging over all 72 months for the households in each decile and state) are shown in Tables 1 and 2. We note that the poorest deciles d_1 and d_2 and the low income states s_1, s_2, and s_3 have negative savings rates with households in the lowest decile and households in the low income, high expenditure state having the lowest savings rates. It is unlikely, however, that these two groups contain the same households, because d_1 and s_3 vary vastly in terms of their monthly income and expenditure levels. The similarity in savings rate is rather because of averaging effects and the fact that s_3 (much like s_7) is a sparsely populated state. The states s_4, s_5 and s_6 can be compared to d_4, d_5 and d_6 in terms of income levels. Similarly, s_9 and d_{10} are comparable in terms of expenditure levels. The entire time series of monthly savings rates is displayed for the deciles and states in Figures 1,2 and 3,4, respectively.

Moving on to document correlations, we first present the regression results obtained from regressing the WPI level on the household-level savings rate, in Table 3 for deciles and states. The coefficient on the household-level savings rate is positive and statistically significant at the 1% level for all except the poorest decile, and for all except the low income states. The *R-squared* is the highest for the deciles around the median of the income distribution (specifically, d_3, d_5 and d_6) and for two of the middle income states (specifically s_5 and s_6) and one of the high income states (specifically, s_8) Broadly similar results are obtained from regressing the WPI inflation rate on the household-level savings rate, as shown in Table 4 for deciles and states.

When the WPI is replaced by the CPI, for both the level (Table 5) and the inflation rate (Table 6), the coefficient on the household-level savings rates turns negative but remains statistically significant at the 1% level for almost all deciles and all states. The only departures happen with regard to the lack of statistical significance for some of the poorer deciles when the CPI level is the LHS variable. The *R-squared* in the decile regressions for the CPI level and the CPI inflation rate are uniformly quite a bit lower than the *R-squared* in the decile regressions for the WPI level and the WPI inflation rate, respectively. The same is mostly, though not uniformly, true for the *R-squared* in the state regressions, when comparing CPI versus WPI.

Aside from the WPI and CPI, we also analyze another price level, namely the interest rate. Table 7 shows the decile and state regression results, for the RBI's WALR, while Table 8 shows the corresponding results for the 10-year GoI Bond Yield. These tables are illustrative of our findings for most of the interest rate measures – the coefficient on the household-level savings rate is statistically significant in only a few instances here and there among the decile and state regressions, and the *R-squared* is uniformly low, mostly in the 0-15% range and never rising above 20%. The only interest rate measure for which we find strong evidence of correlation with the household-level savings rate is the PLR. The regression results are shown in Table 9. We find that in the decile regressions, the coefficient on the household-level savings rate is always positive and statistically significant at the 1% level, except for d_1, and the *R-squared* is particularly high (30-45% range) for the regressions around the median of the income distribution (d_4 and d_5). In the state regressions, the coefficient on the household-level savings rate is always statistically significant at the 1% or 5% levels for six of the nine states, but uniformly positive only for the middle and high income states, and the *R-squared* is particularly high, at 42%, for the middle income state s_6.

Turning from prices to quantities at the monthly frequency, we consider first the unemployment rate. Tables 10, 11 and 12 show the regression results for the overall unemployment rate, the urban unemployment rate, and the rural unemployment rate respectively. For deciles d_4 and above, and the middle and high income states, the coefficient on the household-level savings rate is mostly negative and statistically significant at the 1% or 5% levels. For the other deciles (only d_1, incidentally) and states, the coefficient, when statistically significant, is positive. However, the *R-squared* remains below 15% for most of the regressions, and never rises above 20%.

For IIP, we look at the overall growth rate, and also the growth rate for specific categories of industrial production such as primary goods, consumer durables, etc.[7] Tables 13 and 14 show the regressions for the growth rates of overall industrial production and consumer durables, respectively. We find that the coefficient on the household-level savings rate is statistically significant only in some cases, and when it is, it does not always take the same sign across deciles or states. The *R-squared* is also quite low in all the regressions, exceeding 20% only for two of the low income states in the case of consumer durables, and here the coefficient on the household-level savings rate is positive and statistically significant at the 1% level. As opposed to overall industrial production and consumer durables, we observe more consistency in the regression results for the growth rate of primary goods production. As Table 15 shows, the coefficient on the household-level savings rate is statistically significant at the 1% or 5% levels most of the time, and is negative for all deciles (except for d_1, the poorest decile) and for all the middle and high income states. Although these regressions demonstrate consistency, they do not indicate a high degree of predictive power. The *R-squared* sometimes exceeds 20% but always remains well below 25% in all the regressions.

The final set of macro-aggregate variables that we consider at a monthly frequency is the one containing various measures of real bank credit growth. Table 16 shows the decile & state regressions for overall real bank credit growth. We find that the coefficient on the household-level savings rate is statistically significant at the 1% or 5% levels for most deciles, and where it is so, it is negative. But the *R-squared* in these regressions is uniformly low, not rising above 12%. For states, the results are more mixed. The coefficient is statistically significant for only five of the nine states, and for one of these, namely s_3, it is positive while for the other four, it is negative. In one of these latter

[7] Primary goods as those which are directly obtained from natural sources and are used for further processing and consumption in manufacturing and power-generating activities. For example, ores, minerals, fuels etc. Consumer durables are products directly used by consumers and have long durability (more than 2-3 years). For example, Pressure cookers, Air conditioners, tyres etc. See here: http://mospi.nic.in/sites/default/files/iip/IIP_Manual_3apr18.pdf

four regressions, the one for s_4, the *R-squared* is 27%, but otherwise, these regressions have little or no predictive power. Tables 17 and 18 show the regression results for real bank credit growth for food and non-food, respectively. Here, the only notable result by way of a statistically significant coefficient on the household-level savings rate (that is negative) and a high *R-squared* (that is 28%) is the non-food credit growth regression for the middle income state s_4. It is when we turn to the category of personal loans that we find more impressive results. Table 19 shows the regressions for real bank credit growth for personal loans. The coefficient on the household-level savings rate is negative and statistically significant at the 1% level for all the deciles except the poorest one, and for six of these nine deciles, the *R-squared* is in the 30-40% range. In the case of the state regressions, the coefficient on the household-level savings rate is negative and statistically significant at the 1% level for all the middle and high income states, and the *R-squared* is as high as 54% for s_4, and 46% for s_5.

Next, we turn to analysis at the quarterly frequency. We begin with GDP growth rates. Table 20 shows the decile and state regressions for the overall GDP growth rate, followed by Tables 21, 22, 23, which show the corresponding regressions for agriculture, industry and services, in turn. For the overall GDP growth rate, the coefficient on the household-level savings rate is negative and statistically significant for all the deciles except for the poorest one. Furthermore, the *R-squared* is quite high around the median of the income distribution, 49% for d_4 and 38% for d_5. A comparable result is obtained in the state regressions only for s_6, where the coefficient on the household-level savings rate is negative and statistically significant at the 1% level, and the *R-squared* is 45%. We observe a negative and statistically significant coefficient in the regressions for s_5 and s_9 also, but the *R-squared* in these regressions is much lower, in the 30% range. Turning next to sector-wise GDP growth rates, we see that most of the action in the decile regressions for overall GDP growth is being driven by the industry sector, where the decile regressions exhibit an almost exactly similar pattern as the decile regressions for overall GDP. The household-level savings rate appears to have very little to do with the growth rates of GDP for the agriculture and services sectors. Further, we observe for the state regressions a somewhat similar pattern as we do for the decile regressions - when the household-level savings rate matters for overall GDP growth (for state s_6), it does so also for industry-sector GDP growth.

Moving on to the BIS data, we present decile and state regressions in Table 24 for household credit as a share of GDP, and in Table 25 for the growth rate of household credit. For the first of these variables, we find no noteworthy results, but for the second one, we find a negative and statistically significant (at the 1% level) coefficient on the household-level savings rate for all deciles except the poorest one, and for all the middle and high income states. The *R-squared* is quite high for some of the decile regressions

(49% for d_3, 43% for d_6), and higher still for many of the state regressions (63% for s_4, 62% for s_7, 52% for s_5, 43% for s_8).

We close our discussion of results by presenting the regressions for the 3-month ahead inflation expectations, presented in Table 26. As can be seen from these tables, there are no noteworthy results. Nor are there any noteworthy results (and therefore we do not display them) when the 3-month ahead inflation expectations variable is replaced by current inflation expectations or the 1-year ahead inflation expectations. For the sake of completeness, we also considered the RBI's Current Situation Index and Future Expectations Index as left hand side variables, and found no noteworthy results. The coefficient on the household-level savings rate was not statistically significant even at the 10% level in most, if not all, of the above regressions.

5 Discussion & Conclusion

Among the results presented in the previous section, the most convincing ones demonstrate strong relationships between the household-level savings rate and a small selection of macro-aggregate variables for certain deciles and states. By "strong", we mean that the coefficient on the household-level savings rate is statistically significant at the 1% level, and the *R-squared* is above 30%. The 30% threshold is more a matter of judgment than an arbitrary choice, since across all the regressions that we ran, that number does serve as a kind of break point for the *R-squared*s, which are mostly well below 30%, in the 0-20% range, and yet we do not wish to aim for a threshold any lower than 30%. We are also interested in categorizing a relationship as "strong" if we find it in both decile and state regressions.

With that definition of "strong" in place, we may summarize our results thus:

(*i*) There is a strong contemporaneous positive relationship between the household-level savings rate around the median of the income distribution and for middle income households, and the WPI as well as its rate of change.

(*ii*) The only other price level for which the household-level savings rate has a strong predictive power is the PLR. Here, the results are similar to those for the WPI and its rate of change – namely, that the contemporaneous relationship is positive and strong for the median of the income distribution and for middle income households.

(*iii*) The only quantity variable measured at a monthly frequency that exhibits a strong contemporaneous relationship with the household-level savings rate is the growth rate of (real) bank credit for personal loans. Here, the *R-squared* is above 30%, and in some cases well above 30%, and the coefficient is negative, for most deciles except the poorest ones and most states except for the low income ones.

(*iv*) At a quarterly frequency, there is a strong contemporaneous negative relationship between the household-level savings rate and overall GDP growth, around the median of the income distribution and for one of the states (middle income, high expenditure). We find that this strong relationship is almost entirely driven by the industry component of GDP.

(*v*) The only other quantity variable measured at a quarterly frequency that exhibits a strong contemporaneous relationship with the household-level savings rate is the growth rate of (real) household credit. Again, we find this strong relationship around the median of the income distribution and for the middle income states. The coefficient on the household-level savings rate in these regressions is negative (as with GDP growth and industry sector GDP growth).

(*vi*) We note the absence of any strong relationship between the household-level savings rate and any of the forward-looking expectations variables.

We are hesitant to interpret these results through a macro-theoretic lens for various reasons that we have already described in Section 1. Nevertheless, result (*vi*) remains very puzzling for us, since even without a consensus view about what a workhorse macro model for the Indian economy might look like, it would appear reasonable to expect a strong relationship in these instances. We can only conjecture that these expectations are not being measured properly.

Our conjecture carries some weight in view of the strong results we otherwise find for the median of the income distribution and the middle income states. Indeed, one might even argue that these results are indicative of the validity of a "representative agent" approach to thinking about the Indian macroeconomy, and yet this representative agent is not the unitary individual of traditional macroeconomic theory but rather, a household, i.e., a social unit. For us, this is a significant conclusion and one that we would like to highlight as one the main contributions of our paper.

Another contribution of our paper is to show that the empirical analysis of household-level economic behavior, and in particular the household-level savings rate, can yield rich insights about the overall macroeconomic condition. This is true in the general case of summary aggregate price and quantity variables such as WPI and its rate of change, and industry sector GDP. It is also true in the particular case of household-sector credit and bank credit for personal loans. As to why we find no evidence for a strong relationship between the household-level savings rate and CPI or its rate of change, or why indeed we find evidence of a strong relationship with the household-level savings rate for both the WPI *and* its rate of change, and in the same direction that too (i.e., positive) – these are questions we leave to future research.

A third contribution of our paper is the finding that overall macroeconomic conditions do not give us any information about what is happening at the extremes of the income distribution. This is significant for policy, and particularly for development policy, where there is a rather vocal emergent strain of thinking, partly occasioned by the Chinese experience of the last 40 years or so, that the best way to lift people out of poverty is not to design policy specifically for the so-called "bottom of the pyramid", but to aim for overall macroeconomic growth.

We end our paper on the optimistic note that our results will spur more empirical research in this methodological vein, and that there is much more to be discovered by attempting to correlate household-level economic behavior and macro-aggregate behavior. We propose to take up this research agenda ourselves in future work, as a first and immediate step forward to further investigate some of the relationships we document in this paper.

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Figures

Figure 1: Time series of cyclical components of monthly savings rate for all deciles.

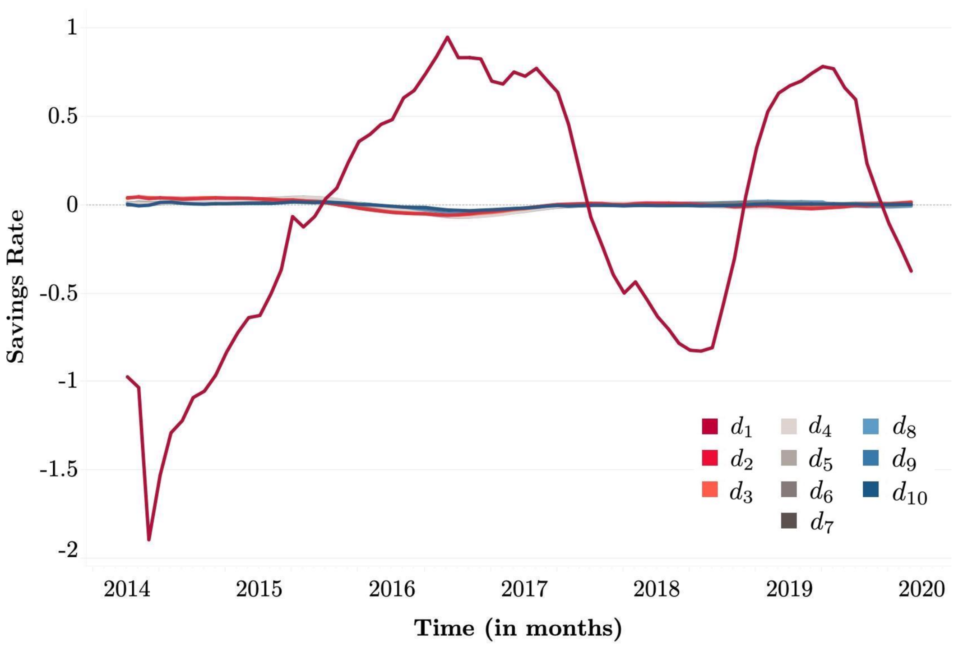


Figure 2: Time series of cyclical components of monthly savings rate for all deciles except d_1.

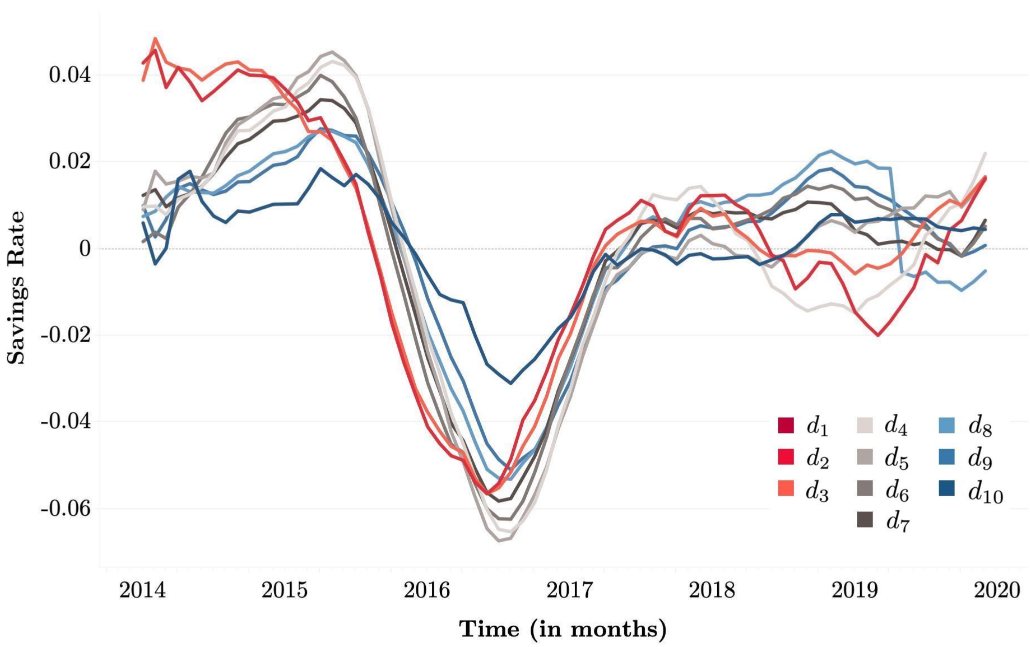


Figure 3: Time series of cyclical components of monthly savings rate for all states.

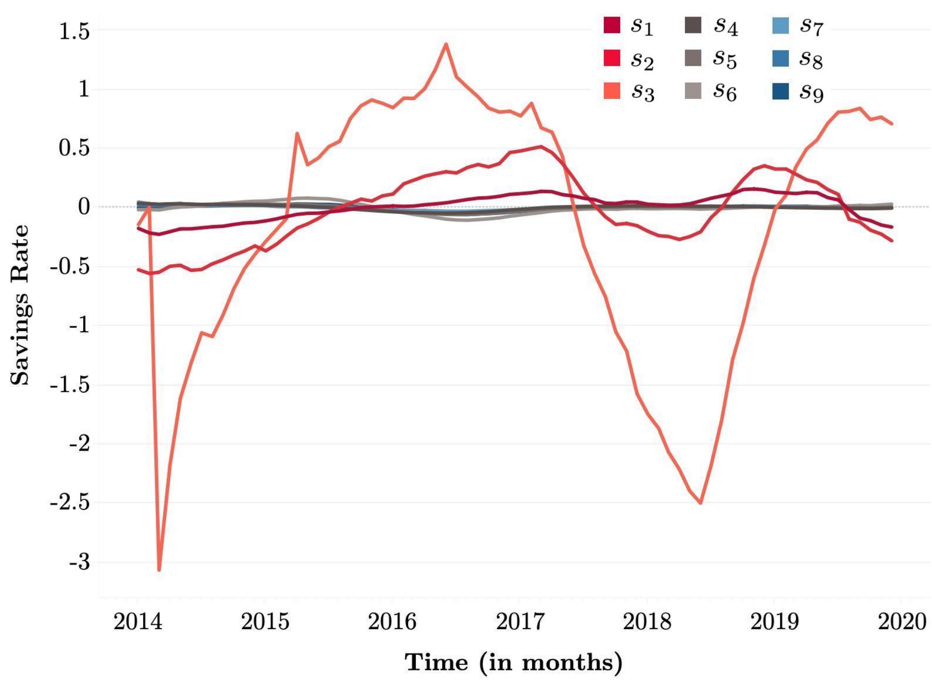
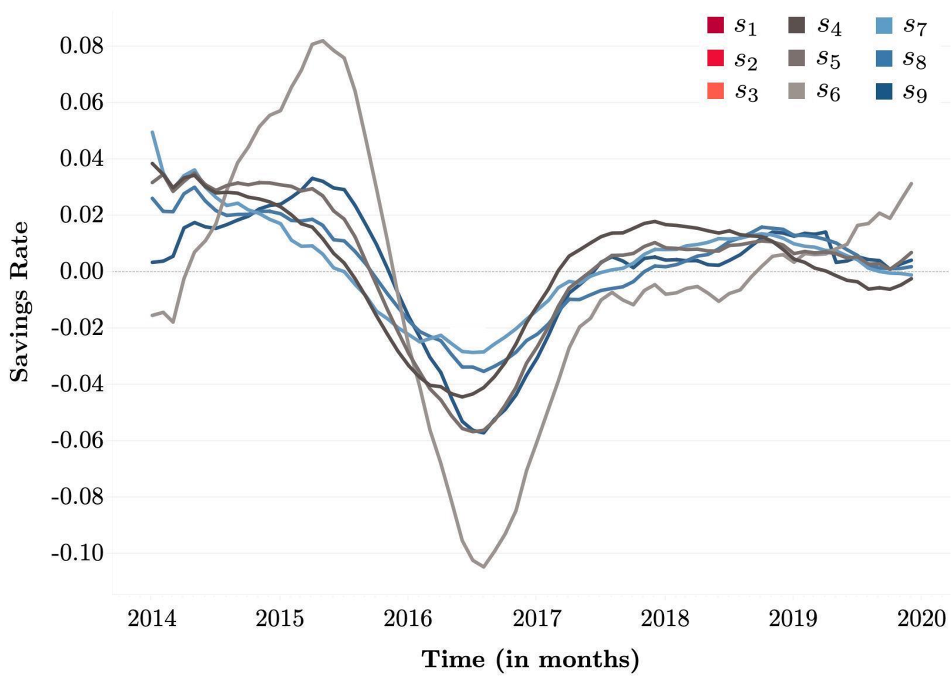


Figure 4: Time series of cyclical components of monthly savings rate for all states except s_1, s_2 & s_3.



Tables

Table 1: Summary statistics, deciles

Decile	Quantile	Monthly income	Monthly expenditure	Monthly savings rate	Average observations
d_1	[0.0,0.1]	2165	7271	-4.1910	26944810
d_2	(0.1,0.2]	5934	6349	-0.0810	27450215
d_3	(0.2,0.3]	7521	7224	0.0326	25955743
d_4	(0.3,0.4]	9025	8060	0.1005	26269641
d_5	(0.4,0.5]	10635	8675	0.1770	25633225
d_6	(0.5,0.6]	12541	9399	0.2438	25974350
d_7	(0.6,0.7]	15209	10274	0.3196	26178495
d_8	(0.7,0.8]	19204	11482	0.3974	26242359
d_9	(0.8,0.9]	26524	13168	0.4962	25806746
d_{10}	(0.9,1.0]	54928	17626	0.6387	25894299

Table 2: Summary statistics, states

States	Income group	Expenditure group	Monthly income	Monthly expenditure	Monthly savings rate	Average observations
s_1	low	low	5621	5245	-0.3889	54136185
s_2	low	middle	5644	8395	-1.7963	25787263
s_3	low	high	4512	13762	-5.0640	9205989
s_4	middle	low	11314	5855	0.4668	24815736
s_5	middle	middle	11654	8642	0.2354	38424014
s_6	middle	high	12365	13240	-0.1046	23351628
s_7	high	low	24931	5976	0.7227	8552880
s_8	high	middle	26222	8848	0.6044	23245160
s_9	high	high	35189	17004	0.4112	54894789

Table 3: Wholesale Price Index (WPI)

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	-0.488**	(0.232)	0.060	72
d_2	27.227***	(6.043)	0.225	72
d_3	42.911***	(6.546)	0.380	72
d_4	29.253***	(6.244)	0.239	72
d_5	35.251***	(5.821)	0.344	72
d_6	37.911***	(6.330)	0.339	72
d_7	39.769***	(7.016)	0.315	72
d_8	18.677***	(6.128)	0.117	72
d_9	42.419***	(8.249)	0.274	72
d_{10}	31.038***	(10.955)	0.103	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	-2.645*	(1.426)	0.047	72
s_2	-1.286**	(0.499)	0.087	72
s_3	-0.160	(0.144)	0.017	72
s_4	48.232***	(9.347)	0.276	72
s_5	45.224***	(7.096)	0.367	72
s_6	21.742***	(3.612)	0.341	72
s_7	57.994***	(11.57)	0.264	72
s_8	60.538***	(9.976)	0.345	72
s_9	32.237***	(7.112)	0.227	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: WPI inflation rate

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	-0.001	(0.002)	0.002	72
d_2	0.229***	(0.056)	0.190	72
d_3	0.351***	(0.063)	0.304	72
d_4	0.174***	(0.062)	0.101	72
d_5	0.244***	(0.059)	0.197	72
d_6	0.329***	(0.059)	0.306	72
d_7	0.335***	(0.066)	0.267	72
d_8	0.190***	(0.055)	0.146	72
d_9	0.354***	(0.078)	0.229	72
d_{10}	0.272***	(0.101)	0.094	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	0.031**	(0.013)	0.075	72
s_2	0.003	(0.005)	0.004	72
s_3	-0.003**	(0.001)	0.080	72
s_4	0.622***	(0.067)	0.549	72
s_5	0.411***	(0.065)	0.364	72
s_6	0.102**	(0.039)	0.09	72
s_7	0.685***	(0.092)	0.441	72
s_8	0.539***	(0.092)	0.327	72
s_9	0.266***	(0.067)	0.185	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Consumer Price Index (CPI)

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	-0.010	(0.162)	0.000	72
d_2	-4.012	(4.623)	0.011	72
d_3	-9.780*	(5.508)	0.043	72
d_4	-5.039	(4.808)	0.015	72
d_5	-9.667**	(4.726)	0.056	72
d_6	-14.904***	(4.961)	0.114	72
d_7	-14.154**	(5.483)	0.087	72
d_8	-11.979***	(4.177)	0.105	72
d_9	-24.429***	(5.870)	0.198	72
d_{10}	-23.087***	(7.329)	0.124	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	-2.298**	(0.950)	0.077	72
s_2	-0.385	(0.350)	0.017	72
s_3	0.267***	(0.093)	0.106	72
s_4	-28.919***	(6.583)	0.216	72
s_5	-19.696***	(5.562)	0.152	72
s_6	-3.222	(2.988)	0.016	72
s_7	-42.149***	(7.617)	0.304	72
s_8	-33.425***	(7.326)	0.229	72
s_9	-16.013***	(5.132)	0.122	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: CPI inflation rate

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.005***	(0.002)	0.100	72
d_2	-0.169***	(0.055)	0.120	72
d_3	-0.282***	(0.062)	0.226	72
d_4	-0.168***	(0.057)	0.109	72
d_5	-0.164***	(0.058)	0.103	72
d_6	-0.258***	(0.059)	0.217	72
d_7	-0.252***	(0.065)	0.175	72
d_8	-0.175***	(0.051)	0.143	72
d_9	-0.241***	(0.077)	0.123	72
d_{10}	-0.123	(0.097)	0.022	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	0.009	(0.012)	0.007	72
s_2	0.009**	(0.004)	0.057	72
s_3	0.004***	(0.001)	0.128	72
s_4	-0.505***	(0.071)	0.418	72
s_5	-0.313***	(0.066)	0.243	72
s_6	-0.087**	(0.036)	0.076	72
s_7	-0.484***	(0.099)	0.254	72
s_8	-0.367***	(0.095)	0.175	72
s_9	-0.213***	(0.064)	0.137	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Weighted Average Lending Rate (WALR)

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	-0.006	(0.009)	0.006	72
d_2	0.381	(0.254)	0.031	72
d_3	0.425	(0.309)	0.026	72
d_4	0.575**	(0.260)	0.065	72
d_5	0.216	(0.269)	0.009	72
d_6	0.158	(0.292)	0.004	72
d_7	0.271	(0.317)	0.010	72
d_8	0.007	(0.245)	0.000	72
d_9	-0.055	(0.364)	0.000	72
d_{10}	0.163	(0.435)	0.002	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	-0.077	(0.054)	0.028	72
s_2	-0.001	(0.020)	0.000	72
s_3	0.009*	(0.005)	0.040	72
s_4	0.289	(0.412)	0.007	72
s_5	0.144	(0.335)	0.003	72
s_6	0.147	(0.167)	0.011	72
s_7	-0.723	(0.500)	0.029	72
s_8	-0.580	(0.459)	0.022	72
s_9	0.152	(0.304)	0.004	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: 10-year GoI bond yield

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.069	(0.041)	0.038	72
d_2	0.473	(1.213)	0.002	72
d_3	1.725	(1.457)	0.020	72
d_4	-0.497	(1.265)	0.002	72
d_5	1.973	(1.249)	0.034	72
d_6	2.087	(1.355)	0.033	72
d_7	1.551	(1.488)	0.015	72
d_8	0.910	(1.149)	0.009	72
d_9	3.758**	(1.653)	0.069	72
d_{10}	3.995**	(1.990)	0.054	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	0.189	(0.257)	0.008	72
s_2	0.091	(0.092)	0.014	72
s_3	0.012	(0.026)	0.003	72
s_4	1.600	(1.934)	0.010	72
s_5	2.731*	(1.544)	0.043	72
s_6	1.059	(0.777)	0.026	72
s_7	7.057***	(2.232)	0.125	72
s_8	7.791***	(1.972)	0.182	72
s_9	2.030	(1.411)	0.029	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Prime Lending Rate (PLR)

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	-0.015	(0.012)	0.022	72
d_2	1.058***	(0.325)	0.132	72
d_3	1.555***	(0.379)	0.194	72
d_4	2.041***	(0.269)	0.451	72
d_5	1.774***	(0.297)	0.338	72
d_6	1.392***	(0.358)	0.177	72
d_7	1.653***	(0.382)	0.211	72
d_8	0.654**	(0.322)	0.056	72
d_9	1.675***	(0.449)	0.166	72
d_{10}	1.721***	(0.550)	0.123	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	-0.241***	(0.068)	0.151	72
s_2	-0.057**	(0.026)	0.065	72
s_3	0.014*	(0.007)	0.053	72
s_4	0.812	(0.549)	0.030	72
s_5	1.537***	(0.414)	0.165	72
s_6	1.224***	(0.172)	0.420	72
s_7	0.148	(0.684)	0.001	72
s_8	1.313**	(0.605)	0.063	72
s_9	1.512***	(0.369)	0.194	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Unemployment rate, overall

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.309**	(0.126)	0.078	72
d_2	-3.888	(3.754)	0.015	72
d_3	-6.783	(4.511)	0.031	72
d_4	-10.681***	(3.732)	0.105	72
d_5	-10.048**	(3.774)	0.092	72
d_6	-12.413***	(4.026)	0.120	72
d_7	-14.257***	(4.349)	0.133	72
d_8	-9.290***	(3.419)	0.095	72
d_9	-20.600***	(4.735)	0.213	72
d_{10}	-12.048*	(6.210)	0.051	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	0.023	(0.805)	0.000	72
s_2	0.692**	(0.276)	0.083	72
s_3	0.257***	(0.074)	0.147	72
s_4	-19.163***	(5.603)	0.143	72
s_5	-16.275***	(4.515)	0.157	72
s_6	-5.968**	(2.347)	0.085	72
s_7	-20.611***	(7.014)	0.110	72
s_8	-21.162***	(6.304)	0.139	72
s_9	-13.217***	(4.169)	0.126	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Unemployment rate, urban

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.328*	(0.173)	0.049	72
d_2	-4.845	(5.068)	0.013	72
d_3	-8.696	(6.092)	0.028	72
d_4	-14.650***	(5.021)	0.108	72
d_5	-14.628***	(5.046)	0.107	72
d_6	-16.915***	(5.420)	0.122	72
d_7	-19.635***	(5.844)	0.139	72
d_8	-14.175***	(4.541)	0.122	72
d_9	-30.052***	(6.235)	0.249	72
d_{10}	-18.892**	(8.293)	0.069	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	-0.222	(1.085)	0.001	72
s_2	0.885**	(0.373)	0.074	72
s_3	0.279***	(0.102)	0.096	72
s_4	-22.391***	(7.710)	0.108	72
s_5	-22.020***	(6.084)	0.158	72
s_6	-9.517***	(3.105)	0.118	72
s_7	-26.138***	(9.524)	0.097	72
s_8	-30.813***	(8.385)	0.162	72
s_9	-20.339***	(5.498)	0.164	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Unemployment rate, rural

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.298***	(0.111)	0.093	72
d_2	-3.253	(3.331)	0.013	72
d_3	-5.736	(4.005)	0.028	72
d_4	-8.659**	(3.340)	0.088	72
d_5	-7.804**	(3.385)	0.071	72
d_6	-10.240***	(3.601)	0.104	72
d_7	-11.587***	(3.902)	0.112	72
d_8	-7.026**	(3.074)	0.069	72
d_9	-16.092***	(4.322)	0.165	72
d_{10}	-8.723	(5.554)	0.034	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	0.119	(0.713)	0.000	72
s_2	0.601**	(0.245)	0.079	72
s_3	0.245***	(0.064)	0.171	72
s_4	-17.550***	(4.939)	0.153	72
s_5	-13.480***	(4.050)	0.137	72
s_6	-4.228**	(2.115)	0.054	72
s_7	-17.981***	(6.230)	0.106	72
s_8	-16.592***	(5.685)	0.108	72
s_9	-9.841**	(3.773)	0.089	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: IIP growth, overall

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.008***	(0.002)	0.147	72
d_2	-0.143*	(0.074)	0.051	72
d_3	-0.199**	(0.089)	0.067	72
d_4	-0.268***	(0.072)	0.164	72
d_5	-0.165**	(0.077)	0.062	72
d_6	-0.116	(0.085)	0.026	72
d_7	-0.146	(0.092)	0.035	72
d_8	-0.113	(0.071)	0.035	72
d_9	-0.127	(0.106)	0.020	72
d_{10}	-0.139	(0.127)	0.017	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	0.076***	(0.013)	0.313	72
s_2	0.022***	(0.005)	0.198	72
s_3	0.000	(0.002)	0.000	72
s_4	-0.135	(0.120)	0.018	72
s_5	-0.160	(0.097)	0.038	72
s_6	-0.127***	(0.047)	0.095	72
s_7	-0.073	(0.149)	0.003	72
s_8	-0.137	(0.135)	0.014	72
s_9	-0.179**	(0.087)	0.057	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: IIP growth, consumer durables

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.022***	(0.005)	0.197	72
d_2	-0.382**	(0.160)	0.075	72
d_3	-0.418**	(0.195)	0.062	72
d_4	-0.467***	(0.164)	0.104	72
d_5	-0.190	(0.173)	0.017	72
d_6	-0.077	(0.188)	0.002	72
d_7	-0.176	(0.204)	0.010	72
d_8	-0.053	(0.158)	0.002	72
d_9	0.021	(0.234)	0.000	72
d_{10}	0.021	(0.280)	0.000	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	0.139***	(0.031)	0.221	72
s_2	0.049***	(0.011)	0.213	72
s_3	0.004	(0.003)	0.022	72
s_4	-0.311	(0.263)	0.020	72
s_5	-0.201	(0.215)	0.012	72
s_6	-0.149	(0.106)	0.027	72
s_7	-0.057	(0.327)	0.000	72
s_8	-0.011	(0.298)	0.000	72
s_9	-0.100	(0.196)	0.004	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: IIP growth, primary goods

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.008***	(0.003)	0.092	72
d_2	-0.329***	(0.077)	0.205	72
d_3	-0.401***	(0.093)	0.208	72
d_4	-0.386***	(0.078)	0.261	72
d_5	-0.341***	(0.081)	0.202	72
d_6	-0.251***	(0.094)	0.093	72
d_7	-0.352***	(0.098)	0.155	72
d_8	-0.194**	(0.079)	0.079	72
d_9	-0.368***	(0.114)	0.130	72
d_{10}	-0.322**	(0.141)	0.069	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	0.061***	(0.017)	0.156	72
s_2	0.016**	(0.006)	0.086	72
s_3	0.001	(0.002)	0.005	72
s_4	-0.347**	(0.132)	0.090	72
s_5	-0.363***	(0.104)	0.148	72
s_6	-0.225***	(0.049)	0.228	72
s_7	-0.286*	(0.167)	0.040	72
s_8	-0.382**	(0.149)	0.086	72
s_9	-0.342***	(0.094)	0.161	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Real bank credit growth, overall

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.269	(0.315)	0.010	72
d_2	-20.324**	(8.765)	0.071	72
d_3	-23.047**	(10.669)	0.062	72
d_4	-23.846**	(9.044)	0.090	72
d_5	-17.110*	(9.300)	0.046	72
d_6	-28.621***	(9.731)	0.110	72
d_7	-32.292***	(10.545)	0.118	72
d_8	-19.006**	(8.338)	0.069	72
d_9	-27.333**	(12.407)	0.065	72
d_{10}	-13.112	(15.245)	0.010	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	-3.001	(1.902)	0.034	72
s_2	-0.235	(0.691)	0.002	72
s_3	0.379**	(0.187)	0.056	72
s_4	-63.720***	(12.399)	0.274	72
s_5	-32.893***	(11.147)	0.111	72
s_6	-6.812	(5.840)	0.019	72
s_7	-41.826**	(17.158)	0.078	72
s_8	-24.693	(16.061)	0.033	72
s_9	-20.133*	(10.445)	0.050	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Real bank credit growth, food

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	2.319	(2.407)	0.013	72
d_2	-53.043	(69.280)	0.008	72
d_3	-60.289	(83.978)	0.007	72
d_4	-11.309	(72.521)	0.000	72
d_5	-2.101	(72.834)	0.000	72
d_6	-76.794	(78.364)	0.014	72
d_7	-99.826	(85.064)	0.019	72
d_8	-107.143	(64.852)	0.038	72
d_9	-108.103	(97.283)	0.017	72
d_{10}	-18.484	(117.208)	0.000	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	-32.762**	(14.274)	0.070	72
s_2	-1.340	(5.288)	0.001	72
s_3	4.947***	(1.345)	0.162	72
s_4	-345.373***	(103.369)	0.138	72
s_5	-139.782	(88.859)	0.034	72
s_6	23.129	(45.018)	0.004	72
s_7	-323.694**	(131.114)	0.080	72
s_8	-169.739	(123.249)	0.026	72
s_9	-74.561	(81.501)	0.012	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Real bank credit growth, non-food

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.251	(0.299)	0.010	72
d_2	-20.521**	(8.281)	0.081	72
d_3	-23.056**	(10.095)	0.069	72
d_4	-24.156***	(8.529)	0.103	72
d_5	-17.933**	(8.784)	0.056	72
d_6	-28.540***	(9.182)	0.121	72
d_7	-32.050***	(9.952)	0.129	72
d_8	-18.547**	(7.902)	0.073	72
d_9	-27.530**	(11.731)	0.073	72
d_{10}	-14.266	(14.453)	0.014	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	-2.783	(1.807)	0.033	72
s_2	-0.237	(0.656)	0.002	72
s_3	0.353*	(0.177)	0.053	72
s_4	-61.063***	(11.734)	0.279	72
s_5	-32.384***	(10.536)	0.119	72
s_6	-7.429	(5.529)	0.025	72
s_7	-39.877**	(16.288)	0.079	72
s_8	-24.675	(15.224)	0.036	72
s_9	-20.251**	(9.886)	0.057	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Real bank credit growth, personal loans

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.335	(0.313)	0.016	72
d_2	-37.097***	(7.893)	0.240	72
d_3	-56.594***	(8.634)	0.380	72
d_4	-44.456***	(7.801)	0.317	72
d_5	-45.592***	(7.755)	0.331	72
d_6	-53.817***	(8.002)	0.392	72
d_7	-55.767***	(8.973)	0.356	72
d_8	-31.070***	(7.759)	0.186	72
d_9	-59.856***	(10.578)	0.314	72
d_{10}	-48.177***	(14.126)	0.142	72

State	Coefficient	Std. Error	R^2	Obs.
s_1	-1.294	(1.920)	0.006	72
s_2	0.494	(0.686)	0.007	72
s_3	0.312	(0.187)	0.038	72
s_4	-89.057***	(9.823)	0.540	72
s_5	-66.372***	(8.689)	0.455	72
s_6	-23.173***	(5.175)	0.223	72
s_7	-89.603***	(14.204)	0.362	72
s_8	-75.870***	(13.489)	0.311	72
s_9	-47.857***	(9.006)	0.287	72

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: GDP growth, overall

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.128	(0.212)	0.016	24
d_2	-12.777**	(5.399)	0.203	24
d_3	-16.875**	(6.053)	0.261	24
d_4	-19.786***	(4.273)	0.494	24
d_5	-17.469***	(4.774)	0.378	24
d_6	-17.612***	(5.408)	0.325	24
d_7	-19.284***	(5.786)	0.336	24
d_8	-14.763**	(6.268)	0.201	24
d_9	-20.022**	(7.073)	0.267	24
d_{10}	-25.184**	(10.783)	0.199	24

State	Coefficient	Std. Error	R^2	Obs.
s_1	1.936	(1.231)	0.101	24
s_2	0.416	(0.470)	0.034	24
s_3	-0.143	(0.140)	0.045	24
s_4	-15.666*	(8.380)	0.137	24
s_5	-19.009***	(6.351)	0.289	24
s_6	-11.790***	(2.789)	0.448	24
s_7	-11.669	(11.799)	0.043	24
s_8	-19.551*	(10.193)	0.143	24
s_9	-19.900***	(6.229)	0.317	24

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: GDP growth, agriculture

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	-0.552	(0.530)	0.047	24
d_2	15.372	(15.003)	0.046	24
d_3	9.642	(17.761)	0.013	24
d_4	-0.847	(15.245)	0.000	24
d_5	-6.246	(15.318)	0.008	24
d_6	-0.548	(16.717)	0.000	24
d_7	3.081	(18.011)	0.001	24
d_8	1.090	(17.808)	0.000	24
d_9	-7.902	(20.910)	0.006	24
d_{10}	0.222	(30.587)	0.000	24

State	Coefficient	Std. Error	R^2	Obs.
s_1	1.742	(3.275)	0.013	24
s_2	0.064	(1.213)	0.000	24
s_3	-0.602*	(0.341)	0.124	24
s_4	32.910	(21.805)	0.094	24
s_5	6.653	(19.077)	0.005	24
s_6	-8.709	(9.351)	0.038	24
s_7	28.099	(30.028)	0.038	24
s_8	-2.234	(27.958)	0.000	24
s_9	-5.713	(19.099)	0.004	24

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: GDP growth, industry

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.341	(0.538)	0.018	24
d_2	-40.099***	(12.787)	0.309	24
d_3	-50.595***	(14.295)	0.363	24
d_4	-48.875***	(11.164)	0.466	24
d_5	-42.106***	(12.514)	0.340	24
d_6	-40.903***	(14.294)	0.271	24
d_7	-43.659**	(15.468)	0.266	24
d_8	-22.972	(17.154)	0.075	24
d_9	-37.547*	(19.428)	0.145	24
d_{10}	-69.506**	(26.815)	0.234	24

State	Coefficient	Std. Error	R^2	Obs.
s_1	5.943*	(3.048)	0.147	24
s_2	0.837	(1.202)	0.022	24
s_3	-0.455	(0.352)	0.071	24
s_4	-39.918*	(21.306)	0.138	24
s_5	-43.910**	(16.719)	0.239	24
s_6	-25.880***	(7.794)	0.334	24
s_7	-39.412	(29.496)	0.075	24
s_8	-41.861	(26.548)	0.102	24
s_9	-41.035**	(17.057)	0.208	24

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: GDP growth, services

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	0.330	(0.220)	0.093	24
d_2	-5.596	(6.431)	0.033	24
d_3	-7.094	(7.464)	0.039	24
d_4	-5.131	(6.401)	0.028	24
d_5	-4.515	(6.478)	0.022	24
d_6	-5.394	(7.027)	0.026	24
d_7	-9.013	(7.432)	0.063	24
d_8	-13.810*	(6.991)	0.151	24
d_9	-10.279	(8.663)	0.060	24
d_{10}	-6.299	(12.959)	0.011	24

State	Coefficient	Std. Error	R^2	Obs.
s_1	-0.412	(1.401)	0.004	24
s_2	0.465	(0.507)	0.037	24
s_3	0.321**	(0.139)	0.194	24
s_4	-20.174**	(8.758)	0.194	24
s_5	-11.213	(7.790)	0.086	24
s_6	-1.099	(4.054)	0.003	24
s_7	-15.667	(12.608)	0.066	24
s_8	-12.490	(11.609)	0.050	24
s_9	-10.445	(7.842)	0.075	24

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Credit as a share of GDP

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	-0.023	(0.027)	0.031	24
d_2	-0.212	(0.789)	0.003	24
d_3	-0.562	(0.912)	0.017	24
d_4	-0.685	(0.771)	0.035	24
d_5	-1.018	(0.761)	0.075	24
d_6	-1.478*	(0.800)	0.134	24
d_7	-1.259	(0.888)	0.084	24
d_8	-0.967	(0.893)	0.051	24
d_9	-1.847*	(1.005)	0.133	24
d_{10}	-2.464	(1.484)	0.111	24

State	Coefficient	Std. Error	R^2	Obs.
s_1	-0.305*	(0.157)	0.147	24
s_2	-0.028	(0.062)	0.009	24
s_3	0.000	(0.019)	0.000	24
s_4	-1.619	(1.127)	0.086	24
s_5	-1.419	(0.937)	0.094	24
s_6	-0.576	(0.475)	0.063	24
s_7	-2.073	(1.512)	0.079	24
s_8	-1.907	(1.38)	0.000	24
s_9	-1.330	(0.943)	0.083	24

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25: Growth rate of household credit

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	1.016	(0.823)	0.065	24
d_2	-63.995***	(19.867)	0.320	24
d_3	-91.921***	(20.082)	0.488	24
d_4	-53.694**	(21.012)	0.229	24
d_5	-61.435***	(20.267)	0.295	24
d_6	-81.054***	(19.741)	0.434	24
d_7	-77.737***	(22.921)	0.343	24
d_8	-67.010**	(24.024)	0.261	24
d_9	-80.099***	(28.148)	0.269	24
d_{10}	-94.262**	(43.595)	0.175	24

State	Coefficient	Std. Error	R^2	Obs.
s_1	1.500	(5.163)	0.004	24
s_2	2.098	(1.851)	0.055	24
s_3	0.726	(0.551)	0.073	24
s_4	-133.324***	(22.007)	0.625	24
s_5	-101.727***	(20.760)	0.522	24
s_6	-30.899**	(13.434)	0.194	24
s_7	-177.155***	(29.711)	0.618	24
s_8	-135.587***	(33.018)	0.434	24
s_9	-76.273***	(25.253)	0.293	24

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: Inflation expectations, 3-month ahead

Decile	Coefficient	Std. Error	R^2	Obs.
d_1	-0.095	(0.195)	0.011	24
d_2	1.448	(5.545)	0.003	24
d_3	3.532	(6.422)	0.014	24
d_4	-2.756	(5.482)	0.011	24
d_5	-1.251	(5.554)	0.002	24
d_6	-0.362	(6.045)	0.000	24
d_7	-1.773	(6.507)	0.003	24
d_8	-0.805	(6.438)	0.001	24
d_9	-1.015	(7.583)	0.001	24
d_{10}	-1.537	(11.057)	0.001	24

State	Coefficient	Std. Error	R^2	Obs.
s_1	-1.214	(1.163)	0.047	24
s_2	-0.322	(0.433)	0.025	24
s_3	-0.009	(0.132)	0.000	24
s_4	-0.305	(8.283)	0.000	24
s_5	0.223	(6.918)	0.000	24
s_6	-0.625	(3.445)	0.001	24
s_7	9.270	(10.895)	0.032	24
s_8	5.206	(10.051)	0.012	24
s_9	-1.413	(6.915)	0.002	24

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$