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MACROECONOMIC EXPECTATIONS AND CREDIT CARD SPENDING

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ABSTRACT

How do macroeconomic expectations affect consumer decisions? We examine this question using a natural field experiment with 2,872 credit card customers from a large commercial bank. We conduct a survey to measure consumer expectations about future inflation and the nominal exchange rate and combine this with an information-provision experiment that generates exogenous variation in these expectations. We merge the survey and experimental data with detailed administrative data on the subjects' credit card transactions and balances. The experiment is designed to test three standard predictions from models of intertemporal consumption choice: inflation expectations should affect spending on durables; exchange rate expectations should affect spending on tradables; and, holding constant the nominal interest rate, inflation expectations should affect borrowing. We find that the information provided to participants strongly affects subjective expectations. However, we do not find any significant effects on actual consumer behavior (as measured in administrative data) or self-reported consumption plans (as measured in survey data). Our preferred interpretation is that consumers are not sophisticated enough to factor inflation and exchange rate expectations into their consumption decisions. The absence of a link between consumer expectations and behavior has potentially important implications for macroeconomic policies such as forward guidance.

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1 Introduction

Macroeconomic models typically assume that the consumption choices of households respond to changes in their macroeconomic expectations. This notion is so deeply ingrained in economic thought that it is often taken for granted. However, surprisingly little causal evidence exists on the effect of macroeconomic expectations on consumer behavior.

Recent insights from behavioral economics provide several reasons why the link between macroeconomic expectations and household consumption might be more tenuous than is generally assumed. The typical household may, for example, not be sophisticated enough to understand how to optimally revise consumption choices in response to a change in macroeconomic expectations. Macroeconomic indicators might also not be sufficiently salient for consumers, for instance, because they face more pressing concerns when they make spending decisions. The resulting failure of consumers to factor macroeconomic expectations into their consumption behavior could have far-reaching consequences for macroeconomic policies, given that many of these policies are explicitly based on the premise that changes in expectations will affect real economic activity (Bernanke, 2007). The Federal Reserve, for example, explains on its website that "when central banks provide forward guidance, individuals and businesses will use this information in making decisions about spending and investments. Thus, forward guidance about future policy can influence financial and economic conditions today."[1]

In this paper, we provide novel evidence on the causal effect of macroeconomic expectations on consumption decisions. We focus on two macroeconomic factors that receive arguably the most attention in macroeconomic models: the inflation rate and the foreign exchange rate. We use an information-provision experiment with credit card customers to examine how shocks to inflation and exchange rate expectations affect households' consumption decisions.

We collaborated with the consumer finance division of a large Malaysian bank and integrated a randomized experiment into the bank's customer communications. The experiment was administered as part of a phone survey with the partner bank's credit card customers and proceeded in the following steps. First, we elicited the respondents' exchange rate and inflation expectations. Second, we provided randomly chosen subsets of the sample population with expert forecasts of inflation, the exchange rate, or both. Third, we elicited participants' posterior beliefs and self-reported spending plans. Finally, we merged survey responses with data on credit card spending provided by the partner bank. This approach allows us to examine the impact of macroeconomic expectations on *actual* consumption behavior.

The setting and customer population we use in our experiment are well-suited to study the link between macroeconomic expectations and economic decisions for several reasons. Macroeconomic trends in Malaysia are arguably representative of many small, open economies and,

1. See `www.federalreserve.gov/faqs`.

as such, provide an interesting contrast between the evolution of inflation and exchange rates. On the one hand, the inflation rate has been stable at low levels over the past decades: since 2005, the inflation rate has hovered between 1% and 3% per year. The nominal exchange rate, on the other hand, has been highly volatile, with two-digit depreciation swings over the same period: since 2005, the exchange rate has fluctuated between 3.08 and 4.45 MYR per USD. This volatility means that, at least according to models of inattention, it may be more important for consumers to keep up to date with their exchange rate expectations and factor them into their spending decisions. Another advantage of our setting lies in the characteristics of the sample population. Individuals in our sample are among the most educated and financially experienced and thus should be the most likely group to respond to macroeconomic expectations. As they are relatively affluent, their consumption bundle contains significant shares of durable goods and tradable goods corresponding to the consumption categories expected to change in response to exchange rate and inflation expectations.

We present two main results. The first result is that the information provided in the experiment has a significant effect on the formation of expectations. Some individuals whose inflation and exchange rate expectations disagree with the expert forecasts update their expectations in response to our information treatments. Specifically, a 1 percentage point (pp) increase in the information shock about future inflation increases inflation expectations by 0.237 pp (p-value<0.001). In turn, a 1 pp increase in the information shock about the future nominal exchange rate increases exchange rate expectations by 0.065 pp (p-value=0.036). Indeed, the finding that individuals are less prone to incorporate information about the exchange rate than about inflation is consistent with the view that they have greater incentives to be informed about the exchange rate and thus have stronger prior beliefs.

The second result is that changes in macroeconomic expectations induced by our experiment do not translate into changes in actual consumption behavior. Specifically, we test three basic predictions from a simple model of optimal inter-temporal consumption: (i) higher inflation expectations should increase durable spending; (ii) higher expected exchange rate depreciation should increase spending on tradable durable goods; and (iii) conditional on the nominal interest rate, higher inflation expectations should increase credit card borrowing. We do not find empirical support for any of these predictions. Instead, the effects of information shocks induced by the experiment on spending are close to zero and statistically insignificant. While we cannot rule out small effects on any specific outcome, we have sufficient statistical power to rule out moderate or large effects. Moreover, shocks to expectations do not affect self-reported spending plans, which we elicit immediately after the information-provision part of the survey experiment.

Our preferred interpretation of these results is that consumers are not sophisticated enough to re-optimize their spending plans based on revised macroeconomic expectations. Indeed, substantial evidence suggests that consumers fail to optimize in even simpler economic decisions, either due to behavioral biases or lack of knowledge (see Campbell et al., 2011; Beshears et al., 2018). In the context of credit card spending, Ponce, Seira, and Zamarripa (2017) and Gathergood et al. (2019) show that consumers do not borrow using the lowest interest rate card and do not prioritize repayment of the card with the highest interest rate, and Chetty et al. (2020) show that credit card spending fails to react to anticipated income shocks. To the extent that shielding against inflation and exchange rate risks entails complex decision-making, it is perhaps not surprising that individuals fail to factor their macroeconomic expectations in their spending decisions.

We discuss, and provide evidence against, some alternative interpretations. One such interpretation is that individuals update their spending plans but cannot follow through on those plans due to self-control problems. We provide a direct test of this hypothesis. If self-control were responsible, we would expect the information treatments to still affect spending plans. Instead, we show that providing information has no impact on self-reported spending plans, which are elicited immediately after the information-provision part of the survey experiment.

Another possibility is that the effects of the information shocks on expectations do not last long enough to affect decision making. We provide some evidence against this interpretation. First, we find that our results are robust if, instead of looking at spending behavior in the subsequent three months, we look at shorter time horizons.[2] Second, we show that information shocks do not affect spending plans, which are self-reported immediately after the information-provision experiment when one would expect the information to still be fresh and salient. Third, evidence from several other studies suggests that providing information through an experiment tends to have long-lasting effects on expectations. For instance, the effects of information shocks on inflation expectations last for at least a few months (Cavallo, Cruces, and Perez-Truglia, 2017).[3] Fourth, information experiments similar to the one in this study have been shown to affect high-stakes decisions measured in administrative data: e.g., employees work harder after increasing their expectations of future salary increases (Cullen and Perez-Truglia, 2018), home sellers are less likely to sell their homes when their home price expectations increase (Bottan and Perez-Truglia, 2020b), and employees revise savings decisions in response to feedback about the choices of their peers (Beshears et al., 2015).

Our study of macroeconomic expectations and consumer behavior relates to several strands of literature. First and most directly, our paper relates to the literature on subjective expectations in macroeconomics and finance. While traditional economic theory assumes that individuals form statistically optimal expectations based on all available information, survey

2. These results are available upon request.

3. Additionally, shocks to other types of economic beliefs have been found to last from months (Bottan and Perez-Truglia, 2020a) to even a year (Fehr, Mollerstrom, and Perez-Truglia, 2019).

data indicate large information frictions in the acquisition and processing of information about macroeconomic factors, such as inflation (Armantier et al., 2016; Malmendier and Nagel, 2016; Cavallo, Cruces, and Perez-Truglia, 2016, 2017), home prices (Armona, Fuster, and Zafar, 2019; Fuster et al., 2020; Bottan and Perez-Truglia, 2020b), and GDP growth (Roth and Wohlfart, 2020). Growing evidence shows how these expectations are formed. Less is known, however, about whether individuals actually factor macroeconomic expectations into their consumption decisions (Bachmann, Berg, and Sims, 2015; Armantier et al., 2015; Coibion et al., 2019; D'Acunto et al., 2019; Bottan and Perez-Truglia, 2020b). For example, Bachmann, Berg, and Sims (2015) shows that inflation expectations and survey measures of readiness to spend are not positively correlated. And Coibion et al. (2019) present evidence from a survey experiments that, if anything, inflation expectations have a negative impact on durable spending.

We contribute to this literature in two ways. We are the first to measure the impact of expectations on actual, rather than self-reported, consumer behavior using detailed administrative data on credit card spending. This exercise overcomes several limitations specific to survey data, such as measurement error or experimenter demand effects. Indeed, we provide direct evidence that the concerns about survey data should be taken seriously, as we document a weak correlation between self-reported spending plans and the corresponding actual spending decisions. Second, we add to this line of research by studying exchange rate expectations. In recent years, inflation rates have been low and stable in most of the world and are thus arguably of little importance for most households. In contrast, large fluctuations in the nominal exchange continue to be commonplace around the world and have meaningful economic consequences for many households (Gouvea, 2020; Cravino and Levchenko, 2017). Despite the economic importance of exchange rates, there is little evidence on how households form exchange rate expectations and how such expectations may affect consumption decisions.

This study also relates to a literature on household finance and the impacts of consumer expectations on personal financial decisions. Giglio et al. (2020a) and Giglio et al. (2020b) use survey data to test how macroeconomic beliefs affect the decisions of retail investors. They show that beliefs are reflected in asset allocations and change in response to discrete macroeconomic events, such as a stock market crash. Aaronson, Agarwal, and French (2012), Agarwal, Liu, and Souleles (2007), and Agarwal and Qian (2014) use credit card data to test consumer responses to minimum wage increases, tax changes, and unanticipated income shocks and find effects inconsistent with models of fully rational expectations.[4] We make both an empirical and methodological contribution to this literature. On the empirical side, we merge information on consumer beliefs, as elicited via survey, with rich administrative data that covers the universe of credit card transactions. On the methodological side, we generate exogenous variation in beliefs

4. Related evidence shows that behavioral factors, such as social norms and conspicuous consumption, affect spending and debt repayment decisions (e.g. Bursztyn et al., 2018; Bursztyn et al., 2019)

through an experiment and measure the effects on spending using the administrative data.

The remainder of the paper is structured as follows. Section 2 provides a theoretical framework to motivate our experimental design and develop our hypotheses. In Section 3, we summarize the setting, research design, and implementation of the experiment. In Section 5, we describe additional data sources and provide descriptive statistics. Section 6 reports the results, and Section 7 concludes.

2 Theoretical Framework and Hypotheses

We use a standard model of intertemporal consumer choice to motivate our experimental design. Letting subscript t denote the time period, we assume that the consumer faces an exogenous stream of nominal income Y_t and can have positive or negative holdings of an asset A_t that pays an exogenous nominal interest rate R_t. There are four types of consumption goods, which we can classify according to their durability and tradability: durable tradables (denoted X_t^T), durable nontradables (X_t^N), nondurable tradables (C_t^T), and nondurable nontradables (C_t^N). We assume that durable goods depreciate at a rate of δ, tradable goods (both durable and nondurable) have an exogenous price P_t^T, and nontradable goods (both durable and nondurable) have price P_t^N. The consumer gets utility $U(C_t^N, X_t^N, C_t^T, X_t^T)$ from a given combination of goods, which is concave in each of its arguments and has a discount factor β.

The consumer's optimization problem can thus be summarized as follows:

$$\max_{\{C_t^N, X_t^N, C_t^T, X_t^T, A_t\}_t} \quad \sum_{t=1}^{T} \beta^t U(C_t^N, X_t^N, C_t^T, X_t^T) \tag{1}$$

subject to

$$\begin{aligned} P_t^N(C_t^N + X_t^N - X_{t-1}^N + \delta X_{t-1}^N) + P_t^T(C_t^T + X_t^T - X_{t-1}^T + \delta X_{t-1}^T) + A_{t+1} \\ \leq P_t Y_t + R_t A_t \end{aligned}$$

We denote the exogenously given rate of inflation from period t to $t+1$ as π_{t+1}, which is defined as follows:

$$\pi_{t+1} = \frac{P_{t+1}^N(\bar{C}_t^N + \Delta\bar{X}_t^N) + P_{t+1}^T(\bar{C}_t^T + \Delta\bar{X}_t^T)}{P_t^N(\bar{C}_t^N + \Delta\bar{X}_t^N) + P_t^T(\bar{C}_t^T + \Delta\bar{X}_t^T)} = w_t\pi_{t+1}^N + (1-w_t)\pi_{t+1}^T$$

$$\text{where} \quad w_t \equiv \frac{(\bar{C}_t^N + \Delta\bar{X}_t^N)}{(\bar{C}_t^N + \Delta\bar{X}_t^N) + P_t^T/P_t^N(\bar{C}_t^T + \Delta\bar{X}_t^T)}$$

$\bar{Z}$ is the average value of variable Z in the economy.

We make the following simplifying assumptions. First, an increase in inflation cannot be accompanied by a decrease in inflation in any specific category of goods:

Assumption 1 $\frac{d\pi^N_{t+1}}{d\pi_{t+1}} \geq 0, \quad \frac{d\pi^T_{t+1}}{d\pi_{t+1}} \geq 0$

Second, defining $d_{t+1} = \frac{E_{t+1}-E_t}{E_t}$ as the exchange rate depreciation between period t and t+1 (E_t denotes the spot exchange rate of the Malaysian Ringgit to the US Dollar at time t), we assume non-zero pass-through of exchange rate depreciation to tradables:

Assumption 2 $\frac{d\pi^T_{t+1}}{dd_{t+1}} \geq 0$

Third, we assume Cobb-Douglas instantaneous utility:

Assumption 3 *Let consumption utility be Cobb-Douglas with parameters α and θ corresponding to the weights of non-durables and non-tradables, respectively:*

$$U(C^N_t, X^N_t, C^T_t, X^T_t) =$$
$$\alpha\theta \log C^N_t + \alpha(1-\theta)\log C^T_t + (1-\alpha)\theta \log X^N_t + (1-\alpha)(1-\theta)\log X^T_t$$

This model yields the following three predictions (for proofs of each proposition, see Appendix A), which motivate the design of our field experiment:

Proposition 1 *Spending on durables (tradable and non-tradable) $P^N_t \Delta X^N_t + P^T_t \Delta X^T_t$ increases with expected inflation π_{t+1}.*

The intuition for this standard result (see, for example, Bachmann, Berg, and Sims, 2015) is that one can buy durables to shield against the inflation tax.

The second proposition describes the effect of nominal exchange rate depreciation:

Proposition 2 *Spending on tradable durables $P^T_t \Delta X^T_t$ increases with future exchange rate depreciation E_{t+1}.*

The intuition is equivalent to that of the previous proposition: consumers want to consumer durable tradables to shield against the depreciation tax. If consumers expect the exchange rate to depreciate, they might be more likely to buy durable tradables such as electronics (as in one of our survey questions) now, because doing so in the future will be more expensive.

The last result describes the relationship between inflation expectations and debt:

Proposition 3 *Net borrowing $A_t - A_{t+1}$ increases with inflation π_{t+1}.*

This proposition states that when deciding how much debt or savings to accumulate, individuals care about the real interest rate. Holding constant the nominal interest rate, an increase in inflation will reduce the real interest rate. As a result, an increase in the expected rate of inflation will make it attractive for consumers to borrow more (or save less).

3 Background and Setting

3.1 Macroeconomic Context

We conduct a natural field experiment with credit card customers from a large commercial bank in Malaysia. Malaysia is representative of many small, open economies in that inflation has been stable and low in recent decades, whereas the exchange rate has been volatile at times. Figure 2 presents historical data to illustrate these points. The figure first shows the evolution of the consumer price index over the last four decades. The country experienced a short period of high inflation in the early 1980s. However, since then, inflation has been generally moderate and stable at around 2% to 5% annually. Figure 2 also shows the evolution of the nominal exchange rate with respect to the U.S. Dollar. The exchange rate has been markedly more volatile than the rate of inflation. Indeed, the difference in volatility would be even more pronounced if we looked at weekly rather than yearly data, as inflation is stable over the year, while the exchange rate is characterized by sharp changes at shorter time intervals. Exchange rate volatility was most pronounced during the Asian financial crisis that began in 1997, and during which the Malaysian Ringgit depreciated by more than 50% against the U.S. Dollar. Following this experience, the Malaysian Ringgit was pegged to the U.S. Dollar at a rate of 3.20 MYR/USD between 1998 and 2005. Since the end of the currency peg, the exchange rate has fluctuated between 3.08 and 4.45 MYR/USD. Several large exchange rate fluctuations have occurred in recent years, triggered by external and domestic events, such as oil price shocks and political instability surrounding national elections.

Because of its greater volatility and the relatively high share of imported goods in total consumption, it seems plausible that in our setting, the foreign exchange rate plays a more important role in consumer decisions than the rate of inflation. As our theoretical framework in Section 2 highlights, consumers can partially offset the effect of higher inflation by shifting their consumption towards durable goods. We therefore predict that a consumer who expects higher inflation will increase the relative share of durable goods in credit card spending to insure against inflation risk. However, given that inflation in our setting is typically between 2 and 5 percent, this is unlikely to be very meaningful for the consumer's overall finances. In contrast, when considering the purchase of tradable goods, such as consumer electronics or a car, the same consumer might be substantially affected by exchange rate fluctuations due to the magnitude in our setting. If the consumer, for example, expects a 20–25% exchange rate depreciation, the timing of such a purchase could amount to substantial savings.

To examine whether, in our context, changes in the exchange rate are in fact more salient to households than changes in the inflation rate, we exploit data on online searches and newspaper articles. Figure 3 plots data from Google Trends that tracks the frequency of online searches. These data have been used in several previous studies to measure public interest in specific topics (see, for example, Perez-Truglia, 2020). Figure 3.a plots the frequency of online searches related to the terms "inflation" and "exchange rate", where dark bars correspond to keywords related to inflation and lighter-colored bars correspond to keywords related to the exchange rate. Google reports online searches only in relative terms. We therefore normalize the series, with the nominal exchange rate taking the value 100 in the first period. The figure shows that consumers seek information about the exchange rate more frequently than information about the inflation rate: in an average week of 2019, there were approximately 18 times more searches about the exchange rate than searches related to inflation.[5]

This result is supported by a comparison of newspaper articles mentioning either inflation or the exchange rate. Figure 3.b plots the frequency of articles in Malaysia's most widely read English language newspaper in which either term is mentioned.[6] As in Figure 3.a, both series are normalized so that the nominal exchange rate takes the value 100 in the first period. In an average week of 2019, there were approximately twice as many newspaper articles that referred to the exchange rate than newspaper articles mentioning the inflation rate. The two different data sources indicate both higher demand and higher supply for news about the exchange rate, rather than news about the inflation rate, in our setting.

3.2 Partner Institution

Our partner institution is one of the largest commercial banks in Asia and has more than a million customers in Malaysia. Nearly all of our partner bank's retail banking customers have debit cards, and a significant share additionally have credit cards linked to their account. Although our partner bank covers a broad, socially and geographically diverse customer base, its clients are naturally not a fully representative sample of the population. They are on average younger, more educated, more likely to reside in urban areas, and wealthier (for more details, see Section 5). Credit card usage in this setting is high and in fact comparable to high-income economies. Using the bank's administrative data, we estimate that monthly credit card spending in our data accounts, on average, for 32% of consumers' estimated monthly income. In comparison, Ganong and Noel (2019) use data from the JP Morgan Chase Institute and find that average credit and debit card spending accounted for 51% of monthly income in the United States.[7]

5. The 2019 data cover the period when our experiment was conducted and are similar to other years.

6. *The Star*, whose archive is available at www.thestar.com.my.

7. This share was calculated based on results from Table 1 of Ganong and Noel (2019), which uses a sample of credit and debit card customers in the 3 months prior to becoming unemployed.

4 Research Design

4.1 Overview

Figure 1 provides a graphical summary of the research design. Our intervention is designed as an information provision experiment and administered through a phone survey with our partner bank's credit card customers. In addition to survey data, we observe pre-treatment and post-treatment administrative data covering the universe of credit card transactions for all participants of our study.

The intervention proceeds in the following four steps. First, all respondents are asked a set of standard questions on demographics and their general economic situation. Second, a survey module elicits macroeconomic expectations and provides randomly selected subsets of respondents with information about inflation, the exchange rate, or both. Third, we measure posterior beliefs to assess whether our information treatments affect respondents' expectations. Finally, we combine survey responses with administrative data on credit card spending to test whether the information provided affects subsequent consumption in the manner predicted by economic theory. We provide additional details on each of these steps in the following sections.

4.2 Sample Population

To construct the sample frame for our experiment, we first requested a list of credit card customers from our partner bank. We specified that this list should be restricted to customers who opened their accounts within the previous three years. We received a random sample of 33,000 credit card customers and invited these customers to participate in a phone survey, which included our information experiment.

The survey was conducted by a team of 11 call center operators who were trained to administer a short phone survey and supervised in person by a member of the research team. At the beginning of each workday, the operators were provided with a randomly selected list of credit card customers to call. The operators introduced themselves as surveyors working on behalf of researchers from UCLA and asked participants if they were willing to participate in a short survey about their economic expectations. If operators were unable to reach a respondent on the first attempt, they were instructed to make at least one further attempt at a later time.

4.3 Information Experiment

We integrated our experiment into this credit card customer survey administered by our partner bank. The survey instrument, which is available in C, can be divided into five parts: (i) collecting baseline information, (ii) eliciting prior beliefs, (iii) providing information to a random subset of respondents, (iv) eliciting posterior beliefs, and (v) self-reporting of consumption plans for all respondents. In this section, we describe each component of the intervention in turn.

4.3.1 Baseline Information

We begin with a set of standard questions on the respondent's socio-economic background, including employment status, highest level of education attained, marital status, and dependents. We do not ask about gender, age, or income as this information is available in the administrative records obtained from the partner bank. We also include one question about the expected economic conditions in the country over the next 12 months, for which the possible responses are "better off," "about the same," and "worse off." The language in this question, and all other questions about expectations, closely follows the wording used in the most widely used surveys of consumer expectations, such as the University of Michigan's Survey of Consumers and the Federal Reserve Bank of New York Survey of Consumer Expectations (see, for example, Bachmann, Berg, and Sims, 2015; Fuster et al., 2020).

4.3.2 Elicitation of Prior Beliefs

Next, we elicit participants' inflation and exchange rate expectations at two points in time: immediately before the treated individuals receives information from the experimenter (*prior beliefs*) and after a randomly chosen subset of respondents is provided with an inflation or exchange rate forecast (*posterior beliefs*). The wording in both rounds is closely modeled on that used in standard surveys of consumer expectations, and was adjusted to the context of our study through qualitative interviews and an online pilot.

We elicit beliefs about the future inflation rate and exchange rate. To avoid artificially making one belief more salient than the other, we randomized the order of these two questions. To elicit inflation expectations, the surveyors first provide a definition of inflation by explaining that "[...] inflation is the measure of how prices in Malaysia change in general" and then elicit the respondent's expected inflation rate over the following 12 months. Our wording is similar to that used in one of the most widely used surveys of inflation expectations, the Federal Reserve Bank of New York *Survey of Consumer Expectations*, which asks about the inflation rate directly.[8] Participants are asked to give their response in percentage points.

As documented in Section 3.1, the nominal exchange rate is already salient in news media and online searches in the country of study. This makes it more straightforward to elicit exchange

8. Another widely used source of data is the *Michigan Survey of Consumers*, conducted by the Survey Research Center at the University of Michigan, which asks about *prices in general* instead of asking about inflation directly. See Armantier et al. (2016) for a discussion on how these differences in wording might affect responses. Given the similarity of the questions used to elicit expectations, we can benchmark our results to those of related studies that have used the *Survey of Consumer Expectations* data and, with some caveats that have been highlighted by Armantier et al. (2016) among others, to studies that used the *Michigan Consumer Survey* data.

rate expectations. To elicit respondents' nominal exchange rate expectations, the surveyor informs the respondent of the current nominal exchange rate ("as of April 2019, 1 U.S. Dollar is worth around 4.05 Malaysian Ringgit") and then asks what, in their opinion, "[...] the exchange rate will be 12 months from now, in April 2020". This way of eliciting beliefs is consistent with previous work by Cavallo, Cruces, and Perez-Truglia (2017) and was adapted to our research setting through a series of pilot tests and consumer interviews.

4.3.3 Information Provision

In the information provision stage of the experiment, all respondents are first read the following message: "In this stage, we randomly select respondents to receive some feedback about the previous questions." Each respondent is then randomly assigned to one of the following three treatment groups with equal probability:

(a) **Treatment *Inflation***: In the first treatment condition, respondents receive a signal about the future inflation rate: "The consensus among experts from the government and private sector is that inflation in Malaysia will be 2.3% over the next 12 months."

(b) **Treatment *Exchange Rate***: In our second treatment condition, respondents receive a signal about the future nominal exchange rate: "The consensus among experts from the government and private sector is that 1 U.S. Dollar in Malaysia will be worth 4.10 Malaysian Ringgit 12 months from now."

(c) **Treatment *Exchange Rate and Inflation***: In our final treatment condition, respondents receive two signals. The first one relates to the inflation rate: "The consensus among experts from the government and private sector is that inflation in Malaysia will be 2.3% over the next 12 months". The second one relates to the exchange rate: "The consensus among experts from the government and private sector is that 1 U.S. Dollar will be worth 4.10 Malaysian Ringgit 12 months from now".The order of these two pieces of information was consistent with the (randomized) order of the questions on prior beliefs: i.e., if the prior inflation expectations was elicited before the prior exchange rate expectations, then feedback about inflation would come before the feedback about the exchange rate.

The inflation and exchange rate information we provide is based on forecasts published on popular forecasting websites, including Statista.com, TradingEconomics.com, and WalletInvestor.com. These sources are widely known and respected in our setting and comparable to professional forecasting sources that have been used in similar information-provision experiments (see, for example, Cavallo, Cruces, and Perez-Truglia, 2017; Fuster et al., 2020; Roth and Wohlfart, 2020). It is worth noting that our research design does not include an information treatment where no respondent receives information. The decision to omit the no information condition from our research design was based on results from a pilot, in which surveyors found it difficult to re-elicit beliefs when no new information had been provided to the respondent. Since this treatment condition is not necessary to estimate the effects of information, we chose to exclude it from our experimental design altogether.

4.3.4 Elicitation of Posterior Beliefs

The second round of belief elicitation takes place immediately after respondents are provided with information about inflation, the exchange rate, or both. To ensure that the responses are comparable to the elicitation of prior beliefs, the second round of belief elicitation uses the exact same wording as the first. The goal of this second round of belief elicitation is to understand whether individuals incorporate the information provided to them through the information treatments into their expectations.

4.3.5 Elicitation of Consumption Plans

While the main goal of our experiment is to estimate the effect of information on *actual consumption*, as measured objectively in administrative data, we also asked a series of questions on respondents' *consumption plans*. These responses were collected after the elicitation of posterior beliefs and serve two purposes. First, they allow us to test whether our information treatments affect intended behavior. With that goal in mind, we measure expected future spending in the main consumption categories highlighted by the theoretical framework (durable goods, tradable goods, and credit card debt), as well as other categories that act as useful proxies or benchmarks. Second, these questions allow us to confirm that survey responses have predictive content by testing whether predicted consumption correlates with actual future consumption.

The first of these questions elicit respondents' expected change in total credit card expenditures (which corresponds to the total expenditures we observe in administrative data). Specifically, respondents were asked: "Do you expect your credit card spending to go up, stay the same, or go down during the next 3 months?" We code this and other similar questions on a simple three-step scale. the variable takes the value -1 if the individual responded "go down," 0 if the individual responded "stay the same," and +1 if the individual responded "go up." Another pair of questions uses similar language to elicit total spending, not limited to spending on credit cards, and spending on groceries for comparison.

The next set of questions on expected spending asks about spending on durable goods and uses wording that closely follows the Michigan Survey of Consumers. We first ask respondents: "Do you think now is a good time, a bad time, or neither a good nor a bad time to buy household items, such as furniture or a refrigerator?" We code responses using the same $\{-1, 0, +1\}$ scale as before. The variable takes the value -1 if the individual responded "No, it's a bad time," 0 if the individual responded "It's neither a good nor a bad time," and +1 if the individual responded "Yes, it's a good time." We include three additional questions using this same language, but instead of asking about durable expenditures, we ask about electronics, vehicles, and credit card borrowing, respectively.

One potential concern with our design is that the information treatments could affect behavior through a mechanism other than intertemporal optimization of consumption. Intuitively, information about inflation and the exchange rate could affect spending by changing respondents' general optimism or pessimism about the economy. For example, individuals who learn that there will be inflation or depreciation in the future may infer that these are symptoms of an economic downturn and interpret this as bad news for their personal economic situation. We include two questions to shed light on this potential mechanism in the questionnaire. The first asks respondents about their expectations for the economy overall, the second asks about the individual's own financial outlook: "Looking forward, would you say that you and your family living with you will be better off or worse off financially than you are now?" We code both outcomes using the same $\{-1, 0, +1\}$ scale: -1 if the individual responds "Worse off," 0 if the individual responds "About the same," and +1 if the individual responds "Better off."

5 Data and Descriptive Statistics

5.1 Sample and Survey Implementation

We implemented the experiment over a 4-month period between April and July 2019. During this time, the survey team attempted to reach 28,958 credit card clients and completed 2,872 surveys, implying a 10% response rate.[9] The median respondent took 7 minutes to complete the interview. Surveys were offered in English and Malay, and 47% of respondents chose to complete the survey in English, while the remaining 53% responded in Malay. The partner bank shared detailed administrative records for all participants who responded to the survey, as well as a representative sample of clients who were invited to the survey but did not respond.

Table 2 provides descriptive statistics for our sample based on administrative data. Column (1) reports data for a random sample from the universe of the bank's credit card clients, which includes both survey respondents and non-respondents. In this sample, 62% of clients are male,

9. This final sample excludes individuals who started the survey but did not make it to the end. There are only 174 partially complete surveys and we cannot reject the hypothesis that the respondents are missing at random after the information-provision stage of the survey. Our final sample excludes 274 individuals who reported extreme prior beliefs about the nominal exchange rate (above 4.65 or below 3.7 Ringgit per U.S. dollar) because the system used by the surveyors prevents us from knowing the exact expectations of those respondents. We would have excluded those extreme prior beliefs anyway to avoid sensitivity to outliers, as is standard in studies based on expectations data (Fuster et al., 2020).

they are on average 33.6 years old, have an average monthly income of $3,087 and monthly credit card expenditures of $1,106.

As one might expect, the summary statistics shown in column (1) of Table 2 indicate that clients of the partner bank are not representative of the entire Malaysian population. On the one hand, the age and gender composition of our sample is not substantially different from the country average: data from the Malaysian Department of Statistics for 2020 indicate that 51.4% of the Malaysian population is male (compared to 62% in our sample of bank customers) with a mean age of 31.4 years (compared to 33.6 years in our sample). On the other hand, we find substantial income differences. According to data from the Salaries and Wages Survey Report,[10] the average Malaysian household earned $1,767 (compared to $3,087 in our sample).

However, Table 2 also shows that there is no indication of selection into treatment. Customers who participated in our experiment are similar to non-respondents. Columns (2) and (3) compare the characteristics of the 2,872 clients who answered our survey (reported in column (2)) to the sample of 3,126 clients who were invited to the survey but did not respond (column (3)). Comparing columns (2) to (3) indicates that although there are some statistically significant differences in average characteristics, none of these differences are meaningful in magnitude. For example, the average age is 33.28 years among survey respondents as compared to 33.88 among non-respondents. The average monthly income is $3,129 among survey respondents as compared to $3,050 among non-respondents. The average credit card expenditures are $1,135 among survey respondents and $1,080 among non-respondents. The one possible exception is gender, where we find that men are more represented among survey respondents (67%) than among non-respondents (57%).

Table 3 provides additional descriptive statistics, based on survey and administrative data, and presents a test of randomization balance. Column (1) is based on the sample of all 2,872 survey respondents. The summary statistics show that the respondents in this sample are highly educated (87% have a college degree), around half (54%) are married, and around 10% are self-employed. In columns (2) through (4) of Table 3, we compare the baseline characteristics and expenditures of the three treatment groups. Column (5) reports p-values for the null hypothesis that these characteristics are equal across all three treatment groups. The results indicate that, consistent with successful random assignment, pre-treatment observables are balanced across treatment groups. As expected, all differences across treatment groups are economically small. The difference is statistically significant (p-value=0.09) for only one of the 11 characteristics reported in the table: the number of dependents. This result is within expectations, given that 1 out of every 10 differences are expected to be statistically significant at the 10% level simply by chance. We nonetheless follow standard practice and include the number of dependents as a control variable in all regressions.

10. Source: Malaysian Department of Statistics, 2017.

5.2 Credit Card Data

Our partner bank shared administrative data on credit card transactions for all customers in the sample. These data allow us to measure spending and borrowing behavior of all customers in our sample for 12 months prior to the intervention and 3 months after the intervention. The dataset contains detailed records of all credit card transactions that occurred during this time period, which include the transaction amount, description, vendor name, and spending category code.[11] The credit card data also include information about outstanding balances and repayment, which we use to measure consumers' willingness to take on debt. Importantly for our purposes, each transaction in the data contains the standardized Merchant Category Code (MCC), a 4-digit identifier that classifies a business by the types of goods or services it sells. The MCC makes it possible to assign each transaction to a specific spending category. Importantly, for the goal of our analysis, the MCC allows us to distinguish between spending on durable, nondurable, tradable, and nontradable goods. To classify spending into durable versus nondurable goods, we follow the standard categorization used in the literature (see Aaronson, Agarwal, and French, 2012; Agarwal and Qian, 2014; Ganong and Noel, 2019; Chetty et al., 2020). For example, some durable spending items include apparel, consumer electronics, and furniture. To the best of our knowledge, no other paper has used MCCs to classify credit card spending into tradable and non-tradable expenditures. We therefore created our own categorization by manually inspecting each individual MCC and classifying it as tradable or nontradable. In our classification, all codes for services are assigned to the nontradable category, whereas codes for goods are assigned to the tradable category if those goods are typically imported or exported. For example, some tradable spending items include apparel and consumer electronics.

We summarize both MCC categorizations in Table 1. As there are thousands of individual MCCs, we report summary statistics using standard groupings of MCCs that are commonly used by financial institutions and in the academic literature. Column (1) reports the average spending for each MCC group in our sample. Column (2) indicates the fraction of spending within that MCC group that is classified as durable (the remainder is classified as nondurable by construction). Column (3) indicates the fraction of spending within the MCC group that is classified as tradable (with the remainder classified as nontradable). For example, the third row corresponds to the MCC group "automotive expenditures", in which 100% of codes are classified as durables and 0% as non-durables, and 64% of the spending in this MCC group is classified as tradable versus 36% as nontradable (primarily codes corresponding to services). The last row of the table summarizes codes that we group as "uncategorized." These miscellaneous MCCs do not contain enough information to categorize them as durable, as opposed to nondurable, or tradable, as opposed to nontradable, expenditures.

11. We do not obtain data on debit card transactions because that they account for a negligible fraction of spending according to pre-intervention summary data (debit cards are used primarily for cash withdrawals).

Figure 4 summarizes the breakdown of spending between durable and tradable categories. Each rectangle corresponds to one unit of spending. The blue rectangles towards the right, denoted as uncategorized, correspond to the 10% of spending that cannot be categorized. Among the transactions that can be categorized (90% of all spending), 31% are categorized as tradable and the remaining 69% as nontradable. Among the transactions that can be categorized, 32% are durable and 68% nondurable. Figure 4 also shows substantial orthogonal variation between the two categorizations. That is, not all tradables are durables and vice-versa.

Table 2 also shows average spending statistics for each key spending category used in our analysis. Specifically, column (2) shows that customers who participated in the experiment used their credit cards to spend average monthly amounts of $371 (33% of the $1,135 total credit card spending) on durables and $275 (24% of total spending) on tradable durables. On average, subjects had $1,805 in outstanding credit card debt, equivalent to 1.5 months of spending.

6 Results

6.1 Spending: Survey versus Administrative Data

Existing research has generally studied the impact of economic expectations on consumption using survey data, which may suffer from a number of well-known limitations, such as measurement error, selection problems, and surveyor demand effects. To assess whether this is a source of concern in our study, we explicitly test the relationship between self-reported consumption plans and *actual* future consumption in our data. If survey measures of consumption track actual consumption closely, measuring consumption in administrative data has few benefits. If, however, there is a disconnect between survey responses and actual spending, this would suggest that using administrative data could be crucially important to avoid spurious results.

Our survey elicited expectations about future credit card spending by asking respondents whether they expect their credit card spending to increase, decrease, or remain the same. Comparing these self-reported consumption plans to actual spending can reveal the extent to which survey measures predict actual consumption. Figure 5 presents the results. The x-axis corresponds to the actual change in monthly credit card spending in the 3 months after the survey completion. The y-axis corresponds to self-reported consumption plans on a 3-point scale from -1 (“go down”) to +1 (“go up”).

We find a statistically significant (p-value=0.020) relationship between the expected change in credit card expenditures and the actual change in spending, indicating that self-reported consumption plans do have some information content. This relationship is, however, weak. The estimated slope (0.034) implies that a one-standard-deviation increase in actual future expenditures is associated with an increase in expected future expenditures of only 0.03 standard deviations.[12] This is also highlighted by a low R^2 of 0.021. These results indicate that survey predictions are a useful but very weak indicator of actual future spending.

There are several possible explanations for this finding. One possibility is that individuals may make consumption decisions spontaneously and are therefore not very good at predicting their spending over longer time horizons. Alternatively, individuals may have a clear idea of their future spending but may fail to follow through on their plans, for example due to a lack of self-control or financial constraints (although the latter is unlikely given that all participants of our experiment have access to credit card borrowing by definition). Another explanation could be measurement error and different types of response bias. Consumers may have a clear idea of their future spending but fail to communicate this accurately in their survey responses. This interpretation is somewhat unlikely to apply in our population, given that the participants of our experiment are highly educated, and financially experienced (87% of respondents in our sample have a college degree) and that we elicited survey expectations following standard questionnaires that were adapted and tested for this specific population.

Taken together, the evidence suggests that using survey data to measure treatment effects may be misleading, and provides a strong rationale for using administrative data to measure actual rather than planned consumption.

6.2 Prior Beliefs

Figure 6 shows the distribution of inflation and exchange rate expectations at baseline. In Figure 6.a, we plot the distribution of prior beliefs about the future inflation rate. On average, prior expectations about inflation (3.39 pp) are close to the expert forecast (2.3 pp) and close to a recent rate (1.4 pp).[13] There is, however, significant dispersion in predictions across individuals, with individuals in the bottom decile of the distribution predicting an inflation rate of 0 pp and individuals in the top decile of the distribution predicting an inflation rate of 10 pp. In Figure 6.b, we plot the distribution of exchange rate expectations. The figure shows that beliefs about the future exchange rate follow a similar pattern as those for the future rate of inflation: prior expectations about the nominal exchange rate (4.13 MYR per USD) are centered close to the expert forecast (4.10 MYR per USD), but there is significant dispersion in individual predictions, with some individuals (bottom 10%) expecting the exchange rate to rise to 3.90 Ringgit per US Dollar and others (top 10%) expecting it to decline to 4.40 Ringgit per U.S. Dollar.

The finding that expectations are centered around the professional forecast but dispersed has been documented widely in the literature on inflation and exchange rate expectations (Armantier

12. The standard deviation of the variable shown in the x-axis is $602, and the standard deviation of the variable shown in the y-axis is 0.665.

13. The 1.4 pp annual rate of inflation corresponds to the estimate for July 2019, according to the Malaysian Department of Statistics.

et al., 2016; Cavallo, Cruces, and Perez-Truglia, 2017), as well as in other contexts (see, for example, Fuster et al., 2020). Our information-provision experiment leverages this dispersion in prior beliefs.

6.3 Effect of Information on Posterior Beliefs

We next examine how the information feedback provided through our treatment conditions affects macroeconomic expectations. To do so, we use the standard econometric approach that has been used in information-provision experiments on a wide range of topics, such as inflation (Armantier et al., 2016; Cavallo, Cruces, and Perez-Truglia, 2017), cost of living (Bottan and Perez-Truglia, 2020a), and housing prices (Fuster et al., 2020).

Let subscript i index the participants of our experiment and denote $\pi_{i,t}^{prior}$ as individual i's prior belief about the inflation rate, where t denotes the point in time when the belief is elicited and π the expected inflation between time t and t + 12 months. This is the belief about the inflation rate right before the individual reaches the information-provision stage of the experiment. Let $\pi_{i,t}^{signal}$ be the value of the signal that we may or may not show to the individual (the expert forecast at time t of the inflation rate in 12 months). Let $T_{i,t}^{\pi}$ be a binary variable that takes the value 1 if individual i is shown the signal and 0 otherwise. We denote the corresponding posterior belief as $\pi_{i,t}^{post}$. That is, the expected inflation rate after the individual sees, or does not see, the signal.

When priors and signals are distributed normally, Bayesian learning implies that after the individual sees the signal, the mean of the posterior belief should be a weighted average between the signal and the mean of the prior belief, $\pi_{i,t}^{post} = \alpha \cdot \pi_{i,t}^{signal} + (1-\alpha) \cdot \pi_{i,t}^{prior}$, where the parameter α depends on the relative precision of the prior belief and the signal (Hoff, 2009). The parameter α, the learning rate, ranges from 0 (individuals ignore the signal) to 1 (individuals fully adjust to the signal). We can rearrange this identity as follows:

$$\pi_{i,t}^{post} - \pi_{i,t}^{prior} = \alpha \cdot \left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) \tag{2}$$

In other words, the Bayesian model predicts that the belief updates ($\pi_{i,t}^{post} - \pi_{i,t}^{prior}$) should be a linear function of the gap between the signal and the prior belief ($\pi_{i,t}^{signal} - \pi_{i,t}^{prior}$). That is, respondents who overestimate the inflation rate will revise their expectations downward when shown the signal, and those who underestimate the inflation rate will revise their beliefs upward when shown the signal. The model also predicts that the slope of that relationship should be equal to the learning rate, α.

In practice, several "spurious" reasons may explain why individuals revise their beliefs in the direction of the feedback, even if they received no signal. For example, some may take additional time to think when asked a question a second time and may get closer to the truth as a result.

This may be particularly true in phone surveys where participants interact with a caller and may feel social pressure to report different beliefs when asked about their expectations again, even if they were not given new information. To allay concerns of such potentially spurious updating, we exploit the randomized assignment from the information provision experiment, following standard specifications in the literature (see Armantier et al., 2016; Cavallo, Cruces, and Perez-Truglia, 2016):

$$\pi_{i,t}^{post} - \pi_{i,t}^{prior} = \alpha \cdot \left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) \cdot T_{i,t}^{\pi} + \beta \cdot \left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) + \epsilon_i \tag{3}$$

In this specification, the parameter β picks up spurious reversion towards the signal and α picks up true learning (i.e., changes in beliefs caused by the information provision) above any spurious revisions. Note that we do not expect subjects to fully update to the signal we provided ($\alpha = 1$) because the signal is an expert forecast that most respondents will correctly interpret as uncertain. Moreover, some individuals may not fully trust the source of the forecast and therefore place lower weight on the forecast. Nevertheless, we should expect α to be significantly greater than zero.

The same logic applies to expectations about the nominal exchange rate. Let $d_{i,t}^{prior}$ denote participant i's prior belief about the depreciation rate (i.e., the growth rate of the nominal exchange rate) before the individual reaches the information-provision experiment. Let $d_{i,t}^{signal}$ be the value of the signal that we may or may not show to the individual (i.e., the forecast). Let $T_{i,t}^{d}$ be a binary variable that takes the value 1 if we showed that signal to individual i and 0 if not. Denote $d_{i,t}^{post}$ as the corresponding posterior belief, that is, the expected depreciation rate after the individual sees, or does not see, the signal.

Our experiment provides respondents with information about inflation and the nominal exchange rate. Thus, it is possible that individuals use feedback about the inflation rate to update beliefs about the exchange rate and vice versa. Indeed, we might expect this type of cross-learning based on macroeconomic evidence. For example, after a devaluation of the local currency, there is partial pass-through to inflation (Dornbusch, 1987). We therefore expand the learning model to accommodate the possibility of cross-learning and estimate the following set of equations:

$$\begin{aligned} \pi_{i,t}^{post} - \pi_{i,t}^{prior} &= \alpha_1 \cdot \left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) \cdot T_{i,t}^{\pi} + \alpha_2 \cdot \left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) \cdot T_{i,t}^{d} + \\ &\qquad \beta_1 \cdot \left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) + \beta_2 \cdot \left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) + X_{i,t}\gamma_1 + \epsilon_i \end{aligned} \tag{4}$$

$$\begin{aligned} d_{i,t}^{post} - d_{i,t}^{prior} =& \alpha_3 \cdot \left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) \cdot T_{i,t}^{\pi} + \alpha_4 \cdot \left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) \cdot T_{i,t}^{d} + \\ &\qquad \beta_1 \cdot \left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) + \beta_2 \cdot \left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) + X_{i,t}\gamma_2 + \epsilon_i \end{aligned} \tag{5}$$

Note that this equation also includes a vector of control variables denoted $X_{i,t}$. Given random assignment, this vector of control variables should not change the point estimates but help absorb the variance of the error term and improve statistical power. We use the exact same set of control variables in all regressions presented in this paper: a set of 10 surveyor dummies, four dummies for the week of the year when the respondent completed the survey, the number of dependents, and 20 variables to control flexibly for the pre-treatment spending patterns.[14]

The main parameters of interest are α_1, measuring how individuals incorporate feedback about inflation into their inflation expectations, and α_4, measuring how individuals incorporate feedback about the exchange rate into their exchange rate expectations. The parameters α_2 and α_3 measure cross-learning by capturing how individuals incorporate exchange rate feedback into their inflation expectations and inflation feedback into their exchange rate expectations.

Before presenting the regression results, Figure 7 provides a graphical summary of the impact of our information treatments on macroeconomic expectations. Figure 7.a shows a binned scatterplot corresponding to the effects of the inflation feedback. The x-axis corresponds to the potential update in response to the provision of feedback (i.e., the difference between the feedback on inflation expectations and the corresponding prior belief). The y-axis shows the actual belief update (i.e., the difference between the posterior belief and the prior belief). The gray circles correspond to the control group (i.e., individuals who do not receive inflation feedback). The slope of this linear relationship (the gray line) corresponds to the coefficient β in the learning equation (3), which measures "spurious" learning. We find significant spurious learning, which is consistent with findings from related studies (see, for example, Fuster et al., 2020; Cullen and Perez-Truglia, 2018).[15] In turn, the red squares correspond to the treatment group (i.e., individuals who receive the inflation feedback). Most importantly, the slope of the relationship is significantly larger (p-value=0.000) in the treatment group (0.472) than in the control group (0.247). This difference in slopes corresponds to the coefficient α from the learning equation (3) (i.e., the true rate of learning that can be attributed to the information provision). Figure 7.b is similar to Figure 7.a, but reports updating on exchange rate expectations instead of inflation expectations. Again, consistent with genuine learning from the feedback, we find that the slope is stronger in the treatment group than in the control group, although the difference is smaller in magnitude (0.317 vs 0.255) and statistical significance (p-value=0.046).

We next turn to the regression results, presented in Table 4. The first two columns of this table correspond to the regression specifications given by equations (4) and (5), respectively.

14. More specifically, we include a set of four variables with the average monthly spending over each of the last four quarters before the survey date, as well as the corresponding set of variables for each of the following spending categories: durable, tradable durable, and nondurable.

15. In terms of magnitude, however, the degree of spurious learning seems larger in our data. Our preferred interpretation for this difference is that, unlike other surveys experiments that are conducted online, our survey was conducted via phone. As a result, some individuals may have felt pressured to revise their posterior beliefs even if they did not receive any feedback.

In column (1), the dependent variable is the updating on inflation expectations. In column (2), the dependent variable is the updating on the expected exchange rate depreciation. These results differ from the simpler binned scatterplots in Figure 7 in that they include additional control variables and allow for cross-learning. Table 4 reports the coefficients of the two key independent variables, corresponding to the interactions between the treatment assignments and the size of the information shock. For simplicity, we refer to these variables as information shocks.

The first coefficient from column (1) of Table 4 indicates that information about inflation has a significant effect on inflation expectations: a 1 pp increase in inflation shock increases inflation expectations by 0.237 pp (p-value<0.001). The second coefficient from column (1) of Table 4 is close to zero (-0.031) and statistically insignificant (p-value=0.189), indicating that the information shock about the exchange rate does not have a significant effect on inflation expectations. In other words, individuals use the feedback in a compartmentalized manner.

The magnitude of the pass-through from the inflation feedback to the inflation expectations is in the same order of magnitude as the pass-through estimated in other information experiments. For example, Bottan and Perez-Truglia (2020b) shows that a 1 pp increase in feedback about future home prices increases the home price expectations by 0.205 pp. However, the degree to which subjects incorporate the information is lower than that reported in other studies. For example, Cavallo, Cruces, and Perez-Truglia (2017) find that, when forming inflation expectations, the average Argentine respondent assigns a weight of 0.432 to the feedback and the remaining 0.568 to their prior beliefs (coefficient α-statistics reported in Panel B, column (1) of Table 1). The fact that individuals are less prone to incorporating information in our context may reflect a more educated and financially savvy population that has more confidence in their prior beliefs. However, this difference in rates of learning could be attributed to differences in the survey methods. For example, other studies provide information and elicit beliefs on a computer screen, whereas our study uses phone surveys, which could arguably make the information less salient. Also, other studies where subjects are paid to fill out the survey could generate experimenter demand effects. Subjects in our survey were not paid for their participation.

The second coefficient in Table 4, column (2), indicates that information about the exchange rate has a significant effect on exchange rate expectations: a 1 pp information shock increases expectations of a nominal exchange rate depreciation by about 0.065 pp (p-value=0.036). Again, we find compartmentalized learning about the exchange rate: the first coefficient in column (1) is close to zero (0.033) and statistically insignificant (p-value=0.206), indicating that information about the inflation rate does not have a significant effect on participants' exchange rate expectations. We find that the magnitude of the learning effects for the exchange rate (coefficient of 0.065) is lower than the magnitude of learning effects for inflation (0.237), and the difference between the two is statistically significant (p-value<0.001). Following a Bayesian learning approach, we offer two potential interpretations for this difference. First, individuals may have stronger prior beliefs about the exchange rate than about the inflation rate. This interpretation is consistent with the evidence documented in Section 3.1 showing substantially more interest in learning about the exchange rate than the rate of inflation, presumably because it is more consequential for everyday economic decisions. An alternative interpretation is that individuals do not trust the precision of the signal. That is, they are less likely to trust expert forecasts about inflation than about the exchange rate. However, as we do not provide specific information about the sources of inflation and exchange rate forecasts used in our experiment, this interpretation seems less likely.

6.4 Effect of Information on Spending

Having shown that our information treatments are effective at shifting beliefs, we turn to their impacts on consumption. The main goal of our experiment is to test whether changes in macroeconomic expectations affect actual spending, as measured in administrative data covering the universe of credit card transactions for bank customers in our sample. To examine this question, we estimate the following regression equation:

$$\begin{aligned} Y_{i,t+1} \; = \; & \alpha_Y^{\pi} \cdot \left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) \cdot T_{i,t}^{\pi} + \alpha_Y^{d} \cdot \left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) \cdot T_{i,t}^{d} + \\ & \beta_Y^{\pi} \cdot \left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) + \beta_Y^{d} \cdot \left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) + X_{i,t}\gamma_Y + \epsilon_i \end{aligned} \tag{6}$$

Note that the right-hand-side of equation (6) is identical to the learning equations in (4) and (5). The only difference is that the dependent variable is now a generic outcome $Y_{i,t+1}$. For example, this dependent variable may be the average monthly spending in the 3 months post-treatment. Recall that in the set of control variables ($X_{i,t}$), we include the pre-treatment spending, which exploits the persistence in spending patterns to help reduce the variance of the error term and improve statistical power (see McKenzie, 2012).

Table 4 reports the results. In columns (1) and (2), we estimate the relationship between the information shock and the resulting change in self-reported macroeconomic expectations. The results confirm that participants update their macroeconomic expectations in response to the information provided to them through our experiment. In Table 4, columns (3) through (6), we use the same empirical specification to examine whether the changes in macroeconomic expectations documented in columns (1) and (2) translate into changes in consumption behavior. To do so, we estimate equation (6), with spending on durables, tradable durables, credit card debt, and total spending as the respective outcomes. Each outcome is measured in the administrative data obtained from our partner bank. We observe credit card spending for 3 months after the intervention and average the monthly spending over the entire period to mitigate concerns about outliers or seasonality of expenditures. Total credit card debt is measured as the amount of outstanding credit card debt after the monthly repayment due date.

The results in columns (3) through (5) of Table 4 test the key predictions of the theoretical framework presented in Section 2. The first coefficient in column (3) measures the effect of the inflation shock on durables consumption. This is a direct test of Proposition 1, which states that spending on durables should increase with expected inflation. We do not find support for this prediction in the data. While the point estimate has the correct sign, the coefficient is small in magnitude (1.960) and not statistically different from 0 (p-value=0.483). The information shock delivered by our experiment moves inflation expectations by an average of 0.088 standard deviations, but our estimate implies that it increases average monthly spending on durables by only 0.006 standard deviations (or less than $2).

Similarly, the second coefficient estimate in column (4) of Table 4 provides a test of Proposition 2, which states that a decrease in the expected exchange rate (an increase in the expected rate of depreciation) should increase spending on tradable durables. We also do not find evidence consistent with this prediction. The point estimate is negative, small in magnitude (-2.514), and not statistically significant (p-value= 0.196). While our intervention moves exchange rate expectations by an average of 0.023 standard deviations, this coefficient estimate implies a negligible impact on spending on tradable durables, shifting expenditures in this category by only 0.007 standard deviations.

Finally, column (5) of Table 4 shows that, consistent with Proposition 3, an increase in the expected inflation rate leads to a slight increase in total credit card debt. However, this coefficient is statistically insignificant and small in magnitude: it implies that for each 1 pp increase in the inflation shock, individual credit card debt increases by just 0.014 standard deviations.

In column (6), we consider an additional hypothesis that is not motivated by the intertemporal consumption models. As argued by Coibion et al. (2019), individuals may see future inflation and exchange rate depreciation as signs of a weak economy. According to that view, an increase in expected inflation and depreciation may discourage the individual from spending in general, for precautionary reasons. To explore this additional hypothesis, column (6) of Table 4 uses total spending as the dependent variable. We do not find any evidence that inflation and exchange expectation shocks have significant effects on total spending. The coefficients are negative but economically small and statistically insignificant. For example, a 1 pp inflation shock reduces total spending by just 0.002 standard deviations (p-value=0.739), while a 1 pp depreciation shock reduces total spending by just 0.005 standard deviations (p-value=0.429).

As an additional robustness test to check the regression specification, we leverage data on pre-treatment spending, which allows us to conduct a falsification test in the spirit of an event-study analysis. We estimate the same regression but use pre-treatment instead of post-treatment spending as the dependent variables. The outcomes are measured before participants receive information and thus should not show effects of the information on pre-treatment spending. Appendix B.1 presents the results. As expected, we find no effects of the information shocks on pre-treatment spending outcomes.

6.5 Magnitude of Coefficients

In the previous section, we show that our information treatments shift expectations but do not have a statistically significant effect on consumption. However, this does not necessarily mean that the effects are precisely zero. To get a better quantitative sense of the effect sizes, we take a hypothetical information shock of 1 pp and estimate its impact on the outcomes of interest in terms of dollars and standard deviations. We first consider the effect of an inflation shock on durable consumption and find that a 1 pp information shock is predicted to increase durable spending by a statistically insignificant $1.960, equivalent to less than 0.010 standard deviations of the corresponding outcome. To examine the possibility of an undetected increase in durable spending, we inspect the confidence interval of our estimate. The upper bound of the 95% confidence interval is approximately 7.45, which rules out positive effects larger than $7.44. Relative to the standard deviation of the outcome variable, we can rule out effects above 0.022 standard deviations, which is very close to zero.

Note that our estimates are intention-to-treat (ITT) effects, because the information shock given to the subjects only partially translates into changes in their posterior beliefs. For this reason, we refer to equation (6) as the reduced-form effects of the information experiment. For a more direct measure of the effect of expectations on behavior, we can use an instrumental variables version of the reduced-form equation but with two endogenous variables corresponding to the belief updates for inflation and exchange rate expectations.

We report the results from the instrumental variables regressions in Table 5. The first prediction of interest is that an increase in inflation expectations should increase durable expending. The coefficient on inflation expectations in Table 5, column (1), indicates that a 1 pp increase in inflation expectations causes an increase in durable spending of $14.3, or only 0.042 standard deviations for this outcome. Looking at the upper bound of the 95% confidence interval, we rule out an increase in this outcome above $39.1, or 0.114 standard deviations. This suggests that, while we cannot rule out that inflation expectations have small effects on spending behavior, we can rule out moderate to large effects.

The results are similar for other hypotheses that we tested. The second prediction of our theoretical framework is that an increase in expected depreciation should increase spending on tradable durables. Contrary to this prediction, the coefficient from column (2) indicates that a 1 pp increase in the expected devaluation reduces rather than increases spending on tradable durables by \$33.1, which is equivalent to a reduction of 0.130 standard deviations. Inspecting the bounds of the 95% confidence interval, we rule out an increase of more than 0.117 standard deviations for this outcome. The third prediction of the theoretical framework is that an increase in inflation expectations should increase credit card borrowing. The coefficient from column (3) indicates that a 1 pp increase in expected inflation increases credit card debt by only \$31.8, which is equivalent to 0.042 standard deviations. Moreover, the 95% confidence interval rules out positive effects of more than 0.123 standard deviations. Last, column (4) shows the effects of expectations on total spending. The results indicate that a 1 pp increase in inflation expectations increases total spending by \$1.47, or 0.002 standard deviations. In turn, a 1 pp increase in depreciation expectations decreases total spending by \$73.8, or 0.080 standard deviations.

These results involve tests of multiple related predictions, involving multiple combinations of expectations and spending margins. The small and statistically insignificant coefficients across the board suggest that while expectations may have some effect on spending behavior, those effects appear to be very small and therefore difficult to detect.

As an additional test to rule out the presence of economically meaningful effects, we estimate the relationship between expectations and credit card spending using the full variation in expectations, rather than restricting our attention to the exogenous variation generated by our experiment. Table 6 presents the results. The results reported in the table correspond to the ordinary least squares equivalent of the instrumental variable regressions reported in Table 5. There is a simple trade-off between these two approaches. On the one hand, the experimental estimates provide better identification of the causal relationship between expectations and consumption. On the other hand, the OLS estimates exploit all available variation in expectations and thus lead to substantially more precisely estimated coefficients.

The results from the two approaches are qualitatively consistent: the estimated effects of expectations on behavior are close to zero and statistically insignificant. However, the OLS estimates from Table 6 are substantially more precisely estimated than the corresponding IV estimates from Table 5. As a result, the non-experimental estimates can rule out even smaller effects. Take for example the effect of inflation expectations on durable consumption. According to the coefficient from column (1) of Table 6, a 1 pp increase in inflation expectations is associated with a reduction in durable expenditures of less than \$2. If we take the upper bound of the 95% confidence interval, we can rule out increases in durable expenditures above \$2.18, which is equivalent to 0.006 standard deviations of that outcome and thus an arguably negligible effect. In summary, both experimental and non-experimental data support the conclusion that our estimates provide evidence of null or small effects of macroeconomic expectations on spending behavior.

6.6 Effect of Information on Self-Reported Spending Plans

There are several possible interpretations of this result. One possibility is that individuals update their *intended* behavior but cannot follow through on their consumption plans, for example due to self-control problems or liquidity constraints. Since our survey collected data on spending plans, we can test this hypothesis directly. We estimate equation (6) using self-reported spending plans measured post-treatment as the dependent variable, rather than actual spending observed in the credit card data. The results show that individuals do not change their stated spending plans in response to information about inflation or the exchange rate, as shown in Table 7. For reference, columns (1) and (2) reproduce the treatment effects of information shocks on the inflation and exchange rate expectations. In columns (3) through (6), we report the results of estimating equation (6) using self-reported spending plans for the four specific sub-categories of spending. Each of these outcomes is measured on a subjective 3-point scale that takes the values -1 (if the respondent anticipates spending less in the future), 0 (if they anticipate spending about the same), or +1 (if they anticipate spending more). Each outcome in columns (3) to (6) of Table 7 corresponds to the survey equivalents of the consumption behavior measured with administrative data in columns (3) to (6) of Table 4. In column (3), the dependent variable is the stated intention to increase or decrease spending on durable goods. The prediction from the macroeconomic model is that higher inflation expectations should increase intended spending on durables. We find no evidence of such an effect. The impact of increased inflation expectations on total consumption is close to zero (-0.006), statistically insignificant and small in magnitude: a 1 pp inflation shock is associated with a reduction in expected durable spending of only 0.001 standard deviations. In column (4), the dependent variable is intended future spending on electronic goods, which is our survey proxy for durable tradables. These estimate test the prediction that expected depreciation should result in an increase in planned spending on durable tradables. Contrary to this prediction, the coefficient on the exchange rate shock is close to zero (0.008) and statistically insignificant. In column (5), the dependent variable is the expected change in borrowing. The theoretical prediction is that an increase in inflation expectations will lead to higher expected borrowing. We do not find support for this hypothesis. The coefficient on inflation shock is close to zero (-0.003) and statistically insignificant. In column (6), the dependent variable is the intention to increase total spending. This regression tests the hypothesis that expectations of inflation or exchange rate depreciation may be interpreted as a sign of an overall economic slowdown and should therefore lead to a decline in spending. Instead, we find that the coefficients on the inflation shock and the exchange rate shock are both close to zero (-0.006 and 0.003) and statistically insignificant.

Taken together, these results suggest that shocks to macroeconomic expectations do not affect consumption plans even when elicited immediately after information provision. This effectively rules out the possibility that changes in macroeconomic expectations do not affect consumption because individuals are unable to follow through on their consumption plans.

7 Conclusion

How do macroeconomic expectations affect individual consumption decisions? To explore this question, we conducted a field experiment with 2,872 credit card customers of a large commercial bank. We then created exogenous variation in macroeconomic expectations through an information-provision experiment in which participants were provided with expert forecasts of inflation and the exchange rate. We measure the effects of these information shocks on consumers' subsequent macroeconomic expectations (based on survey data), their self-reported consumption plans (measured in survey data), and their *actual* spending (measured in administrative data). We test several predictions from standard macroeconomic models, such as whether an increase in inflation expectations increases spending on durables. We find that information provision shifts beliefs but does not change consumers' actual spending behavior.

Our preferred interpretation of the findings is that consumers fail to incorporate revised macroeconomic expectations into their decision-making process, thus not re-optimizing their consumption plans when new information becomes available. Several recent findings support this interpretation. First, related work has found that agents fail to optimize in much simpler economic environments (see Campbell et al., 2011; Beshears et al., 2018). Specific to the context of credit card spending, Ponce, Seira, and Zamarripa (2017) and Gathergood et al. (2019) find that consumers do not borrow using the lowest interest rate card nor prioritize payment of the card with the highest interest rate. Chetty et al. (2020) shows that credit card spending does not react to anticipated income shocks. Second, and in contrast with the competing hypothesis that information provision is not meaningful (for example, because individuals mistrust the source or because it is not salient), growing evidence in similar settings indicates that participants retain information provided in the context of an information treatment for months after the experiment (see Cavallo, Cruces, and Perez-Truglia, 2017; Bottan and Perez-Truglia, 2020a) or even a year later. This suggests that it is unlikely that participants in our experiment simply discard the acquired information when making consumption decisions. Lastly, providing information with similar methods has been shown to affect behavior significantly in other contexts. For instance, individuals change their effort after updating beliefs about their future earnings potential (Cullen and Perez-Truglia, 2018) and delay home sales when updating beliefs about future home prices in the area (Bottan and Perez-Truglia, 2020b).

Our results have direct implications for the transmission of macroeconomic policy. Many macroeconomic policies are explicitly based on the premise that changes in economic expectations will affect households' consumption choices. For example, central banks may try to engineer higher inflation expectations to stimulate spending (Bachmann, Berg, and Sims, 2015), or they may try to manipulate expectations about the exchange rate to affect the consumption of foreign goods. Our results suggest that such policies might be ineffective, or at least less effective than previously believed, because consumers do not factor macroeconomic expectations into their consumption decisions.

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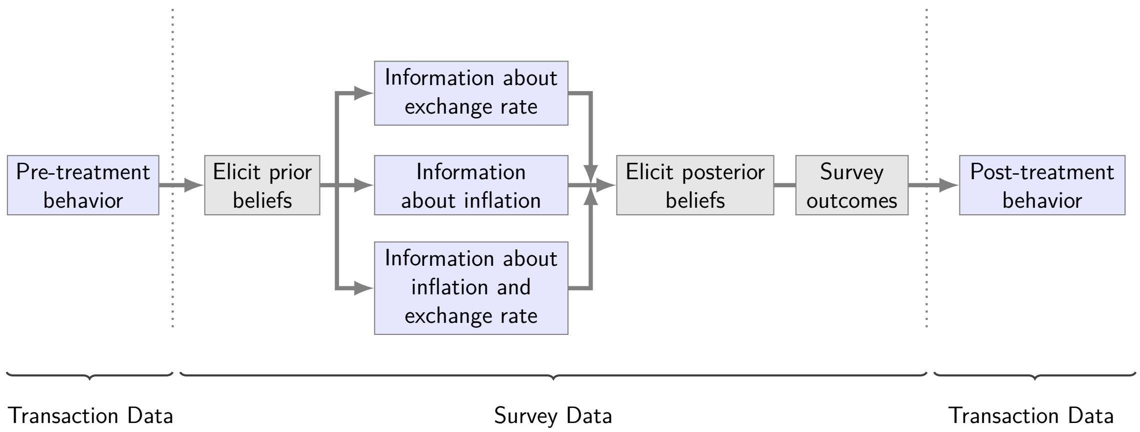
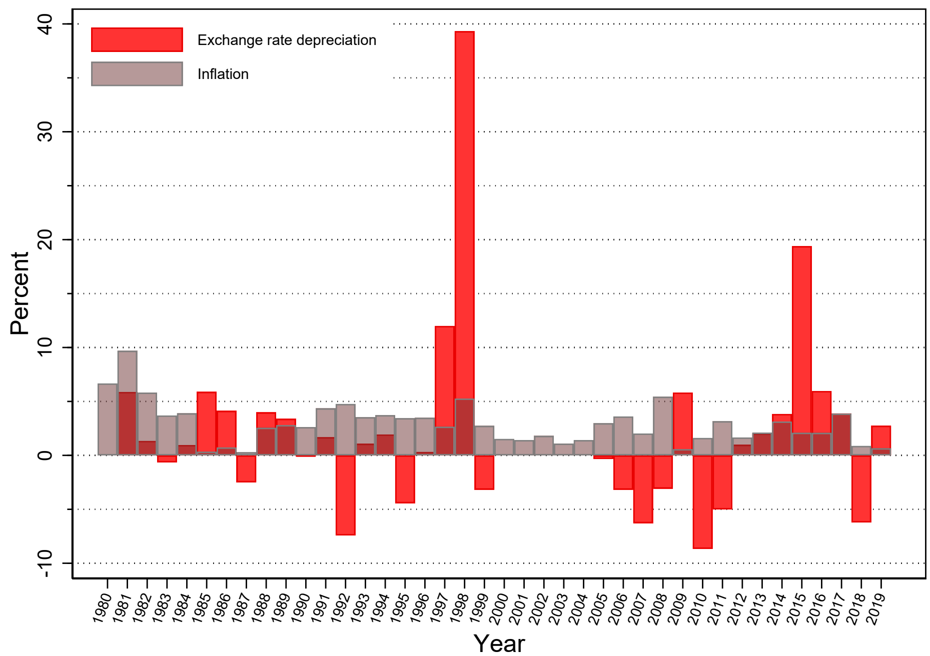
Figure 1: Experimental Design



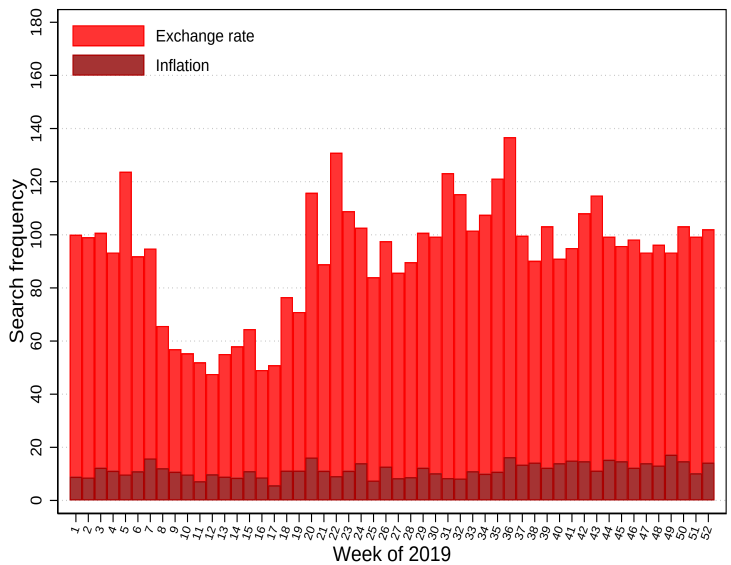
Notes: The figure summarizes the treatment conditions and timeline.

Figure 2: Inflation and Nominal Exchange Rate 1980-2019

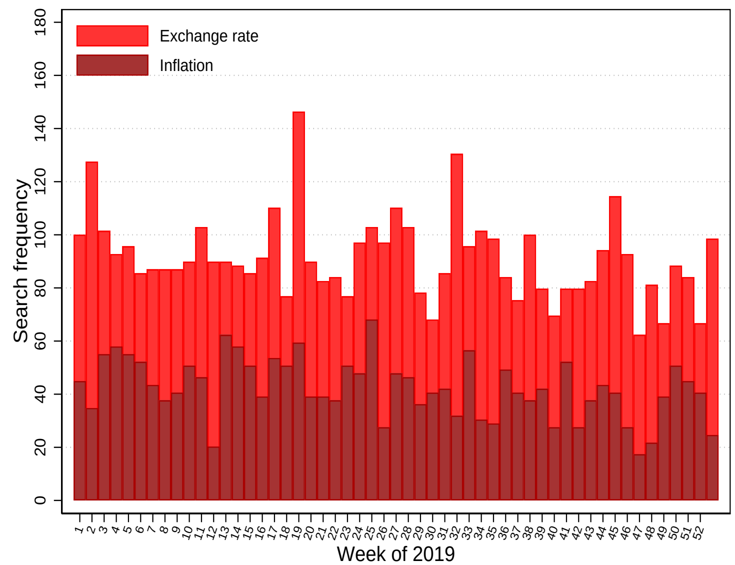


Notes: The figure shows the time series of the annual inflation rate and the time series of changes in the nominal exchange rate of the Malaysian Ringgit against the U.S. Dollar for the period 1980-2019. Source: Federal Reserve Bank of St. Louis.

Figure 3: Public Interest in Inflation and the Exchange Rate



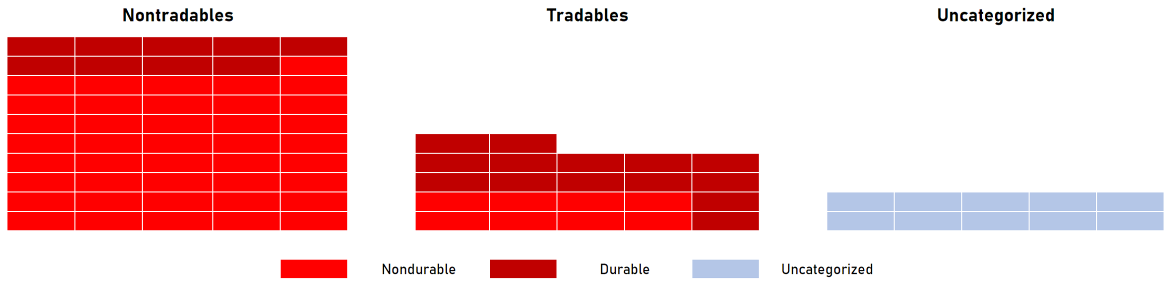
(a) Google Searches



(b) Newspaper Articles

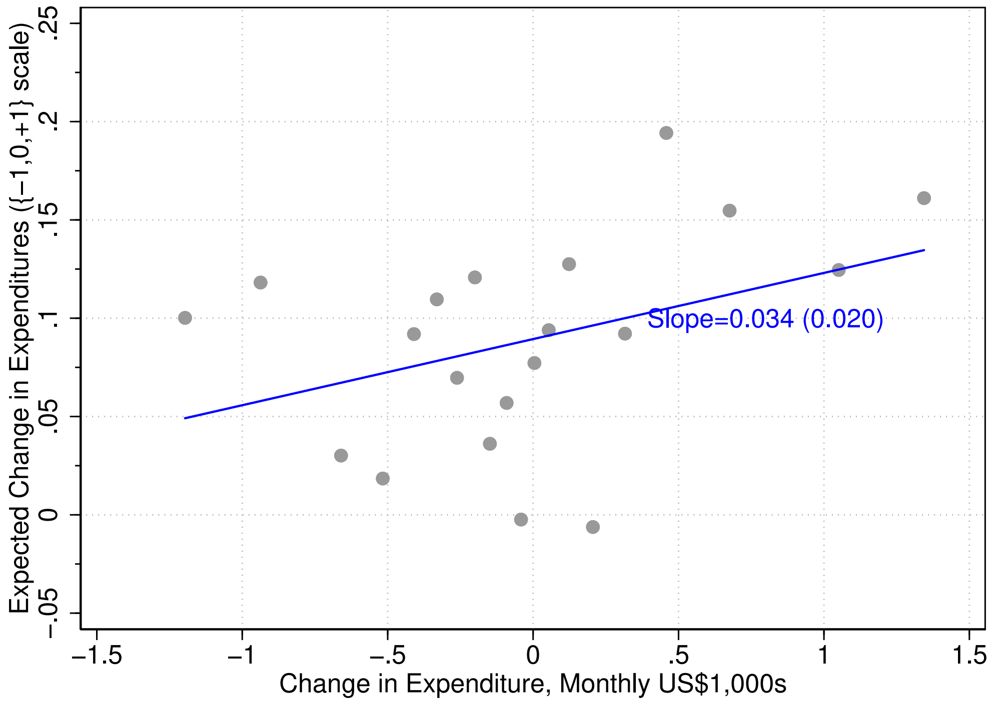
Notes: The figure shows descriptive statistics on public interest in inflation and the nominal exchange rate. Panel (a) shows the frequency of Google searches for the terms "inflation" and "dollar" in English and Malay between January and December 2019. Data on Google searches is reported only in relative terms with reference to a numeraire category. We therefore normalize the series so that exchange rate searches in the first week of 2019 are equal to 100. Panel (b) shows the frequency of articles containing the terms "inflation" and "dollar" in the country's most widely read English language newspaper between January and December 2019 (100=70 articles).

Figure 4: Expenditures by Category



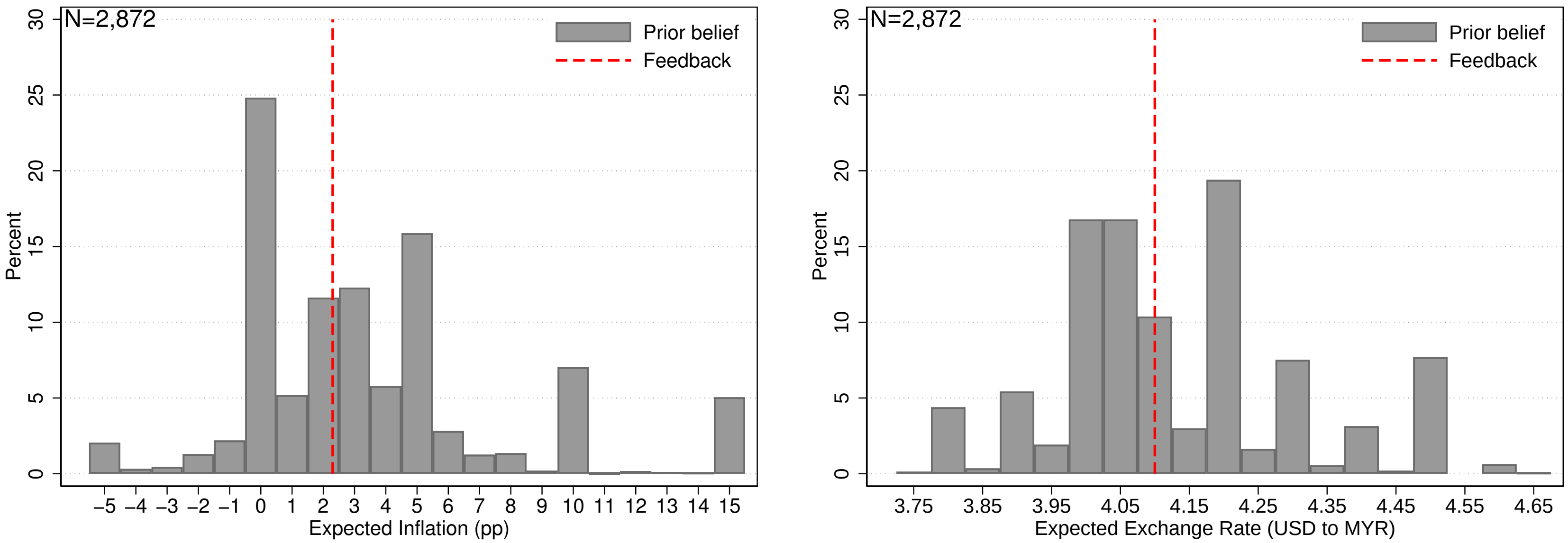
Notes: Each of the 82 squares in the figure represent $\frac{1}{82}$ of the total spending in the credit card data. The leftmost group of squares corresponds to spending on nontradable goods, the middle group corresponds to spending on tradables, the rightmost group corresponds to spending that cannot be categorized. The leftmost and middle groups are subdivided into nondurable spending and durable spending. All expenditures were categorized based on MCCs. For additional details, see Table 1.

Figure 5: Self-Reported Spending Plans versus Actual Spending



Notes: The figure shows the relationship between the actual change in credit card expenditures, measured in administrative data, and self-reported spending plans, based on survey data. The regression controls for surveyor and week fixed effects. Expenditure in administrative data is measured as the difference in average monthly expenditure across three months post-treatment (the post-survey period for which data is available) and average monthly expenditure for the twelve months pre-treatment (the pre-survey period for which data is available). The predicted change in expenditure corresponds to survey responses on planned credit card expenditure, recorded as 1 if a respondent expects to spend more, 0 if they expect to spend about the same, and -1 if they expect to spend less. 'Slope' is the OLS coefficient of the relationship, with robust standard errors in parentheses.

Figure 6: Distribution of Prior Expectations

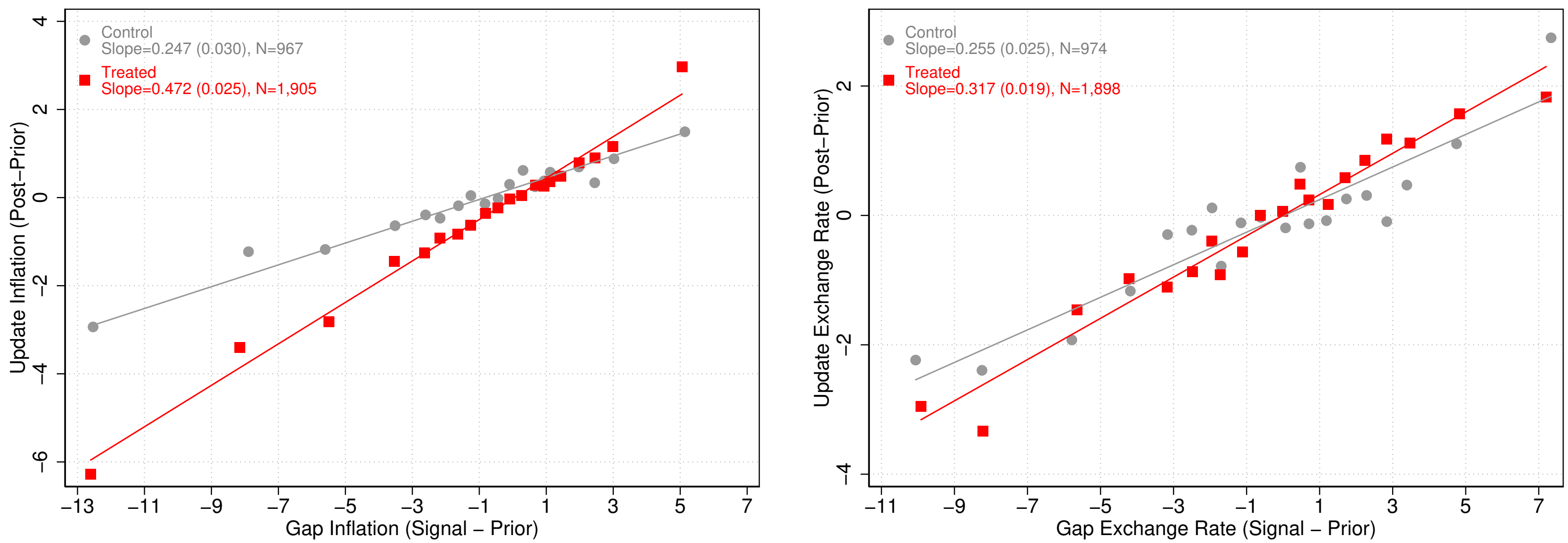


(a) Inflation Priors

(b) Exchange Rate Priors

Notes: The figure shows the distribution of prior beliefs on future inflation in panel (a) and the future nominal exchange rate in panel (b), elicited prior to the information experiment for all survey respondents. Dashed vertical lines correspond to the feedback on the future inflation and exchange rate that was subsequently provided through our intervention.

Figure 7: Belief Updating



(a) Inflation Expectations

(b) Exchange Rate Expectations

Notes: The figure shows the relationship between information shocks provided and changes in inflation expectations in panel (a), and information shocks provided and exchange rate expectations in panel (b). The x-axis in panel (a) plots the gap between the inflation signal shown to respondents and their prior inflation expectations $\pi_{i,t}^{signal} - \pi_{i,t}^{prior}$, while the y-axis plots the difference between prior and posterior inflation expectations $\pi_{i,t}^{post} - \pi_{i,t}^{prior}$. The x-axis in panel (b) plots the gap between the exchange rate signal shown to respondents and their prior exchange rate expectations $d_{i,t}^{signal} - d_{i,t}^{prior}$, while the y-axis plots the difference between prior and posterior exchange rate expectations $d_{i,t}^{post} - d_{i,t}^{prior}$. In panel (a), treatment and control groups denote whether the subject was chosen to receive feedback about the inflation rate or not. In panel (b), treatment and control groups denote whether the subject was chosen to receive feedback about the exchange rate or not. The analysis controls for number of dependents, week fixed effects, surveyors fixed effects, and 20 additional variables controlling for spending patterns during the four pre-treatment quarters.

Table 1: Durable and Tradable Expenditures

	Avg. Monthly Expenditure (1)	Durables (%) (2)	Tradables (%) (3)
Airline and travel	2,746	0	0
Apparel	1,010	100	100
Automotive	1,472	100	64
Books and stationery	168	100	100
Business services	1,706	0	0
Camera and photo	75	33	33
Car rental	58	0	0
Computer equipment	472	100	100
Department store	1,028	100	100
Dept store	1,032	100	100
Dining	2,224	0	0
Direct marketing	1,313	0	0
Education	269	100	0
Electronics	944	100	66
Entertainment	198	0	0
Financial services	663	0	0
Food and beverage	2,054	0	0
Furniture	695	100	66
Government	750	0	0
Groceries	1,970	0	0
Health and beauty	1,143	0	50
Home improvement	539	100	60
Hotel	82	0	0
Insurance	672	0	0
Jewellery and watches	614	100	100
Medical and optical	1,089	100	16
Music store	112	0	100
Others	684	0	7
Petrol	3,105	0	100
Retail	930	0	0
Sporting store	295	100	100
Telecommunication	1,665	100	33
Toys	96	100	100
Utilities	783	0	0
Uncategorized	4,392	–	–

Notes: The table shows average monthly credit card spending by Merchant Category Code (MCC) groups, and the classification of MCC groups according to whether they are tradable or durable. Column (1) shows monthly spending by category. Columns (2) and (3) report the share of purchases in each category that are classified as durable and tradable goods, respectively.

Table 2: Summary Statistics for Participants and Non-Participants

		Responded to survey		
	All	Yes	No	p-value
	(1)	(2)	(3)	(4)
Panel A: demographics				
Male	0.62	0.67	0.57	0.000
	(0.01)	(0.01)	(0.01)	
Age	33.59	33.28	33.88	0.001
	(0.09)	(0.13)	(0.13)	
Monthly income	3,087	3,128	3,049	0.113
	(24.97)	(34.28)	(36.09)	
Panel B: monthly expenditures, pre–treatment				
Total	1,106.26	1,135.15	1,079.74	0.221
	(22.82)	(28.92)	(34.80)	
Durables	349.09	371.08	328.90	0.012
	(8.27)	(13.56)	(9.80)	
Tradable durables	262.52	275.37	250.72	0.091
	(7.20)	(11.90)	(8.45)	
Debt balance	1,811	1,805	1,817	0.863
	(37.81)	(47.52)	(57.93)	
Observations	6,000	2,872	3,128	

Notes: The table reports summary statistics on survey respondents and non-respondents. Panel A reports demographic characteristics, based on the bank's administrative data. Panel B reports summary statistics on pre-treatment spending, based on average monthly credit card spending in the 12 months prior to the experiment. Column (1) reports summary statistics for the full sample, column (2) reports summary statistics for credit card customers who participated in the experiment and column (3) reports statistics for customers that we attempted to contact, but who did not participate in the experiment. Column (4) reports p-values for a test for equality of means between the group of survey respondents and non-respondents. Robust standard errors of the mean in parentheses.

Table 3: Randomization Balance Test

	All	Treatment			
		Exchange Rate	Inflation Rate	Both	*p*-value
	(1)	(2)	(3)	(4)	(5)
Panel A: demographics					
College	0.87	0.86	0.87	0.86	0.36
	(0.01)	(0.01)	(0.01)	(0.01)	
Married	0.54	0.53	0.54	0.52	0.19
	(0.01)	(0.01)	(0.01)	(0.02)	
Number of dependents	0.86	0.82	0.87	0.82	0.09
	(0.02)	(0.03)	(0.03)	(0.04)	
Self-employed	0.10	0.09	0.09	0.09	0.61
	(0.01)	(0.01)	(0.01)	(0.01)	
Monthly income	3,128	3,132	3,128	3,136	0.99
	(34.28)	(42.53)	(41.81)	(60.45)	
Panel B: monthly expenditures, pre-treatment					
Total	1,168.65	1,171.97	1,163.74	1,165.37	0.98
	(33.69)	(44.79)	(40.61)	(66.65)	
Durables	379.15	394.33	360.79	372.50	0.30
	(16.82)	(24.13)	(13.08)	(21.10)	
Tradable durables	277.51	289.64	262.64	271.81	0.37
	(15.34)	(22.33)	(10.31)	(16.64)	
Debt	1,915	1,889	1,939	1,911	0.69
	(47.64)	(57.41)	(61.13)	(88.00)	
Panel C: prior beliefs					
Prior exchange rate	-0.29	-0.37	-0.19	-0.27	0.16
	(0.08)	(0.10)	(0.10)	(0.14)	
Prior inflation	3.39	3.47	3.28	3.32	0.13
	(0.08)	(0.10)	(0.09)	(0.13)	
Observations	2,872	967	974	931	

Notes: The table reports pre-treatment characteristics and a test of randomization balance. Panel A reports demographic characteristics, based on the bank's administrative data. Panel B reports summary statistics on average monthly credit card spending in the 12 months prior to the experiment by category. Panel C reports data on prior beliefs elicited before respondents reached the information provision stage of the experiment. Column (1) reports pre-treatment characteristics for all survey respondents, columns (2) to (4) report the same characteristics for each of the three treatment conditions, that is, for respondents assigned to receive information about the exchange rate, the inflation rate, or both. Column (5) reports p-values of a test for the null hypothesis that the average pre-treatment characteristics are equal between the three treatment groups. Robust standard errors of the mean in parentheses.

Table 4: Effects of Information on Expectations and Behavior: Reduced Form Estimates

	Survey Data		Transaction Data			
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Inflation	Δ Depreciation	Durables	Trad. Dur.	Debt	Total
$\left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) \cdot T_{i,t}^{\pi}$	0.237***	0.033	1.960	1.698	10.388	-2.082
	(0.037)	(0.026)	(2.797)	(2.095)	(6.534)	(6.253)
$\left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) \cdot T_{i,t}^{d}$	-0.031	0.065**	-3.238	-2.514	4.675	-4.835
	(0.023)	(0.031)	(2.599)	(1.944)	(6.901)	(6.114)
Observations	2,872	2,872	2,872	2,872	2,872	2,872
R^2	0.393	0.237	0.256	0.202	0.049	0.367
Outcome mean	-0.369	-0.212	258.810	178.862	96.968	972.570
Outcome SD	2.695	2.837	342.577	254.511	760.368	926.298

Notes: Each column corresponds to a separate OLS regression with the same independent variables but different dependent variables. These regressions present the reduced-form effects of the information provision experiment. Column (1) corresponds to equation (4), column (2) to equation (5) and columns (3) through (6) correspond to equation (6). $\left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right)$ is the gap between the feedback about inflation rate that could be shown to the individual and the individual's prior belief about the inflation rate. $T_{i,t}^{\pi}$ is an indicator variable that takes the value 1 if the feedback was shown to the subject and 0 otherwise. $\left(d_{i,t}^{signal} - d_{i,t}^{prior}\right)$ and $T_{i,t}^{d}$ are the corresponding variables for the exchange rate instead of the inflation rate. All regressions control for $\left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right)$ and $\left(d_{i,t}^{signal} - d_{i,t}^{prior}\right)$ as well as the usual set of additional controls: number of dependents, week fixed effects, surveyors fixed effects, and 20 variables on the spending patterns during the four pre-treatment quarters. The dependent variables are listed as follows. Δ *Inflation* is the difference between the posterior and prior beliefs on the inflation rate (i.e., $\pi_{i,t}^{post} - \pi_{i,t}^{prior}$). Δ *Depreciation* is the difference between the posterior and prior beliefs on the exchange rate (i.e., $d_{i,t}^{post} - d_{i,t}^{prior}$). *Durables* is the monthly average expenditure across 3 months post-treatment in the durables category. *Trad. Dur.* is the monthly average expenditure across 3 months post-treatment in the tradable durables category. *Debt* is the monthly credit card debt accrued in the 3 months post-treatment. *Total* is the total average expenditure across 3 months post-treatment. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effects of Expectations on Behavior: Instrumental Variables Estimates

	Transaction Data			
	(1) Durables	(2) Trad. Dur.	(3) Debt	(4) Total
Δ Inflation	14.276	11.781	31.765	1.468
	(12.681)	(9.379)	(31.557)	(27.079)
Δ Exchange rate	-43.104	-33.132	87.071	-73.771
	(42.963)	(32.161)	(110.008)	(95.844)
Observations	2,872	2,872	2,872	2,872
Outcome mean	258.810	178.862	96.968	972.570
Outcome SD	342.577	254.511	760.368	926.298

Notes: Each column corresponds to a separate Instrumental Variables regression. The endogenous variables are: Δ *Inflation* is the difference between the posterior and prior beliefs on the inflation rate (i.e., $\pi_{i,t}^{post} - \pi_{i,t}^{prior}$); Δ *Exchange Rate* is the difference between the posterior and prior beliefs on the exchange rate (i.e., $d_{i,t}^{post} - d_{i,t}^{prior}$). The excluded instruments are $\left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) \cdot T_{i,t}^{\pi}$ and $\left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) \cdot T_{i,t}^{d}$. All regressions control for $\left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right)$ and $\left(d_{i,t}^{signal} - d_{i,t}^{prior}\right)$ as well as the usual set of additional controls: number of dependents, week fixed effects, surveyors fixed effects, and 20 variables on spending patterns during the four pre-treatment quarters. The dependent variables are listed as follows. *Durables* is the monthly average expenditure across 3 months post-treatment in the durables category. *Trad. Dur.* is the monthly average expenditure across 3 months post-treatment in the tradable durables category. *Debt* is the monthly credit card debt accrued in the 3 months post-treatment. *Total* is the total average expenditure across 3 months post-treatment. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects of Expectations on Behavior: OLS Estimates

	Transaction Data			
	(1)	(2)	(3)	(4)
	Durables	Trad. Dur.	Debt	Total
Δ Inflation	-1.706	-0.352	-5.402	5.793
	(1.982)	(1.405)	(4.849)	(5.114)
Δ Exchange rate	-0.607	-0.686	-6.857	-4.419
	(2.005)	(1.551)	(4.806)	(4.842)
Observations	2,872	2,872	2,872	2,872
R^2	0.255	0.201	0.049	0.367
Outcome mean	258.810	178.862	96.968	972.570
Outcome SD	342.577	254.511	760.368	926.298

Notes: Each column corresponds to a separate OLS regression. Δ *Inflation* is the difference between the posterior and prior beliefs on the inflation rate (i.e., $\pi_{i,t}^{post} - \pi_{i,t}^{prior}$). Δ *Exchange Rate* is the difference between the posterior and prior beliefs on the exchange rate (i.e., $d_{i,t}^{post} - d_{i,t}^{prior}$). All regressions include the usual set of additional controls: number of dependents, week fixed effects, surveyors fixed effects, and 20 variables on spending patterns during the four pre-treatment quarters. The dependent variables are listed as follows. *Durables* is the monthly average expenditure across 3 months post-treatment in the durables category. *Trad. Dur.* is the monthly average expenditure across 3 months post-treatment in the tradable durables category. *Debt* is the monthly credit card debt accrued in the 3 months post-treatment. *Total* is the total average expenditure across 3 months post-treatment. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effects of Information on Expectations and Survey Outcomes: Reduced Form Estimates

	Survey Data					
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Inflation	Δ Depreciation	Dur.	Trad. Dur.	Debt	Total
$\left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) \cdot T_{i,t}^{\pi}$	0.237***	0.033	-0.001	-0.001	-0.003	-0.006
	(0.037)	(0.026)	(0.007)	(0.007)	(0.008)	(0.006)
$\left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) \cdot T_{i,t}^{d}$	-0.031	0.065**	0.005	0.002	0.008	0.003
	(0.023)	(0.031)	(0.007)	(0.007)	(0.007)	(0.006)
Observations	2,872	2,872	2,872	2,872	2,872	2,872
R^2	0.393	0.237	0.029	0.033	0.072	0.037
Outcome mean	-0.369	-0.212	-0.055	0.005	-0.055	0.088
Outcome SD	2.695	2.837	0.857	0.775	0.857	0.665

Notes: Each column corresponds to a separate OLS regression. These regressions present the reduced-form effects of the information provision experiment: column (1) corresponds to equation (4), column (2) to equation (5) and columns (3) through (6) correspond to equation (6). $\left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right)$ is the gap between the feedback about inflation rate that could be shown to the individual and the individual's prior belief about the inflation rate, while $T_{i,t}^{\pi}$ is an indicator variable that takes the value 1 if the feedback was shown to the subject and 0 otherwise. $\left(d_{i,t}^{signal} - d_{i,t}^{prior}\right)$ and $T_{i,t}^{d}$ are the corresponding variables for the exchange rate instead of the inflation rate. All regressions control for $\left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right)$ and $\left(d_{i,t}^{signal} - d_{i,t}^{prior}\right)$ as well as the usual set of additional controls: number of dependents, week fixed effects, surveyors fixed effects, and 20 variables on spending patterns during the four pre-treatment quarters. The dependent variables are listed as follows. Δ *Inflation* is the difference between the posterior and prior beliefs on the inflation rate (i.e., $\pi_{i,t}^{post} - \pi_{i,t}^{prior}$). Δ *Depreciation* is the difference between the posterior and prior beliefs on the exchange rate (i.e., $d_{i,t}^{post} - d_{i,t}^{prior}$). The dependent variables in columns (3) through (6) correspond to the stated future consumption as measured in the survey, and they can take values +1 (if participants say they are going to spend more), 0 (if they say that they are going to spend about the same) or -1 (if they are going to spend less). *Durables* corresponds to the future spending in durables, *Trad. Dur.* correspond to the future spending in electronics, *Debt* corresponds to future credit card borrowing, and *Total* corresponds to total future spending. Robust standard errors in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix (For Online Publication Only)

A Proof of Propositions

A.1 Lemma 1

The three statements are true:
(1) C_t^N and C_t^T are non-decreasing in π_{t+1}^N and π_{t+1}^T.
(2) X_t^N is increasing in π_{t+1}^N. X_t^T is increasing in π_{t+1}^T.
(3) X_t^N is non-decreasing in π_{t+1}^T. X_t^T is non-decreasing in π_{t+1}^N.

Proof:

Observe that Cobb-Douglas structure of preferences allows us to write a closed form solution for C_t^N:

$$C_t^N = \frac{\alpha\theta}{\sum_{k=0}^{\infty}\beta^k}\frac{\sum_{k=0}^{\infty}P_{t+k}^N Y_{t+k}/\prod_{i=1}^k R_{t+i}}{P_t^N} =$$

$$\frac{\alpha\theta}{\sum_{k=0}^{\infty}\beta^k}\sum_{k=0}^{\infty}\frac{\prod_{i=1}^k \pi_{t+i}^N Y_{t+k}}{\prod_{i=1}^k R_{t+i}}$$

Hence:

$$\frac{dC_t^N}{d\pi_{t+1}^N} = \frac{\alpha\theta}{\sum_{k=0}^{\infty}\beta^k}\sum_{k=0}^{\infty}\frac{\prod_{i=2}^k \pi_{t+i}^N Y_{t+k}}{\prod_{i=1}^k R_{t+i}} > 0$$

$$\frac{dC_t^N}{d\pi_{t+1}^T} = 0$$

From the first order conditions, one can obtain:

$$\frac{\theta}{1-\theta}\frac{C_t^T}{C_t^N} = \frac{P_t^N}{P_t^T}$$

This implies similar conditions for C_t^T:

$$\frac{dC_t^T}{d\pi_{t+1}^N} > 0 \quad \text{and} \quad \frac{dC_t^T}{d\pi_{t+1}^T} = 0$$

, which concludes the proof of statement (1).

From the first order conditions one gets:

$$\frac{(1-\alpha)C_t^N}{\alpha X_t^N} = \left(1-(1-\delta)\frac{\pi_{t+1}^N}{R_{t+1}}\right)$$

$$\frac{(1-\alpha)C_t^T}{\alpha X_t^T} = \left(1-(1-\delta)\frac{\pi_{t+1}^T}{R_{t+1}}\right)$$

This implies that for $I \in \{N, T\}$, $\frac{X_t^I}{C_t^I}$ increases in π_{t+1}^I. Since by statement (1), C_t^I does not decrease in π_{t+1}^I, X_t^I has to increase. This proves statement (2).
Finally, since i) the conditions pin down the $\frac{X_t^I}{C_t^I}$ for fixed π_{t+1}^I, and ii) C_t^I is non-decreasing in π_{t+1}^{-I}, X_t^I does not decrease in π_{t+1}^{-I} ($-I$ denotes $\{N, T\} \setminus I$), which proves statement (3).

A.2 Proof of Proposition 1

By Assumption 1, an increase in π_{t+1} does not decrease π_{t+1}^I, $I \in \{N, T\}$ and has to strictly increase at least one of them. By Lemma 1, this implies that X_t^I do not decrease and at least one of them increases. Since X_{t-1}^I and P_t^I are fixed, the same is true for $P_t^I \Delta X_t^I$. Hence, $P_t^N \Delta X_t^N + P_t^T \Delta X_t^T$ increases in π_{t+1}.

A.3 Proof of Proposition 2

By Assumption 2, π_{t+1}^T increases in E_{t+1}. By Lemma 1, this implies that X_t^T increases in E_{t+1}. Hence $P_t^T \Delta X_t^T$ increases in E_{t+1}.

A.4 Proof of Proposition 3

$$A_{t+1} = P_t Y_t + R_t A_t - P_t^N (C_t^N + X_t^N - X_{t-1}^N + \delta X_t^N) -$$

$$-P_t^T (C_t^T + X_t^T - X_{t-1}^T + \delta X_t^T)$$

By Assumption 1, neither π_{t+1}^T nor π_{t+1}^T decrease, and at least one of them increases with π_{t+1}. This and Lemma 1 imply that neither of C_t^I and X_t^I, $I \in \{N, T\}$ decreases, and at least one of X_t^I increases. Hence, A_{t+1} decreases and $A_t - A_{t+1}$ increases.

B Further Details and Analysis

B.1 Event-Study Falsification Tests

we leverage data on pre-treatment spending, which allows us to conduct a falsification test in the spirit of an event-study analysis. We estimate a similar regression as in equation (6) but using pre-treatment instead of post-treatment spending as the dependent variables:

$$\begin{aligned} Y_{i,t-1} \;&= \alpha_Y^{\pi} \cdot \left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) \cdot T_{i,t}^{\pi} + \alpha_Y^{d} \cdot \left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) \cdot T_{i,t}^{d} + \\ &\beta_Y^{\pi} \cdot \left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) + \beta_Y^{d} \cdot \left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) + X_{i,t}\gamma_Y + \epsilon_i \end{aligned} \tag{B.1}$$

The dependent variable $Y_{i,t+1}$ refers to the average monthly spending in the 3 months pre-treatment, and the set of control variables ($X_{i,t}$) include just the number of dependents, week fixed effects, surveyors fixed effects.

The results are presented in Table B.1. Since the outcomes are measured at a point in time when participants had not yet been provided with information, there should be no effects of the information on pre-treatment spending. As expected, we find no "effects" of the information shocks on the pre-treatment spending outcomes. For example, the first coefficient from column (1) indicates that a 1 pp increase in the inflation shock had an "effect" on pre-treatment spending on durables that is close to zero (\$0.185, or <0.001 standard deviations) and statistically insignificant. Likewise, the rest of the coefficients from Table B.1 are close to zero and statistically insignificant.

Table B.1: Effects of Information on Behavior: Event-Study Falsification Tests

	Transaction Data			
	(1)	(2)	(3)	(4)
	Durables	Trad. Dur.	Debt	Total
$\left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right) \cdot T_{i,t}^{\pi}$	-0.185	-1.887	2.579	1.578
	(2.711)	(1.972)	(6.619)	(6.044)
$\left(d_{i,t}^{signal} - d_{i,t}^{prior}\right) \cdot T_{i,t}^{d}$	0.006	-2.489	-10.559	0.929
	(2.724)	(2.098)	(6.915)	(6.329)
Observations	2,872	2,872	2,872	2,872
R^2	0.225	0.165	0.024	0.349
Outcome mean	287.275	197.855	155.947	992.434
Outcome SD	355.020	261.687	798.017	931.151

Notes: Each column corresponds to a separate OLS regression with the same independent variables but different dependent variables. All regression corresponds to equation (B.1). $\left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right)$ is the gap between the feedback about inflation rate that could be shown to the individual and the individual's prior belief about the inflation rate. $T_{i,t}^{\pi}$ is an indicator variable that takes the value 1 if the feedback was shown to the subject and 0 otherwise. $\left(d_{i,t}^{signal} - d_{i,t}^{prior}\right)$ and $T_{i,t}^{d}$ are the corresponding variables for the exchange rate instead of the inflation rate. All regressions control for $\left(\pi_{i,t}^{signal} - \pi_{i,t}^{prior}\right)$ and $\left(d_{i,t}^{signal} - d_{i,t}^{prior}\right)$ as well as the following set of additional controls: number of dependents, week fixed effects, and surveyors fixed effects. The dependent variables are listed as follows. *Dur.* is the monthly average expenditure across 3 months pre-treatment in the durables category. *Trad. Dur.* is the monthly average expenditure across 3 months pre-treatment in the tradable durables category. *Debt* is the monthly credit card debt accrued in the 3 months pre-treatment. *Total* is the total average expenditure across 3 months pre-treatment. Robust standard errors in parentheses. $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Survey Instrument

Hello! My name is [Surveyor name]. I am working for researchers at the University of California, Los Angeles, currently working in Malaysia. We are conducting a short survey to know Malaysians overall economical situation. Do you have 5 minutes to respond to the survey?

- Yes
- No

[**If the answer to the previous question was "yes":**] **Great, thank you so much. By the way, if you'd prefer to do the survey in Alternative Language, let me know. I will start asking a few questions about your background.**

What is your current employment situation?

- Full-time employee
- Part-time employee
- Self-employed
- Not working

What is your highest education level?

- No school
- High school
- College or some college
- After bachelor degree

Are you married or single?

- Married
- Single
- Divorced

Do you have any children or other dependents that you look after?

- Yes
- No

[If the answer to the previous question was "yes":] How many?

- 1
- 2
- 3
- 4
- 5 or more

Regarding business conditions in the country as a whole, do you think that during the next 12 months the Malaysian economy will be better off, about the same, or worse off?

- Better off
- About the same
- Worse off

Now we want to ask you about the annual inflation rate, which is a measure of how prices in Malaysia change in general. In your opinion, what will be the inflation rate over the next 12 months?

- [ ] %

Now we want to ask you about the exchange rate. As of April 2019, 1 U.S. Dollar is worth around 4.05 Ringgit Malaysia. In your opinion, what will the exchange rate be 12 months from now, in April 2020?

- [ ] Ringgit Malaysia

In this stage, we randomly select respondents to receive some feedback about the previous questions... subjects are randomly allocated to one of the following three treatment groups:

Treatment Exchange Rate: **The consensus among economic experts both from the government and the private sectors is that 1 U.S. Dollar will be worth 4.10 Ringgit Malaysia one year from now.**

Treatment Inflation: **The consensus among economic experts both from the government and the private sectors is that the inflation in Malaysia will be 2.3% over the next 12 months.**

Treatment Both: **The consensus among economic experts both from the government and the private sectors is that the inflation in Malaysia will be 2.3% over the next 12 months and 1 U.S. Dollar will be worth 4.10 Ringgit Malaysia one year from now.**

What will the inflation rate be over the next 12 months?

- [ ] %

What will be the exchange rate from U.S. Dollar to Ringgit 12 months from now, in April 2020?

- [ ] Ringgit Malaysia

Regarding business conditions in the country as a whole, do you think that during the next 12 months the Malaysian economy will be better off, about the same, or worse off?

- Better off
- The same
- Worse off

Looking forward, would you say that you and your family living with you will be better off or worse off financially than you are now?

- Better off
- About the same
- Worse off

Do you expect your credit card spending to go up, stay the same, or go down during the next 3 months?

- Go up
- Stay the same
- Go down

Do you expect that your spending on groceries to go up, stay the same, or go down during the next 3 months?

- Go up
- Stay the same
- Go down

Do you expect your total spending to go up, stay the same, or go down during the next 3 months?

- Go up
- Stay the same
- Go down

Do you think now is a good time, a bad time, or neither a good nor a bad time to buy household items, such as furniture or a refrigerator? More examples: television, stove or others

- Yes, it's a good time
- It's neither a good nor a bad time
- No, it's a bad time

Do you think now is a good time, a bad time, or neither a good nor a bad time to buy electronic items, such as a computer, TV, phone, washing machine and so on?

- Yes, it's a good time
- It's neither a good nor a bad time
- No, it's a bad time

Do you think now is a good time, a bad time, or neither good nor a bad time to buy a vehicle, car or motorbike?

- Yes, it's a good time
- It's neither a good nor a bad time
- No, it's a bad time

Do you think now is a good time, a bad time, or neither good or bad time to buy big items on an installment basis? [If asked, provide the following examples: installments such as AEON Credit, Courts Mammoth; items such as a car, motorbike, television set, washing machine and so on.]

- Yes, it's a good time
- It's neither a good nor a bad time
- No, it's a bad time