Borrowing on the Wrong Credit Card? Evidence from Mexico

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We establish new facts about the way consumers allocate debt among their credit cards using data for a representative sample of cardholders in Mexico. We find that relative prices are weak predictors of the allocation of debt, purchases, and payments. Consumers allocate a large fraction of their debt to high-interest cards, incurring a cost of 31% above the minimum. Using an experiment, we find that consumers do not substitute in the price margin, although they respond to salient temporary low-interest offers. We conclude that limited attention and mental accounting best rationalize our results and discuss implications for the market.
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Many individuals devote a significant fraction of their income to paying their debts. It seems reasonable to expect debtors to look for ways to save on interest charges by substituting expensive debt for less costly alternatives. In this paper we explore this hypothesis in the domain of credit card borrowing and find evidence against this assumption. We study how consumers allocate their credit card debt among their existing credit cards, taking the interest rates on such cards as given. In particular, we assess whether consumers minimize financing costs by borrowing on their lower-interest cards. To do this, we build a novel administrative panel data set containing the account records of *all* credit cards held by more than

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10,000 consumers drawn randomly from a nationally representative sample of the population of cardholders in Mexico in 2004 and 2005. The data set contains monthly statements, demographic information, and credit bureau records.

Our analysis takes advantage of the fact that, at the time in Mexico, there were few credit card products on the market and there was little differentiation among them. This enables us to match cards that are comparable to one another for a large number of consumers and to cleanly study arbitrage opportunities across similar financial instruments in a setting in which switching and search costs are small. Our analysis also benefits from substantial variation in the *difference* in interest rates across the cards held by each individual —1.1% *per month* on average— arising from preferential rates offered to banks' customers and from temporary reductions in interest rates (teaser rate offers or TROs).

We find that, on average, consumers allocate a large fraction of their debt to high-interest cards, even when they could save substantially on interest by borrowing on their low-interest cards. The leftmost panel of Figure 1 shows a histogram of the fraction of interest-paying debt allocated to the low-interest card by individuals holding two comparable credit cards. For comparison, the rightmost panel of Figure 1 plots the distribution that would have been observed had these individuals allocated debt up to the credit limit on their low-interest card and the rest to their high-interest card. The difference between these histograms is noteworthy: the average consumer misallocates 24% of her total debt and as a result pays 31% more in interest. We obtain similar results when we analyze the patterns of flow allocations: the average cardholder misallocates 47% of her purchases and 50% of her payments, suggesting that the cost of switching debt across cards is not driving these findings. These results are quite robust across sub-samples, replicate across different data sets, and persist over time. In an exercise similar to that of Agarwal et al. (2013), we find that while consumers learn to avoid salient fees, they do not learn to avoid extra interest.

To complement this analysis, we use a market experiment within our sample to estimate own and cross-card price elasticities. Exploiting random variation in the assignment of one-month and three-month low-interest TROs, we show that consumers respond to salient reductions in the interest rate by increasing their total debt. However, consistent with the documented low substitution across cards, consumers fail to reallocate their debt from high-interest to low-interest cards when receiving these offers. We estimate within card elasticities of debt to one-month and three-month temporary reductions in the interest rate of -0.57 and -0.84, respectively. In contrast, the corresponding cross-price elasticities are not significantly different from zero.

The main results are organized into five stylized facts, discussed in detail in Section III. After firmly establishing these facts, we explore a variety of economic theories that could explain them. To this end, we supplement the data with a battery of auxiliary administrative data sets and a tailor-made survey of 1,005 cardholders conducted in Mexico City by a professional polling company. Using model simulations and these additional data sets, we show that explanations based upon pecuniary switching costs and stochastic interest rates, purchase indivisibilities, uncertainty in credit limits and fees, and heterogeneity in card attributes, among others, are unlikely to rationalize the results. In contrast, the findings could be parsimoniously explained by limited attention and mental accounting, although, due to data limitations, this explanation is tentative. Our interpretation is as follows: consumers seem to pay little attention to contractual interest rates when making purchases or payments on their credit cards as these rates are not salient. They instead rely on mental accounts to organize their credit card purchases and payments. When receiving a TRO on a given card, consumers pay attention to the now salient low interest rate and increase their borrowing on that particular card without decreasing their debt on the other unattended card. The paper ends with a discussion of how our demand-side findings could affect firm behavior and competition.

Our paper contributes to several strands of the literature. First, it adds to the growing body of evidence showing that some consumers seem to make suboptimal financial decisions [Ausubel (1991), Shui and Ausubel (2005), Agarwal et al. (2015a), Benartzi and Thaler (2001), Choi et al. (2011), Hall and Woodward (2012), Stango and Zinman (2009), Lusardi and Mitchell (2008), Lusardi and Tufano (2009)], and it provides evidence pointing to the role of limited attention and mental accounting in explaining this behavior [Agarwal et al. (2013), Malmendier and Lee (2011), Ito (2014), Chetty et al. (2009), and Finkelstein (2009)]. Second, it contributes to the nascent Behavioral Industrial Organization literature by showing that relative prices are not important drivers of behavior in this important market, and that banks have incentives to respond to this low degree of substitution across cards by adjusting their pricing strategies. Third, it complements and helps interpret the literature on choice and borrowing behavior in the credit card market. Previous research has shown that, in the extensive margin, cardholders are sensitive to contractual rates and to introductory low-interest offers when they are prompted to choose between contracts [Ausubel (1999), Shui and Ausubel (2005), and Agarwal et al. (2015a)]. We show that in the intensive margin cardholders are also sensitive to interest rates, but *only* when these rates are made salient. Finally, our paper speaks to the so called "Credit Card Puzzle" (Gross and Souleles (2002) and Bertaut and Haliassos (2006)), which states that by simultaneously having expensive credit card debt and low yielding savings in deposit accounts, consumers forego profitable arbitrage opportunities. Telyukova and Wright (2008) and Telyukova (2013) claim that this puzzle can be explained by the fact that money is more liquid than credit cards. Our work suggests that liquidity differences are only part of the explanation, as we study financial instruments with the same liquidity and still find a puzzle.

The paper most closely related to ours is Stango and Zinman (2015). Using an internet panel of credit card borrowers in the U.S., these authors find that consumers seem to minimize financing costs when allocating their credit card debt, which is counter to our results for Mexico. Their sample, however, consists of a panel of voluntary online survey participants who have higher incomes and education than the U.S. average and therefore, who are potentially more financially sophisticated than the U.S. and Mexican population.[1] Our results are closer to those of Gross and Souleles (2002), who use a large account-level administrative data set from various financial institutions in the U.S. to identify interest rate elasticities of borrowing.

This paper has important advantages over previous research. First, it relies on a very high quality administrative data set that was explicitly drawn to be representative of a country's population and that contains the *full set* of consumers' credit card accounts. This data set is supplemented with industry randomized experiments to cleanly identify own and cross price elasticities, and with an in-depth face-to-face survey that was collected to directly elicit the reasons why cardholders misallocate their debt. Second, it is one of the first papers to study household financial decisions in a middle-income country with low levels of consumer protection and financial education.

The remainder of the paper is organized as follows. Section I presents a brief description of the Mexican credit card industry. Section II introduces the main data sources. Section III presents the stylized facts. Section IV discusses potential explanations for these facts. Section V lays out some conjectures about how our results might map to the workings of the market, while Section VI concludes. Due to space constraints, some analyses are reported in the Online Appendix.

I. The Mexican credit card market

The credit market in Mexico has remained relatively underdeveloped in terms of credit penetration, lending practices, and product development. By 2004 —the beginning of our sample period— there were few credit card products available, little differentiation across suppliers, and shallow market penetration. At the time, there were basically four types of credit card products: Classic cards, Gold and Platinum cards, and store cards.[2] Rewards/benefits, fees, initial credit limits, and contractual interest rates were mostly determined at the credit card-type level (e.g., Classic, Gold, etc.) and did not vary with the cardholder's risk profile or the cardholder's card usage.[3] In addition, due to regulatory constraints, only banks were able to issue credit cards and almost all cards were linked to the

[1]For descriptions of the importance of financial literacy, see Lusardi and Tufano (2009) and Lusardi and Mitchell (2008). For analyses of the incidence of financial mistakes among U.S. consumers and their relationship with cognitive ability, seeAgarwal et al. (2015b) and Agarwal and Mazumder (2013).

[2]Classic cards offered no rewards (points, flyer miles, or cash back) or benefits (discounts at restaurants or travel assistance services) and were homogeneous across suppliers. Approximately 65 percent of the cards in circulation were of this type. Gold and Platinum cards offered rewards programs that had similar structures and comparable items for redemption across suppliers. Store cards were limited to in-store purchases.

[3]This was partly because banks were unsophisticated in their statistical pricing techniques and had limited access to reliable information about potential clients from the credit bureau.

Visa and MasterCard organizations that were universally accepted at all point of sale devices. In spite of these constraints, credit card interest rates varied across consumers, as banks offered preferential rates to deposit-account holders, and across time, as banks often extended temporary low-interest TROs to some of their existing borrowers.[4]

The banking industry in general and the credit card industry in particular were, and still are, highly concentrated. The five largest banks held a steady market share of close to 90% from 2001 to 2012. The average credit card interest rate was close to 34% per year, while the proportion of credit card loans in arrears amounted to 3 percent and the government federal discount rate (TIIE) was about 7 percent (Banxico (2006)). High average prices were accompanied by substantial dispersion in interest rates (see the Online Appendix). These and other market indicators led the competition authority (COFECO) to issue a 2007 opinion claiming there was low competition in the credit card market. During these years, Mexican authorities adopted a number of policies and regulations to foster competition. In spite of these policies and a doubling of the number of credit card issuers from 2004 to 2012, there was no significant change in the market share of the largest five banks (see the Online Appendix) and a negligible reduction in prices.

II. Data

Our analysis relies on several data sources. First, to study how consumers allocate debt among their existing credit cards, we constructed an administrative panel data set containing the credit card records of more than 10,000 randomly selected Mexican consumers who had exactly two comparable cards over a 12 month period from 2004 to 2005. Second, to explore whether consumers organize their credit card bills into mental accounts, we acquired a supplementary data set containing the records of the types of purchases made by consumers holding two cards in the same bank in the period from 2007 to 2012. Third, to assess how prevalent online transactions and automatic payments are, we obtained an auxiliary data set containing the transactions undertaken by a random sample of clients of one of our banks. Finally, to examine consumers' motivations for using different credit cards more directly, we hired a professional polling company to implement a tailor-made face-to-face survey in Mexico City.

A. Administrative Data

Our main data set is a panel of high-quality data containing the full set of credit card accounts held by 10,335 individuals. This data set was constructed

[4]It is useful to highlight the differences between TROs and balance transfer offers (BTOs). The former apply to outstanding credit card balances and are mailed to *existing* customers. The latter apply to the outstanding balances *transferred* from another credit card. These offers are mailed to *potential new* customers. TROs are prevalent in Mexico, while BTOs are non-existent (unlike in the U.S.), likely due to supply-side factors and regulatory constraints that we discuss in the Online Appendix.

in collaboration with the Credit Bureau and the three largest commercial banks in Mexico in order to make it representative of the country's population of cardholders. As a first step, we asked the Credit Bureau to draw a random sample of 100,000 consumers who had at least one open credit card in November 2004. The data set contains information on *all* the credit cards held by these consumers, including account numbers and opening dates. With the account numbers in hand, we asked the three largest banks to provide monthly information for every credit card account in the sample for 2004 and 2005. Since the industry was highly concentrated, we were able to match 69% of the cardholders in our original sample. This administrative data set contains all the information included in the accounts' monthly billing statements, including the level of debt, purchases, payments, minimum payments, credit limits, interest rates, and fees. The data also contain information about the type (Classic, Gold, etc.) and name of the credit card product, the joint account status, and for some accounts demographic information collected during the credit card application process. Importantly, the interest rate information in this data set is very precise and corresponds exactly to the rate that consumers see in their monthly statement, inclusive of low-interest offers. The data cover the period from 2004 to 2005 for two banks and from October 2004 to September 2005 for the third, thus our panel is unbalanced. An observation in this data set is a consumer-month.

For the sake of simplicity and to have a clean comparison between homogeneous cards, we restrict attention to individuals holding exactly two active and comparable credit cards issued by one of our three banks. We consider a card to be active if the account remained open between January 1, 2004 and December 31, 2005, regardless of the payments or purchases made during this period. We consider two credit cards to be comparable if they survive the following two-step selection criteria: first, since rewards and contract terms are set at the credit card-type level, we follow the methodology used by CONDUSEF (the Mexican Consumer Protection Bureau) to compare cards and keep only consumers holding two cards of the same type: Classic-Classic, Gold-Gold, or Platinum-Platinum. Second, for each surviving pair of cards we kept those with identical rewards.[5] Finally, we eliminate individuals with less than six months of information as well as individuals holding joint credit card accounts or store cards.[6] The above trim-

[5]To accomplish this we analyzed the rewards programs of all the credit card products offered by our three banks as of 2005 according to their point accrual, redemption criteria, and rewards, and we held interviews with bank officers to classify the different cards' rewards programs. At the time of the study, there were two basic types of rewards programs. The first type involved frequent flyer miles and points that are branded (e.g., VISA-Aeromexico). We did not include any of these cards in our sample. The second type accrued points that were redeemable for a number of items (mostly consumer electronics). At the time, these cards paid back 1% of the total value of the purchases in points and offered an almost identical catalog of items to redeem across providers. We dropped cards that had different redemption values.

[6]We eliminated joint credit card accounts, because our focus is on a single decision maker. We eliminated store cards (credit cards issued by a store and backed by a bank), because the purchases made with these cards are not perfectly interchangeable with the purchases made with the rest of the credit cards.

ming leaves us with a sample of 10,335 consumers and 114,720 consumer-months. This sample is representative of approximately 11 percent of cardholders in Mexico. In this final data, approximately 70 percent of cardholders had two Classic cards.

B. Auxiliary Administrative Data

We supplement the administrative data with other two data sets. The first, which we call the "Purchase-Type" data (PT), contains administrative monthly records of the types of purchases made by 5,000+ clients holding two cards in a fourth bank between 2007 and 2012. The purchases are classified in 38 categories (e.g., groceries versus gas) obtained from information from point-of-sale devices. An observation in this data set is a consumer-card-purchase type-month. The second data set includes the records of all transactions listed on the credit card billing statements of 1,500 random clients of one of our banks during our sample period. An observation in this data set is a consumer-transaction.

C. Survey Data

We commissioned a face-to-face, 50-minute survey of 1,005 cardholders in Mexico City. The survey was conducted from September 2013 to January 2014 using a combination of intercept point sampling and snowball sampling approaches. It contains questions about the characteristics of the respondents' credit cards (type, credit limit, interest rate, etc.); their usage at the time of the survey (debt, purchases, online purchases, payments, etc.); the reasons/rules for allocating debt, purchases, and payments to certain cards; knowledge of the contract terms on the respondents' cards; the occurrences of certain events (like fraud, loss, or theft) and the subjective expectations of such incidents; and demographic data. The Online Appendix provides further details about the survey.

D. Descriptive statistics

Table 1 shows descriptive statistics for selected variables in the administrative and survey data sets for individuals holding one, two, and three cards. Panel A presents the averages and standard deviations per card at the consumer-month level. The other panels show information at the consumer level. Some facts stand out. First, individuals in our main sample (Column 1) carry high debt and pay interest recurrently on their credit cards, despite high interest rates. The average monthly balance on each card equals \$11,068 pesos,[7] which is close to the cardholders' average monthly income (\$14,941 pesos). The average *monthly* debt-weighted interest rate equals 2.5%, and the average cardholder incurs interest charges 90% of the time. Second, most individuals borrow on both cards: 74%

[7]The symbol for a Mexican peso is \$, and 10.6 Mexican pesos were equivalent to 1 U.S. Dollar as of December 2005.

of individuals carry interest-paying debt on their two cards at least half of the time despite the fact that many have available credit on their low-interest card and that the average monthly interest rate difference is 1.1 percentage points. Third, the average length of account tenure is 8 years, which implies that borrowers are experienced. The median monthly income equals $10,000 pesos, which corresponds to approximately 1.4 times the GDP per capita of Mexico in 2005.

The remaining columns present statistics for other samples. Columns 2 to 4 provide statistics for individuals holding one, two, and three cards in our administrative data set without dropping non-comparable cards. Columns 5, 6, and 7 present the corresponding statistics for individuals in the survey database. Three points are worth noting. First, for the most part, the descriptive statistics of individuals carrying two cards (Column 3) are similar to those of subjects in our main sample (Column 1). This means that focusing on comparable cards does not result in the selection of very different types of consumers. Second, the descriptive statistics of individuals holding one, two, or three cards are relatively similar. The average level of debt per card and the average credit limit increases slightly with the number of cards, while the average purchases and payments do not change significantly. In terms of borrower characteristics, individuals holding two cards are of approximately the same age and have approximately the same length of account tenure and level of schooling as those who carry three cards. Income increases by approximately 20% for each additional card, and there are no significant differences in self-reported awareness of interest rates, measured financial literacy, or measured cognitive ability of individuals holding a different number of cards.[8] In the Online Appendix, we show that these variables display little variation when we split the data by tertiles of the interest rate gap. Finally, there are also relatively minor differences between the descriptive statistics of survey respondents (Columns 5, 6, and 7) and the corresponding figures of subjects in the administrative data (Columns 2, 3, and 4), giving us confidence that the survey's findings are relevant for interpreting the results obtained from our main sample.

E. Interest rate variation

Our empirical analysis exploits the variation provided by the difference in interest rates across the cards held by each consumer. The median difference is 1.1%, with an interquartile range of [0.23%, 1.44%], and the overall standard deviation is 1.18 percentage points, with 68% coming from variation across consumers and the rest from within-consumer time-series variation. An important source of this latter variation is the result of TROs that banks send to existing clients with a duration ranging from one to six months. On average, these short-term offers have a discount of 1.8 percentage points per month. In our sample, there are 3,979 individuals who received at least one such offer on at least one of their cards. In

[8] For details about these measures see the Online Appendix.

spite of these offers, 53% of the individuals in our data never experienced a change in the interest rank of their cards (i.e., a given card was always more expensive).

III. Relative prices as determinants of debt, purchases, and payment allocations

In this section, we document five stylized facts about the way consumers allocate their debt, purchases, and payments among the credit cards they hold. In the analysis, we abstract from inter-temporal considerations and from the optimality of the total levels of debt, purchases, and payments and simply treat them as given. Instead, we focus on the intra-temporal *allocations across cards.* Conceptually, this approach is equivalent to solving a two-stage debt management problem where individuals first decide on the total amount of debt and then on how to allocate it across their cards. By focusing on the second stage, we can simplify the analysis at little cost, as dynamics seem to play a minor role in debt allocation decisions.[9] We also take interest rates as given and treat the supply-side as exogenous.[10] To keep the discussion focused, we first establish the stylized facts and leave their interpretation to Section IV.

A. Allocation of debt

We begin by describing the allocations of credit card debt. For each consumer-month, we define the amount of misallocated debt as the high-interest debt that could be feasibly shifted onto the low-interest card up to its credit limit. To obtain the fraction of misallocated debt we divide this figure by the total credit card debt held by a consumer that month. We also calculate a consumer-level measure by averaging over months.

Panel A of Figure 2 displays the raw distribution of the fraction of debt allocated to the low-interest card. Panels B and C present the distribution of the fraction of misallocated debt at the consumer and consumer-month levels. In both cases, the share of misallocation is not trivial. In Panel B, the mean is 21% and the median is 16%. These figures increase to 44% and 48% respectively for consumer-months that have enough "room for mistakes", defined as those with above median values for total debt, interest rate gap, and total available credit. The average (median) consumer misallocates 24% (15%) of her total debt to high-interest cards (Panel C), suggesting that debt misallocation is fairly persistent over time. These results are very robust to sub-samples where the interest rate gap is above the median,

[9]In the Online Appendix, we show that the optimal allocations produced by a dynamic optimization model with stochastic interest rates calibrated to the data are very similar to the allocations produced by a simple static model.

[10]In Section IV and in the Online Appendix we show that changes in cardholders' debt are unrelated to banks' policies as measured by changes in interest rates or changes in credit limits 3 and 6 months into the future. In our survey, an overwhelming majority of consumers claimed that they had no idea about the banks' pricing policies affecting them, and that they made their borrowing decisions without considering how their choices may influence these policies. This suggests that consumers behave non-strategically and take interest rates as given.

interest is charged on both cards, both cards are Classic cards, the usage rate of both cards is below 60%, both cards were issued by the same bank, the cards have a closing date differential of eight days or less, the total amount of debt is above the median, clients did not receive TROs for either of the cards during the sample period, and the price ranking of the two cards did not change during the sample period (see Online Appendix). In the Appendix, we also show that the interest rate gap and the total level of debt are not related to the fraction of misallocated debt, that the explained variance is close to zero, and that the estimated share of debt-interest rate gap elasticity is less than 2%. We also show that misallocation is not related to income and educational attainment, and that our results replicate in our survey and Purchase-Type data sets.

Misallocation is not only prevalent and robust; it is also costly. We define avoidable or extra costs borne by consumers as the difference between the financing costs that a consumer actually incurs and the minimum costs necessary to finance her total debt. By this measure, the average consumer leaves \$683 pesos per year on the table or 31% of her lowest-financing costs. This is equivalent to approximately 0.4 percent of her annual income. The median consumer foregoes \$451 pesos, while consumers at the 90th percentile leave \$1,701 pesos on the table, incurring a financing cost 43% above the minimum necessary to finance her debt. These costs increase to \$3,227 pesos on average for observations with enough room for mistakes as defined above, which corresponds to an extra financing cost of 110%.[11] To put these figures into perspective, we simulate the distribution of avoidable costs that would arise in our data if consumers allocated their debt randomly.[12] We find that the median consumer allocating her debt randomly incurs a financing cost that is \$262 pesos *lower* than the financing cost incurred by the median consumer in our main sample.

Fact 1 (Misallocated debt): *The average consumer misallocates 24% of her debt by borrowing on high-interest cards, leaving on average \$683 pesos per year on the table or 31% of her minimum financing cost.*

These figures may overstate allocation mistakes, if any. Consumers may find it costly to transfer their stock of debt to their low-interest cards due to balance transfer costs or because they may lack the liquidity to pay off their debt, which would mean that one-time misallocations could be carried forward from prior periods. In the next subsections, we sidestep these concerns by focusing on the allocation of purchases and payments.

[11] As robustness, in the Online Appendix we set up and solve a static cost-minimization model where consumers allocate their credit card purchases and payments (instead of debt) between their cards, taking into account interest rates as well as overdraft and late payment fees. This exercise yields very similar results to those described above.

[12] We compute the fraction of debt allocated to the low-interest card by drawing random values from a uniform distribution over [0,1].

B. *Allocation of Purchases*

Given that consumers cannot use a card if it is full or frozen for lack of payment, and that interest is charged immediately on new purchases if consumers do not pay off their previous balances, for the analysis of this subsection we restrict the sample to observations for which (i) consumers carried outstanding balances and paid at least the minimum due on both cards; (ii) total monthly purchases were strictly positive; and (iii) total monthly purchases could fit on *either* of the cards. This leaves us with a sample of 24,267 consumer-months and 2,680 consumers. These criteria are rather restrictive, but they simplify the exposition considerably. Given that in such a sample credit limits do not bind, we define the amount of misallocated purchases as the purchases made with the high-interest card.

Panels E and F of Figure 2 display the distribution of the fraction of misallocated purchases in this sample. The distributions are close to symmetric and show that consumers often make purchases with their high-interest card. The mean of the value of misallocated purchases at the month and consumer level is 45% and 47%, respectively. In the Online Appendix we show that the distribution of misallocated purchases does not vary with the interest rate gap, the existence of rewards, the size of the stakes, the frequency of interest rate changes, or the level of credit card spending. Using regression analysis, we demonstrate that interest rate differences can explain at most 1 percent of the variance of the fraction of misallocated purchases. We also show that our results are qualitatively similar when we drop selection criteria (i) and (iii), or when we use the survey data.

Fact 2 (Misallocated purchases): *The average consumer misallocates 47% of her purchases to high-interest cards, even though they could have made these purchases with their low-interest card.*

C. *Allocation of Payments*

Consumers can "correct" their misallocated purchases by paying down their high-interest debt. To explore this possibility, we turn to the allocation of credit card payments. To have a meaningful payment allocation problem, we restrict the sample to observations in which individuals have revolving debt on their two cards, made the minimum payment to both cards, and paid strictly more than the minimum on at least one of them.[13] This leaves us with 63,323 consumer-months and 6,666 consumers. In this sample, we define the amount of misallocated payments as payments made to the low-interest card.

Panel G of Figure 2 plots the distribution of the share of misallocated payments. The distribution is quite symmetric. On average, consumers allocate 49% of their

[13] In the Online Appendix we reach similar conclusions when we allow for the possibility that consumers incur late payment fees for not paying the minimum to economize on interest.

monthly payments to the low-interest card. Notably, the 50%-50% payment split is modal, in line with what Benartzi and Thaler (2001) find for retirement savings plans. The pattern of allocations in this Figure, however, could be a reflection of the constraints imposed by the monthly minimum payment. To deal with this, Panels H and I present the distribution of the fraction of misallocated payments above the minimum due.[14] Panel H shows that after covering the minimum due, consumers misallocate on average 50% of their payments towards repaying debt on their low-interest card. In monetary terms, individuals pay on average $1,806 pesos above the minimum to their cheaper card, which is too high to be attributed to rounding off the payment amount. Panel I indicates that the average consumer misallocates 50% of her monthly payments above the minimum to pay down her low-interest card. In the Online Appendix, we show that the distributions of misallocated payments above the minimum due do not vary with the interest rate gap, the amount of total payments, the closing date differentials, or the fact that both cards were issued by the same bank. Using regression analysis, we also show that the interest rate differential explains less than 1% of the total variation in payment allocations and that the estimated interest-payment elasticities range between -4% and -1%. Finally, we demonstrate that our results continue to hold when we allow for the possibility that consumers minimize costs by missing the minimum due and paying a fee, or when we look at the survey data.

Fact 3 (Misallocated payments): *The average consumer misallocates 50% of her monthly payments above the minimum to pay down low-interest debt.*

D. Persistence and Learning

The misallocation of debt, purchases, and payments can be a transitory phenomenon if consumers learn to avoid mistakes. We find evidence against this view. In Panel A of Figure 3, we show that, in the cross section, the share of misallocated debt *does not* decrease monotonically with the length of account tenure. In Panel B, we use within individual time variation to demonstrate that the share of misallocated debt does not decrease with elapsed time in the panel.[15] To formally evaluate whether consumers learn to allocate their debt over time, we follow Agarwal et al. (2013) and estimate a regression of an indicator for incurring extra interest[16] on ten lags of the dependent variable, controlling for card fixed effects

[14] This fraction is defined for each month as the payments made to the low-interest card above the required minimum divided by the difference between the payments made on both cards and the sum of the minimum due on both cards.

[15] We estimated a regression of the fraction of misallocated debt (measured from 0 to 100) against a linear time trend and consumer fixed effects: $Misallocation_{it} = \alpha_i + \beta Time_t + \epsilon_{it}$, which results in $\hat{\beta} = -0.0001$ with a t-stat of 0.74. The trend implies that it would take more than 100 years to eliminate the current fraction of misallocated debt.

[16] We experimented with different thresholds of the amount of extra interest to define this indicator and in all cases obtained similar results.

and a vector of monthly dummies. For comparison, we also use an indicator for incurring a fee as the dependent variable. The bottom panel of Figure 3 plots the coefficients of the ten lags of the dependent variable along with their confidence intervals. As in Agarwal et al. (2013), consumers learn to avoid fees but forget quickly. Paying a fee in the previous month reduces the likelihood of paying a fee in the current month by more than 40 percent. In contrast, consumers *do not* learn to avoid paying extra interest. Incurring extra interest in the previous months neither reduces the likelihood of incurring extra interest in the current month nor in the future.

Fact 4 (Persistence of misallocation and lack of learning): *Paying a fee last month reduces the likelihood of paying a fee in the current month by more than 40%. Incurring extra interest in the preceding month does not reduce the likelihood of incurring extra interest in the current month.*

E. Own and cross price elasticities using random variation in interest rates

In this subsection, we use experimental variation to examine whether consumers respond to temporary reductions in the interest rate and reallocate their debt from high-interest to low-interest cards. In July 2005 one of our cooperating banks ran a large randomized trial of TROs intersecting with our sample. In the experiment, tens of thousands of non-delinquent accounts were randomly assigned to two treatment groups and one control group.[17] The treatments consisted of assigning clients to two cells receiving a one-month or a three-month TRO. The TRO was the same for both groups and reduced the monthly rate by 1.2 percentage points during the teaser period, bringing down the average interest rate from 2.4% to 1.2%. We identified 227 accounts in our sample that received the one-month offer, 209 that received the three-month offer, and 525 that belonged to the control group. In the Online Appendix we show that the treatment and control groups are balanced and that accounts in the experimental sample are not very different from those in the main sample.

Since the TROs were randomly assigned and the price reductions were homogeneous, we estimate regressions of the one-period change of debt (or purchases) on indicator variables of the one-month and three-month TROs for each of the two cards, with two lags, two forwards[18], and controls for changes in credit limits, time dummies, and other non-randomized changes in interest rates. For ease of exposition, we select randomly one of the consumers' credit cards and label it

[17] According to bank officers, the experiment was targeted to the population of clients that were not delinquent at the time. To corroborate this, we estimated regressions of a treatment indicator on various time-varying account characteristics and we could explain at most 5% of the variance of the dependent variable, which is consistent with broad targeting (See Online Appendix).

[18] We include lags to capture effect permanence, and forwards to look for evidence of reverse causality or anticipatory effects. Unfortunately, our sample ends two months after the three-month teaser period.

"card 1". This specification allows us to measure the effect of TROs applicable to card 1 *and card 2* on the outstanding balances on card 1, and therefore estimate own and cross price short-term elasticities.[19] We estimate the regression by OLS clustering standard errors by card.

Before turning to the results, it is important to note that the experimental TROs were accompanied —as is almost always the case— by persuasive advertising, which made them salient and attention-drawing.[20] The Online Appendix provides a copy of the marketing materials accompanying a typical TRO.

Column (1) of Table 2 shows the estimates for a sample of individuals holding ex-ante equally priced cards, i.e., cards for which the interest rate gap is lower than 0.5 percent. We use this sample, because these cardholders have more incentives to switch their debt during the teaser period and fewer incentives to switch it back after this period ends. The average effect of the one-month or the three-month reduction in the interest rate of one card on the outstanding balances *of the other card* is statistically insignificant and economically small. This implies null cross-card price elasticities. In contrast, own-card elasticities are substantial. During the teaser period, individuals in this sample increased their outstanding balances by \$3,657 pesos on the card that received the one-month offer, and by \$4,886 pesos on the card that received the three-month offer. These figures imply own-card elasticities of about -0.57 and -0.84 for the one-month and three-month offers, respectively.[21] Column (2) of Table 2 shows the estimates when we use the full sample of randomized offers. The results are qualitatively similar. In Column (3) we use purchases as the dependent variable and find no substitution across cards and strong own-card responses, which suggests that debt switching costs cannot explain the lack of substitution between cards.[22]

Fact 5 (Response to changes in interest rates): *(a) Debt-interest rate elasticities equal* -0.57 *and* -0.84 *for offers lasting one and three months respectively. (b) In contrast, cross-card debt elasticities are close to zero and are statistically insignificant.*

[19] These elasticities might be smaller than those associated with longer term TROs, as consumers could be reluctant to incur switching costs to take advantage of interest rates that are only temporarily lower.

[20] The announcement is mailed as a colorful letter, congratulating cardholders for their creditworthiness and informing them that their interest rate is reduced for a limited time period. The offer is also presented in a large font. This may be compared to the "on-sale" signs in stores. Marketing literature has argued that firms use price-discount advertisements and "on sale" signs as cues/frames to entice consumers to purchase, managing to increase sales, sometimes without decreasing prices. See for example Bussel et al. (2010).

[21] These results are consistent with those obtained by Gross and Souleles (2002) in the U.S. credit card market using instrumental variables. They estimate short-term and long-term elasticities of approximately -0.8 and -1.3, respectively. We study a different population using randomly generated variation, shorter durations, and find similar effects.

[22] Individuals tend to increase their purchases before the teaser period begins, anticipating that new purchases accrue less interest during the teaser period. In the Online Appendix we check the robustness of our findings to alternative specifications and samples. We estimate censored models and restrict the sample to individuals with low utilization rates, which suggests that binding credit limits are not driving the results.

F. Selection

A possible concern with our analysis is that individuals holding two comparable cards might make systematically different allocation decisions from the rest of the cardholder population. If this were the case, the findings would only apply to 11 percent of the cardholders in Mexico. Fortunately, our results apply more broadly. Table 1 established that in terms of observable account and borrower characteristics, consumers holding two comparable cards are similar to those holding two distinct types of cards or to those holding three cards, both in the administrative data and in the survey data. Here, we supplement this analysis by examining the allocations and the responses to TROs of consumers holding 3 and 4 cards. First, we find that consumers holding three or four cards misallocate an even larger fraction of their debt to higher interest cards. On average, individuals who carry three cards or four cards misallocate 33 and 38 percent of their debt respectively, and therefore pay 38 and 49 percent more in interest. Second, we find that consumers holding 1, 2, 3, and 4 credit cards respond similarly to TROs. The estimated own-card elasticities for these cardholders are -0.41, -0.43, -0.43, and -0.38, respectively. The hypothesis that all elasticities are equal cannot be rejected, confirming that consumers holding more or fewer than two cards are as sensitive to changes in interest rates.[23]

IV. Potential explanations

So far, using naturally occurring as well as randomized variation, we have documented five robust facts showing that relative prices are not good predictors of the allocations of debt, purchases, and payments, and as a result interest costs are much higher than necessary. We also showed that misallocations are not transitory, and that while consumers are sensitive to salient reductions in prices they do not substitute across cards in the price margin. In this section we consider some explanations for these stylized facts. For brevity, we present the details of each model and the full results in the Online Appendix.

A. Switching costs and stochastic interest rates

Consumers may not decide to transfer debt to their low-interest cards if switching costs are significant and there is uncertainty about the future interest rate on each card. This may explain Facts 1 to 4. To examine this, we calibrate a dynamic stochastic model in which consumers choose their debt allocation today to minimize current and *expected* future financing costs —inclusive of the debt

[23]These results are not surprising, as Mexican consumers seem to be passive when it comes to getting a new card. In our survey, only 30 percent of respondents claimed to have actively searched for their last card, while the rest answered that they simply got it because the bank offered it to them. Furthermore, 83 percent of respondents stated that they did *not* compare prices across providers when applying for a new card. These figures do not vary significantly across individuals holding one, two, or three cards.

switching cost— where expectations are formed with respect to the empirical distribution of interest rates. The switching cost makes the problem dynamic and generates an optimal inactivity range that could explain the low substitution we observe.

According to the model, the switching cost necessary to approximate the observed distribution of the share of debt allocated to the low-interest card is greater than \$2,000 pesos or 10% of the average total debt. This cost is not only (too) large, but it produces an amount of switching —changes in the share of debt allocated to each card— that cannot be reconciled with the quantities observed in the data. For a cost of \$2,000 pesos, the model substantially underestimates the amount of switching in the data by a factor of about 20 times. We conclude that stochastic interest rates and switching costs, as modeled, do not explain the low substitution in the data.

B. *Indivisible Purchases*

Consumers could minimize costs by making purchases with their high-interest card today in order to keep available credit to accommodate an indivisible large expense on the low-interest card in the future (explaining Facts 1 and 2). In reality, consumers in Mexico can split a purchase over multiple cards at the counter, which means this explanation is not really operational.[24] In the Online Appendix we set up a simple two-period model to illustrate the basic trade-off of purchase indivisibilities. We find that the difference between the empirical distribution of the fraction of debt allocated to the low-interest card and the simulated distribution is noteworthy, suggesting that this simple model is unable to explain the facts.

C. *Uncertainty in available credit*

Rational consumers may make purchases with their high-interest card if they do not know how much available credit they have on the low-interest card and want to avoid overdraft fees (explaining Facts 1 and 2). According to this explanation, there should be a negative relationship between the fraction of purchases allocated to the low-interest card and the utilization rate of such a card. In the Online Appendix, we show that there is virtually no relationship between these two variables. To examine the issue more formally, we also simulate a parsimonious

[24]The raw data provides evidence suggesting indivisibilities are not important in explaining Facts 1 and 2. In our data, large purchases are uncommon. The 90th percentile of purchases made *with both cards* is 8,267 pesos and the 75th is 5,140 pesos. Most purchases are small relative to the available credit limit: the median purchase is 1,180 pesos and the median available credit after purchases is 6,180 pesos. Furthermore, only 7% of observations that report purchases with the expensive card also include large purchases (>90th percentile) in the next 3 months on the cheap card, making it unlikely that consumers were making room on such a card for a large purchase. Direct survey responses also point to the irrelevance of indivisibilities. The results in Table 3 show some interesting statistics in this regard. When asked, “So far this year, how many times have you used credit cards other than your [name of the cheapest card] card because you wanted to leave enough room on it to make a major purchase?” the mean answer is 0.4 times, with more than 80 percent of respondents reporting zero instances.

static model where consumers are uncertain about the amount of available credit. The predicted distribution of the share of purchases allocated to the low-interest card from this model is significantly different from the allocations observed in the data. This evidence suggests that uncertainty about available credit is not a likely explanation for the patterns of misallocation we find.[25]

D. *Card heterogeneity*

Another possibility is that consumers borrowed on their expensive cards because these cards had unobserved characteristics that made them valuable or more convenient to use.[26] To examine whether heterogeneity could account for Facts 1 to 4 we perform several exercises. First, we replicate our analysis using different samples. In the Online Appendix, we show that results do not change when we examine *more homogeneous* samples of individuals holding two Classic cards that, as we might recall, did not have any reward points during our sample period, two cards issued by the same bank, or both. We also check the robustness of the results to the use of a *more heterogeneous* sample of individuals holding non-comparable cards. We find that misallocation is not greater, suggesting that card heterogeneity is not an important driver of misallocation. Second, we use our ancillary administrative data to assess the prevalence of online transactions and automatic payments, which could be considered differentiators. We find that at the time, these transactions were rare: only 0.2 percent of transactions in this data set correspond to online purchases, and only 6 percent to bills paid automatically. Finally, we use our survey to evaluate whether a rich set of card characteristics could explain misallocation and find that these characteristics explain only 5 percent of the variation.[27] Overall, the evidence suggests that unobserved characteristics are not central in explaining Facts 1 to 4.[28]

[25]Survey data also support this conclusion. The results in Table 3 indicate that in the year before the interview, respondents used their high-interest card to avoid going over the limit of their low-interest card only 0.9 times on average.

[26]Heterogeneity has to be of a particular form if it is to fit the Facts: to explain Fact 3, unobserved card characteristics should entice consumers to make a larger share of payments to their *cheaper* cards, while at the same time, to explain Fact 2, these characteristics should entice consumers to purchase with their more *expensive* cards. While it is possible, although unlikely given our sample design, that unobserved card characteristics explain why consumers purchase with their expensive card, it is harder to think of unobserved characteristics that lead consumers to make payments to their low-interest card instead of their more expensive one. The relative ease of paying, which might be associated with branch locations or better online platforms, is quite similar across banks. Results hold when the two cards are from the same bank.

[27]We regress the fraction of misallocated debt, purchases, and payments on card characteristics such as reward points, type of card, account tenure, perceived prestige, distance to the bank, or subjective probabilities of events like getting the card stolen or denied, or receiving a TRO, among others described in the Online Appendix. Although our survey is of high-quality, this result could be an outcome of measurement error. The evidence, however, does not seem to support this hypothesis. When judged for internal consistency, our survey fares well. In addition, the means of the comparable variables in the survey data are quite close to those in our administrative data.

[28]One could argue that our variables in the survey and the selection procedures in our paper do not capture all relevant sources of heterogeneity. If this were the case, we could interpret our results as indicating that a small number of still unobserved differences are enough to drive substitution across cards to zero.

E. Strategic manipulation of interest rates and credit limits

Consumers may borrow on their high-interest cards to try to influence their contract terms and obtain interest rate discounts or higher credit limits in the future through the rules that banks use to assign these terms (explaining Facts 1 to 4). In the Online Appendix, we estimate various parametric and non-parametric regressions of the likelihood of receiving a TRO or a change in credit limit on a large number of time-varying account characteristics. In all cases, coefficients are small and account for less than 6 percent of the variance in these banks' policies, indicating that it is probably very difficult for consumers to predict the rules that banks use. One could still argue that consumers may *think* that they know the rule the bank uses and act to manipulate it. But they do not: only 11 percent of survey respondents claimed to know the rule that banks use to decide whether to send a TRO, and a mere 2 percent claimed to allocate their balances to influence that rule and obtain a low interest rate offer (see Table 3).

F. Small stakes

Consumers might be indifferent regarding which card to use or pay if the savings on interest charges are small (explaining Facts 1 to 4). Three pieces of evidence weigh against this interpretation. First, consumers do not allocate their debt differently when stakes are higher (see Online Appendix). Second, consumers respond substantially to temporary changes in the interest rate to save a few dollars (Fact 5a): on average, consumers increase their debt by $4,000 pesos to save about $80 pesos, a substantial reaction for such small savings considering that they could save 10 times more on interest charges by just taking the right card out of their wallets. Third, in our survey, the avoidable yearly interest cost incurred is higher than the subjective costs of transferring balances reported by respondents, $240 pesos versus $180 pesos at the medians, respectively.[29]

G. Frequency of interest rate changes

If interest rates change frequently consumers may choose not to learn them and hence misallocate their debt, because the benefits of getting informed are short-lived (Facts 1 to 5). Consumers, however, seem informed about the interest on their cards. In our survey, approximately two-thirds of respondents claim to know the exact interest rate on their two cards, and more than 90 percent

[29]The amount left on the table is not trivial, particularly when compared to other figures in the literature. Zinman (2007) uses the Survey of Consumer Finances for the U.S. to study foregone arbitrage between credit card debt and demand deposit accounts. The paper finds that "fewer than 10% of credit card holders could save as much as $10 USD (about 106 pesos) per month by managing their liquidity more aggressively", while Choi et al. (2011) study 401(k) savings behavior and find that people forego one-time matching opportunities of between $130 and $750 USD. We look at missed arbitrage opportunities between closer substitutes and find similar magnitudes.

claim to know which card is more expensive.[30] In addition, the distribution of misallocated debt, purchases, and payments for consumers who never received a TRO during the sample period is similar to those of individuals in the main sample (see Online Appendix). Finally, in the survey, the subjective probability of receiving a TRO is not correlated with our measures of misallocation.

H. *Limited attention and salience*

Even if consumers know their interest rates, they can still misallocate their debt if they do not pay enough attention to prices at the time of making their purchases and payments. Limited attention —broadly understood as incomplete consideration of elements and/or prices in consumers' choice set— can provide a parsimonious explanation for all of our Facts.[31]. Facts 1, 2, and 3 could be explained by consumers paying little attention to contractual interest rates when making purchases or payments on their credit cards, as these rates are not salient.[32] Fact 4 is also consistent with inattention, since it shows that consumers learn to avoid salient fees, but do not learn to avoid extra interest for which no feedback is provided. Fact 5 shows that consumers are sensitive to TROs, but only on the card that gets the TRO, which could be explained by consumers paying greater attention to the salient low interest rate.[33] We cannot test for limited attention directly in our data, as we neither observe cardholders' attention with respect to interest rates nor shocks to the salience of interest rates other than TROs themselves, which conflate price changes with changes in advertising-induced salience. However, survey evidence provides support for this hypothesis. We asked respondents to indicate how often they compare interest rates when making their credit card purchases. Approximately 61% replied "Seldom" or "Never"; for payments the analogous percentage is 51%.

[30] In Mexico, credit card companies disclose the interest rate that they charge on the consumers' monthly statement. This statement arrives on people's doorstep each month, so search costs are practically zero. We have no way of verifying that respondents indeed know their interest rates, but the fact that the distribution of the reported rates closely matches the actual distribution in our administrative data gives us some confidence in the survey data.

[31] Several recent papers have documented the role of limited attention in consumer decisions: citeasnounLearning, Hall and Woodward (2012), Chetty et al. (2009), Hastings and Shapiro (2013), Abeler and Marklein (2010), Ito (2014), Nicola Lacetera and Sydnor (2012), Bordalo et al. (2013), Bertrand and Morse (2011), Kling et al. (2012), and Stango and Zinman (2014)

[32] In the Online Appendix, we present copies of two monthly billing statements issued during our sample period. Two things are worth noting about them. The first is that banks in Mexico did disclose the annual interest rate on their monthly billing statements. The second is that, even though banks report the annual interest rate ("Tasa Anual"), it is shrouded (not-salient) in a mist of other quantities and is easily lost. In contrast, for several years U.S. banks have used the so-called "Schumer Box", which details salient features of credit card contracts, such as the annual interest rate.

[33] These findings help contextualize the result of Agarwal et al. (2013) by highlighting that consumers learn when the feedback is salient, but fail to learn when counterfactual scenarios need to be evaluated. In relation to this point, it is helpful to compare the billing statements in the Online Appendix with the promotional materials announcing a TRO. In the latter, the low interest rate is displayed more prominently, making it the focal, salient part of the advertisement.

I. Mental accounting

Consumers could misallocate their debt, purchases, and payments if they associate a particular mental budget with a particular credit card, allocating specific types of purchase to such a card or establishing a maximum level of leverage for each particular card separately.[34] Mental accounting can act as a psychological switching cost and as such can explain Facts 1, 2, 3, 4, and 5b.

We use our Purchase-Type data set to examine whether consumers earmark a specific card for certain spending categories (for example, a card for "vacations" and another for "electronics"), assuming that these categories correspond to the consumers' mental accounts.[35] In the Online Appendix, we show that consumers tend to use *the same* card for most of their purchases *in a given* spending category, and use different cards for different categories of expenses. Individuals who use one card for half of their spending categories and the other card for the other half incur a financing cost 28 percent larger compared with the cost incurred by those who specialize on their low-interest card. We also find evidence of mental accounting in the survey. When asked directly about whether they use different cards for different types of purchases, about 53% of cardholders reported using one of their cards for certain expenses and the other for other purchases "almost always" or "most of the time" (Table 3).[36] Table 3 also shows that consumers seem to prefer to spread their debt over many cards.

In a similar vein, when asked about the reasons for making payments on the card on which cardholders paid the most, the two most cited reasons were that they wanted to pay off some of their recent purchases as soon as possible (28%), and because they had more debt on that card (24%), both of which are independent of interest rates. This pattern is also present in the administrative data: the amount of outstanding debt on a particular card is a powerful predictor of the allocation of payments. This suggests that consumers use debt instead of interest rates as a reference to allocate their balances.[37]

[34]According to the theory of mental accounting Thaler (1985), Thaler (1999), consumers categorize their activities into "mental accounts" and make decisions within the context of these narrow frames, for example, by earmarking income for specific purposes, by constraining their spending through implicit or explicit budgets, or by making decisions piecemeal. The existence of these accounts induces consumers to violate the economic principle of fungibility. Mental accounting has been documented in various settings (see, for example, Thaler (1990), Choi et al. (2009) and Hastings and Shapiro (2013)).

[35]We recognize that the assumption that these administrative spending categories represent consumers' mental accounts is ad hoc. Using administrative categories that do not match perfectly with these accounts may make it harder for us to detect that they matter for misallocation should a relationship truly exist. In spite of this, we find card/purchase-type specialization, and a correlation of this specialization with extra interest costs.

[36]We also run a hypothetical choice experiment to ask respondents holding two cards to indicate which of their actual credit cards they would use to purchase a list of specific items. Approximately three quarters of respondents reported the same card for purchases belonging to the same category.

[37]A regression of the fraction of misallocated payments against a five-degree polynomial of the fraction of outstanding balance on the card explains 10% of the variance in the allocation of payments. This is almost ten times more than the percentage of variation explained by a polynomial of the interest rate difference. We estimate an elasticity of 35% (t-stat=44.36) of the fraction of debt on a particular card and the fraction of payment to that card. The Online Appendix shows the explanatory power of this relationship graphically.

J. Assessing the evidence

After evaluating several economic theories of consumer decision making, we conclude that limited attention and mental accounting are the most successful in explaining misallocation, low substitution in the price margin, and a significant sensitivity to within-card interest rate reductions. Our interpretation is as follows: because contractual interest rates are not salient, consumers pay little attention to them when making purchases or payments on their credit cards, instead relying on mental accounts to organize their credit card purchases and payments. A TRO turns the consumers' attention to the now salient low interest rate, leading them to increase their borrowing on that card but not on the others. This explanation is simple and can rationalize all the facts and the survey evidence. Admittedly, due to data limitations we cannot decisively determine what specific mechanism drives our findings; indeed, it is likely that several factors weigh in. Regardless of the underlying cause, the stylized Facts may have an impact on pricing and market outcomes. We turn to this point next.

V. Possible supply-side responses and market implications

In Section III we showed that consumers do not substitute balances away from high-interest toward low-interest cards, leaving on the table an average of $683 pesos per year. In the aggregate, this sum constitutes a non-trivial transfer of resources from consumers to banks. A back-of-the-envelope calculation suggests that these transfers are considerable, totaling about $4 billion pesos per year if we extrapolate them to include consumers who hold more than one card.[38] Given these figures, it is natural to assume that banks will respond strategically to the low degree of substitution across cards.

In this section we discuss how our demand-side findings could affect firm behavior and competition. A first implication is that, in response to the low levels of substitution and the high sensitivity to salient own-card rate changes, banks have incentives to temporarily reduce account specific interest rates (through TROs) to entice consumers to borrow, and then raise them to exploit locked-in consumers. A second implication is that banks may want to offer several cards to potential clients, as consumers tend to spread their debt almost evenly across their cards irrespective of the interest rates. A third implication is that if consumers do not substitute debt across cards, it may be difficult for entrants to compete against incumbent banks as they can attain, at most, a fraction of the existing debt of current borrowers — who are most likely the best credit risks.

In the case of Mexico, we find evidence consistent with these predictions. First, using the administrative data, we find a positive relationship between account tenure and interest rates, controlling for risk, demographics, month, bank, and type of card, as well as individual fixed effects. We present the details in the

[38]There were about 12 million cards in our sample period. If about half of the cardholders had more than one card: 6 million $\times$ \$683 pesos $\approx$ \$4 billion pesos.

Online Appendix. For consumers holding two cards, the interest rate on the card they opened last is initially 10 percent lower than the rate on the card they opened fist, but 15 months later, it is 5 percent *higher* than that of the first card. This is consistent with the notion that banks issuing new cards set prices assuming that consumers will not switch their debt back to their old cards. Second, in Mexico it is common for cardholders to hold various cards, sometimes from the same bank. During a growth period in the 2000s, the number of cards held by consumers with at least one card in Mexico increased from 3.4 in 2006 to 4.2 in 2008.[39] Finally, while banks in Mexico profit from sending temporary TROs to existing clients,[40] they do not attract a large fraction of borrowers' total indebtedness. According to our findings in Fact 5, a back-of-the-envelope calculation shows that despite the fact that borrowers react to TROs, banks only gain 15 percent of cardholders' *total* debt.[41] Although these results are revealing, we recognize that we cannot establish the extent to which demand-side versus supply-side factors have contributed to the competitive environment of the credit card market in Mexico. Future work should combine demand and supply-side factors to formally investigate how and whether the documented consumer behavior affects competition in equilibrium.

VI. Conclusion

This paper uses account records of all the credit cards held by a representative sample of a large fraction of the population of credit card holders in Mexico to document a striking fact: consumers are not sensitive to relative prices when choosing their allocations of credit card debt, even in an environment in which products are fairly homogeneous. However, consumers are sensitive to salient price reductions. The evidence provided here suggests a limited role for traditional explanations such as switching costs and points to limited attention to prices and mental accounting as parsimonious explanations, although more research is needed to establish causality.

Our findings contribute to the recent debate over the extent to which consumers make optimal financial decisions and their implications for market outcomes. From a policy perspective, the case of Mexico is illustrative of a situation in which government actions encouraged entry with the expectation that

[39]In the U.S. the average number of active credit cards per cardholder went from 1 in 1983 to more than 3.5 in 2010 (Bertaut and Haliassos (2006)).

[40]According to (Ponce 2008), banks in Mexico profit from sending temporary TROs to existing clients, as offers generate new debt that is partially locked in after the teaser period expires.

[41]This raises a natural question: if consumers are sensitive to salient interest rate reductions, why do banks in Mexico not use them to entice *potential new* borrowers through BTOs to transfer their balances to a new card? In our view, this is due to a combination of supply side factors and regulatory constraints that prevent banks from accessing credit bureau information unless they have the potential client's physical signature authorizing the bank to check her credit history. These restrictions, in combination with the relatively limited information of the credit bureau and the passivity of consumers in shopping and applying for new credit cards, imply that banks have found it too risky or unprofitable to go after borrowers outside of their existing client base with BTOs or introductory offers. Nonetheless, banks have found it profitable to provide salient low-interest offers to their existing clients (TROs) who have already revealed their creditworthiness and who are likely to increase their debt after receiving them. This is in line with a report by the Central Bank ((Banxico 2013)).

entrants would gain market share and impose price discipline; but in spite of a large supply-side shake up, market shares have not changed. Our results suggest that the demand-side may be an important culprit of Mexico's credit card market outcomes.

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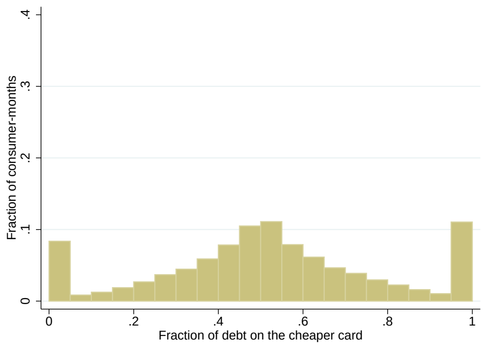
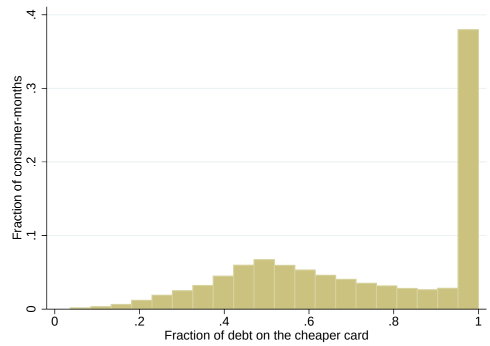


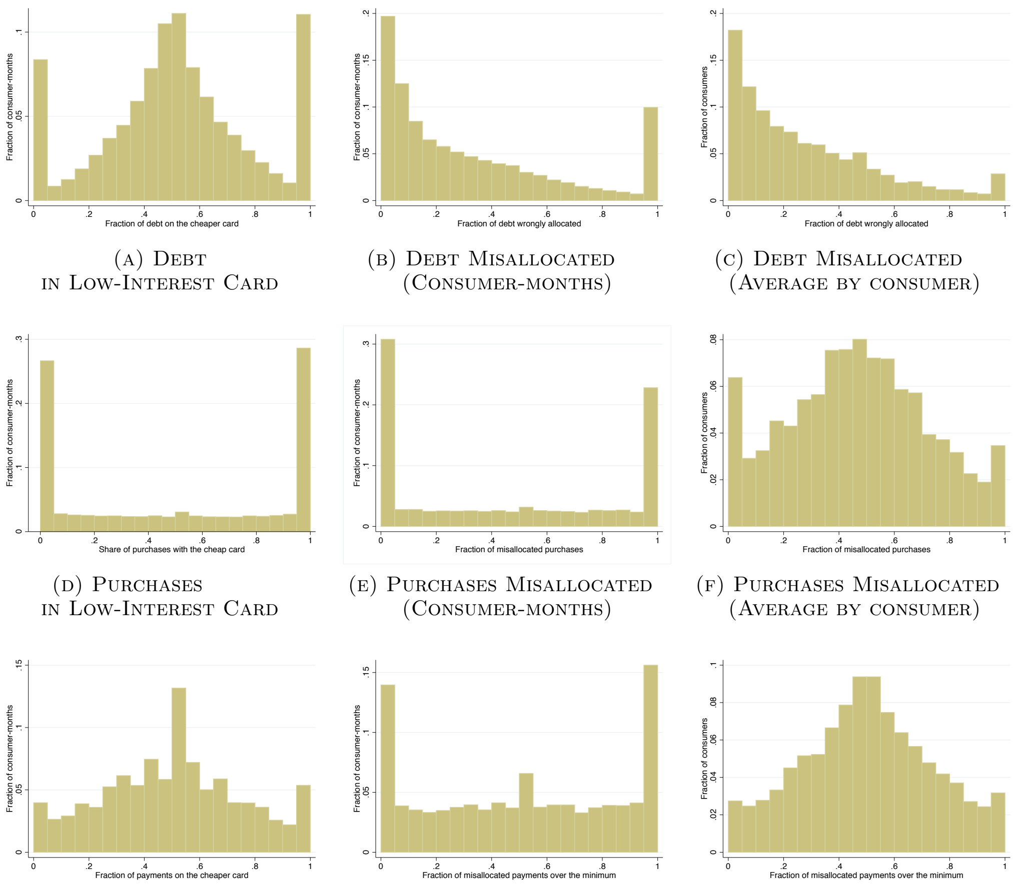
(a) Observed Allocation
(Consumer-months)



(b) Interest-Minimizing Allocation
(Consumer-months)

Figure 1. Allocation of debt to the Low-Interest Card

Note: Data are from the administrative database (2-card sample). An observation is a consumer-month. The figure on the left shows the frequency distribution of the fraction of credit card debt allocated to the low-interest card. The figure on the right shows the frequency distribution of the fraction of debt on the lower-rate card that would have arisen had individuals allocated debt up to the credit limit on their low-interest card and the rest on their high-interest card.



(a) Debt in Low-Interest Card

(b) Debt Misallocated (Consumer-months)

(c) Debt Misallocated (Average by consumer)

(d) Purchases in Low-Interest Card

(e) Purchases Misallocated (Consumer-months)

(f) Purchases Misallocated (Average by consumer)

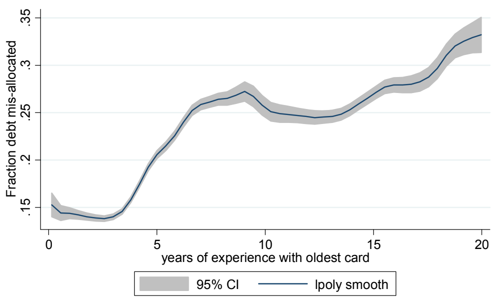
(g) Payments in Low-Interest Card

(h) Excess-payment allocation (Consumer-months)

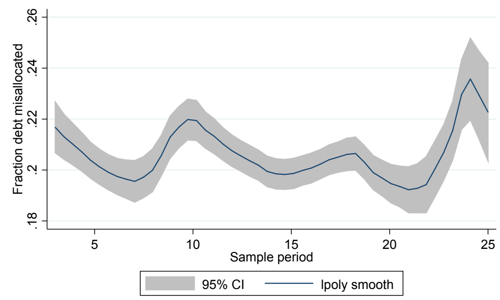
(i) Excess-payment allocation (Average by consumer)

Figure 2. Allocation of debt, purchases, and payments

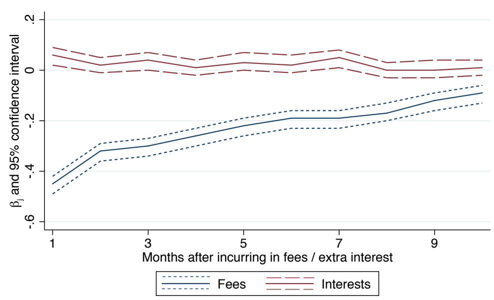
Note: Data are from the administrative database (2-card sample). In Panels (a), (b), (d), (e), (g), and (h), an observation is a consumer-month. In Panels (c), (f), and (i), we average across time, so an observation is a consumer. Panel (a) presents the frequency distribution of the fraction of credit card debt allocated to the low-interest card. Panel (b) shows the frequency distribution of the fraction of credit card debt that was misallocated to the high-interest card. This fraction is calculated for each period as the high-interest debt that could be shifted into the low-interest card up to its credit limit divided by the total credit card interest-paying debt. Panel (c) shows the average of the fraction of misallocated debt taken over the months with information for each consumer. Panels (d), (e), and (f) display the equivalent figures for credit card purchases. Panel (d) presents the histogram of purchases without applying the selection criteria described in the paper, while panels (e) and (f) do apply those selection criteria. Panel (g) shows the frequency distribution of the fraction of credit card payments that were made to the low-interest card. Panel (h) displays the fraction of credit card payments exceeding the minimum that were misallocated to the high-interest card. This fraction is calculated for each period, as the total payments above the required minimum allocated to the low-interest card divided by the total credit card payments made by the consumer during that month. Finally, Panel (i) takes the monthly observations in panel (h) and averages them across time for each consumer. The subsamples used for each distribution are described in the paper.



(a) Misallocation and tenure



(b) Misallocation and Periods in the sample



(c) Likelihood of recurrence

Figure 3. Allocation of debt and Experience/Learning (Kernel regressions)

Note: Point estimates and 95-percent confidence intervals plotted. Data are from the administrative database (2-card sample). An observation is a consumer-month. Panel A displays a kernel regression of the fraction of misallocated debt vs each consumer's tenure with a credit card (Epanechnikov kernel was used). Panel B plots a kernel regression of the fraction of debt misallocated vs a counter for months in our sample (Epanechnikov kernel was used). Panel C shows the β coefficients of regression specification (1) in the text, along with their 95 percent confidence intervals.

Table 1—Descriptive statistics by number of credit cards and data set

	Administrative database (main)				Survey sample		
	2 comparable cards (1)	1 card (2)	2 cards (3)	3 cards (4)	1 card (5)	2 cards (6)	3 cards (7)
Panel A: Monthly statistics							
Debt (average by card)	11,068	8,298	10,333	11,921	10,128	9,490	14,016
	(14,773)	(12,907)	(14,170)	(15,083)	(13,136)	(11,492)	(21,861)
Credit limit (average by card)	25,175	17,930	24,934	25,934	20,932	17,286	21,044
	(17,775)	(23,631)	(27,685)	(26,596)	(56,181)	(22,567)	(26,184)
Purchases (average by card)	1,842	1,816	1,897	1,836	2,180	2,404	2,585
	(4,544)	(3,965)	(3,855)	(3,670)	(2,296)	(2,928)	(2,915)
Payments (average by card)	2,092	1,810	1,976	1,895	1,377	1,592	1,394
	(3,968)	(4,042)	(3,933)	(3,589)	(1,566)	(3,495)	(2,095)
Interest incurred (average by card)	285	167	251	268	338	231	252
	(423)	(327)	(419)	(417)	(989)	(442)	(540)
Fees incurred (average by card)	54	72	60	53	-	-	-
	(105)	(119)	(110)	(105)	-	-	-
Debt weighted monthly interest rate (average by card)	2.5	2.6	2.4	2.2	2.5	1.5	0.9
	(0.7)	(0.9)	(0.9)	(0.8)	(1.28)	(0.92)	(0.61)
Monthly interest rate gap	1.1	-	1.4	2	-	0.66	0.74
	(0.9)	-	(1.2)	(0.6)	-	(0.64)	(0.63)
Panel B: Statistics by consumer							
Percentage of individuals who half the time:							
Pay interest on both cards	74	-	71	-	-	-	-
Could fit their total debt on the low-interest card	42	-	42	38	-	36	18
Could fit their total purchases on the low-interest card	71	-	62	59	-	50	33
Percentage of months in which interest is incurred in at least one card	90	74	88	79	64	75	86
Panel C: Demographics							
Monthly income (mean)	14,941	12,692	15,237	17,442	8,818	12,072	14,847
	(13,608)	(10,358)	(14,647)	(18,442)	(6,475)	(11,178)	(10,277)
Monthly income (median)	10,000	8,000	10,000	12,500	7,500	8,000	12,500
Age	44	42	45	46	34	37	40
	(11)	(10)	(11)	(12)	(12)	(11)	(10)
Years with oldest active card	7.9	6.7	7.5	8.2	4.5	5.7	7.4
	(6.4)	(5.9)	(6.1)	(7.7)	(5.7)	(4.2)	(5.7)
Male (percentage)	60	58	61	60	57	52	57
Have a BA degree or more (percentage)	62	57	64	63	33	34	47
Panel D: Knowledge, financial literacy, and Raven test scores (Survey data)							
Pct. claiming to know the interest rates of all their credit cards	-	-	-	-	71	72	79
Pct. claiming to know the credit limits of all their credit cards	-	-	-	-	97	97	97
Pct. claiming to know the due dates of all their credit cards	-	-	-	-	98	88	79
Pct. stating they knew that balance transfers were possible	-	-	-	-	53	53	50
Financial literacy score (0/100)	-	-	-	-	60	58	59
	-	-	-	-	(32)	(31)	(31)
Raven test score (0/100)	-	-	-	-	39	37	42
	-	-	-	-	(29)	(29)	(31)
Consumers	10,335	33,741	14,703	8,368	120	396	347
Observations	114,720	459,809	179,340	99,213	120	792	1041

Note: This table shows summary statistics for selected variables for individuals in different datasets. Each column represents a sub-population of interest. Column (1) to (4) presents summary statistics for individuals in the administrative dataset. Column (4) to (6) presents summary statistics for the survey sample. Standard deviations are shown in parenthesis. The Raven test consisted in 5 questions and the financial literacy test consisted of 3 questions. About 1/3 of consumers in the administrative sample had demographic information. Variables measures in pesos are expressed in 2004 pesos

Table 2—Response to teaser rate offers

	Δ Debt card 1 Restricted sample (1)	Δ Debt card 1 Full sample (2)	Δ Purchases card 1 Full sample (3)
$\text{TRO1}_{t+2,Card1}$	-207	-237	404
	(284)	(316)	(487)
$\text{TRO1}_{t+1,Card1}$	83	-306	3,263
	(296)	(383)	(1,020)
$\text{TRO1}_{t,Card1}$	3,657	4,049	-1,625
	(601)	(763)	(759)
$\text{TRO1}_{t-1,Card1}$	-2,105	-2,434	-1,317
	(638)	(649)	(453)
$\text{TRO1}_{t-2,Card1}$	-22	-450	704
	(314)	(600)	(568)
TRO3 month 1 $_{t+2,Card1}$	98	-237	358
	(1,400)	(242)	(245)
TRO3 month 1 $_{t+1,Card1}$	403	-584	2,653
	(373)	(475)	(450)
TRO3 month 1 $_{t,Card1}$	2,097	2,242	-1,569
	(460)	(259)	(477)
TRO3 month 2 $_{t,Card1}$	1,561	967	-627
	(417)	(222)	(290)
TRO3 month 3 $_{t,Card1}$	1,228	1,207	-369
	(536)	(397)	(310)
TRO3 month 3 $_{t-1,Card1}$	-91	-391	94
	(107)	(288)	(285)
TRO3 month 3 $_{t-2,Card1}$	-639	24	-659
	(444)	(240)	(267)
$\text{TRO1}_{t+2,Card2}$	-527	-785	-296
	(405)	(590)	(235)
$\text{TRO1}_{t+1,Card2}$	372	315	58
	(234)	(463)	(242)
$\text{TRO1}_{t,Card2}$	-220	850	104
	(171)	(630)	(141)
$\text{TRO1}_{t-1,Card2}$	181	890	-564
	(210)	(978)	(421)
$\text{TRO1}_{t-2,Card2}$	-447	-337	-165
	(843)	(581)	(306)
TRO3 month 1 $_{t+2,Card2}$	694	-775	631
	(538)	(981)	(426)
TRO3 month 1 $_{t+1,Card2}$	607	384	-74
	(498)	(557)	(89)
TRO3 month 1 $_{t,Card2}$	685	485	270
	(581)	(898)	(200)
TRO3 month 2 $_{t,Card2}$	532	255	137
	(488)	(567)	(217)
TRO3 month 3 $_{t,Card2}$	-262	500	-55
	(298)	(758)	(324)
TRO3 month 3 $_{t-1,Card2}$	-171	599	-90
	(900)	(673)	(360)
TRO3 month 3 $_{t-2,Card2}$	418	-704	-337
	(363)	(400)	(362)
Total change, Card 1	4,886	4,416	88
P-value of total change, card 1	0.00	0.00	0.85
Total change, Card 2	955	1240	278
P-value of total change, card 2	0.79	0.20	0.69
Adj/Pseudo R-squared	0.080	0.040	0.010
Consumers	458	961	961
Observations	3,742	6,391	6,390

Note: This table shows the effect of the one-month and three-month interest rate reductions on debt. Data are from the 2-card administrative database (sample of the bank-run experimental TROs). An observation is a consumer-month. Each column represents a separate regression. Columns (1) and (2) report the results of OLS regressions of the change in interest paying debt on the treatment variable and its lags, controlling for changes in credit limit, indicator variables for non-random offers, its lags, and time dummies. Column (1) reports the estimated impact for a sample of consumers holding two cards with an interest rate gap of 0.5 percentage points per month or less during the month before the offer. Column (2) shows the results for the full sample of randomized offers. Column (3) shows the results using the change in purchases as the dependent variable. Standard errors clustered at the individual level are given in parentheses. The second panel shows the total take up for the teaser rate offers along with their corresponding p-values. For debt, total change is defined as $\sum_{k=1}^{3}$ TRO3 month $k_{t,Cardj}$ with $j \in \{1,2\}$ and for purchases total change is defined as $\sum_{k=1}^{3}$ TRO3 month $k_{t,Cardj}$ +TRO3 month $1_{t+1,Cardj}$ with $j \in \{1,2\}$.

Table 3—Patterns of behavior in credit card borrowing as reported by survey respondents

	Percentage
Number of times over the past year that the respondent used the high-interest card (instead of the low-interest card) because:	
He/she wanted to avoid going over the limit on the low-interest card	0.9
He/she wanted to leave enough room on the low-interest card for a major purchase	0.4
The low-interest card was not accepted	0.4
He/she was afraid that the low-interest card might be cloned	0.2
Percentage of consumers who. . .	
Claim to know the rule that the bank follows to determine interest rates	11
Claim to allocate their debt to try to obtain lower interest rates	2
Overall, how much do you take interest rates into account when making your credit card payments?	
A great deal	19
To a certain extent	30
Not much/Not at all	51
Do you compare the interest rates of your cards when making a credit card purchase?	
Almost always	13
Occasionally	25
Seldom / Never	62
[Regarding the last card obtained...] How many banks did you compare?	
I didn't compare any banks	83
I compared 2 banks	12
I compared 3 or more banks	4
Does not know	1
Percentage of respondents that claimed to prefer borrowing on different cards	55
(Regarding purchases), do you prefer to make them with the same card or to use different cards?	
Use different cards	61
Use the same card	39
Stated reasons for using other cards besides the card with the higher balance:	
Prefer to distribute debt over several cards	23
Did not want to go over the limit on the other card	22
Prefer to use specific cards for certain purchases	20
The card has a lower interest rate	11
The card had a low-interest rate offer	10
Have direct debit set up on the card	6
Other	8
Stated reasons for paying a larger amount to this card:	
Wanted to pay off some of my recent purchases as soon as possible	28
Have more debt on this card	24
The due date coincided with the day I had more cash	16
The minimum was higher than the minimum on my other card	12
The card has a higher interest rate	10
Other	10
Some people tend to use one card for certain type of purchases and another card for certain others. For example, some people use their Bancomer card for vacations, while they use the Banamex for the supermarket. Do you tend to organize your expenses in this way and assign only certain purchases for an specific card?	
Almost always	25
Most of the times	28
Rarely	19
Never	27
Does not know	1

Note: This table shows summary statistics for selected variables for respondents in our survey with 2 credit cards who responded positively to the question "do you normally pay interest on your credit card(s)?" (386 observations). Direct responses were constructed from direct questions asked in the survey to people who had at least two cards. The exact wording of the questions used to construct this table as well as responses to related questions are presented in the Online Appendix.