Consumption Response to Credit Tightening Policy: Evidence from Turkey[1]

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Abstract

We study the impact of credit tightening policy implemented by Turkish banking regulation and supervision agency on consumer spending in the period between January 2010 and August 2013. We find that the consumers with high amount of debt were severely affected compared to the group of consumers with low debt. Following the implementation of the policy, relative spending of highly indebted consumers dropped significantly and persisted for many months after the policy date. The policy effect was strongest for consumers that are young, married, and have past credit card debt.

Keywords: Consumption, Spending, Debt, Credit Cards, Household Finance, Banks, Loans, Durable Goods, Discretionary Spending, Fiscal Policy, Liquidity Constraints, Credit Constraints.

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1. **Introduction**

Ever since the seminal paper by Bernanke and Gertler (1995) there has been an ongoing debate about the effect of monetary policy on consumption. Recently, Keys et. al. (2014) and Di Maggio, Kermani and Ramcharan (2014) study the effect of monetary policy change, after the great recession, on consumption in the U.S. Both studies find that expansionary monetary policy had a significant effect on household spending, debt, and savings. The latter finds that this effect is not equal across all types of households. Highly indebted and low home-equity households are unable to benefit from the expansionary monetary policy in terms of refinancing with a lower interest rate or faster repayment of loans, muting their consumption response to the monetary policy.

In light of the debate and the recent interest on the role of monetary policy on consumption, in this paper we analyze a one-time surprise policy announcement by the Turkish Banking Regulation and Supervision Agency (BRSA) to restrain private credit growth in Turkey -- this is a sharper instrument to study consumption response than the blunt instrument like monetary policy. The policy was in response to the recent economic boom in Turkey followed by a sharp drop in the household savings rate and simultaneous explosive growth in private credit (Van Rijckeghem (2010)). Alarmed by such a trend BRSA decided to take action to curb the unsustainable credit growth, and in December 2010, it officially announced a set of steps to be implemented as a part of credit restraint policy, formally go into effect 9 months after the announcement.[2]

We study the response of consumer spending to this policy, focusing on differential response by consumers with low and high credit card debt, respectively. Given the goal of the policy to restrict private debt, we expect that the bigger burden of the policy, relatively speaking, would be on low income and highly indebted consumers, if the policy was effective and reached its intended goal.

We employ a difference-in-difference methodology to extract the gap in response to the credit restraining policy between consumers with low and high credit card debt. We define two groups for our empirical study, “debtors” and “transactors”. Transactors are consumers in the bottom 2 deciles by average credit card debt at the end of the month scaled by credit

[2] Agarwal and Qian (2014) study a similar policy announcement in Singapore that restricted the ability of homeowners to sell their houses as the Government of Singapore was trying to slow down house price growth in an overheated housing market.

card limit. Debtors are consumers in the top tow deciles of average credit card debt at the end of the month, i.e. bank customers who use their credit cards as a primary means to pay for purchases. Debtors are the treatment group, and transactors are the untreated group, as we expect the former to have significant response in spending after the policy. Transactors have on average very little debt on their credit cards at the end of the month, i.e. they use their credit cards primarily as regular debit cards and hence, are assumed to have remained unaffected by the credit policy.

Taking September 2011 as the policy month we find significant divergence in credit card spending of the two groups. The result holds unanimously for aggregate spending and different spending categories. For dynamic analysis of the differences in spending patterns we use a distributed lag model. We report the cumulative coefficients for the months before and after the policy. Again, the pattern of widening difference in spending among low and high credit card debt consumers is very similar across different spending categories.

Our main results can be easily summarized. First, we find that the marginal spending response to policy of high-debt consumers is almost TL -800 ($ -450) per month. The negative coefficient persists for all 8 spending categories we define in our sample, but the highest magnitude is for the "Daily" spending, TL -393. Daily spending category accounts of purchases of groceries and other essential and necessity household goods. The biggest marginal drop in credit card spending after "Daily" is for the "Vehicle" and "Telecommunication" categories. Analysis of dynamics of credit card spending evolution around policy shows that there was also a significant announcement effect in addition to the actual policy implementation effect. Average spending response to policy announcement is TL -175, approximately 4.5 times less than the average response in months after policy enactment. Further, we examine the heterogeneity in response to policy and find consumer that are male, married, young, less educated, live in rural areas, are long-time credit card holder, and have previous credit card debt issues are affected more by the policy relative to other consumers. Using the matched sample based on demographic and account-related data we find very similar, even stronger results, and additional robustness check confirms that difference-in-difference methodology is the appropriate empirical tool for the study at hand.

As mentioned above, our sample also lets us consider the consumer response not just to the policy implementation but also its announcement. Given the 9 month interval between the two, consumers had time to adjust their spending and prepare for the policy as the implementation date was approaching. It is important to note here that the announcement effect can only be expected if the consumers had been well informed about the policy, otherwise it can de facto be treated as an unanticipated policy. Depending on which is true, we would expect a different response in consumer spending. Of course, there is always an option that consumers were informed about the policy after its announcement, but failed to act upon it; however we believe it is not reasonable to expect this, given that all the credit card holders were to be significantly affected by the policy.

Jappelli and Pistaferri (2010) develop a theoretical framework where they claim anticipated changes in income would not cause a significant response in consumption; there would be significant changes in consumption in response to surprise changes in income. While the policy in our study was formally announced, hence anticipated, it is an empirical exercise to show if it indeed, was anticipated or not, based on the response that ensued both after the policy announcement and the policy implementation. Using theoretical prediction of the response in either case, we can argue whether the policy was in practice anticipated or not. As discussed by Gross and Souleles (2002), credit cards play an important role in consumer finances, so they can be quite useful for studying consumer spending behavior. Half of consumers in the US have a credit card, and total credit card debt is close to a trillion dollars in 2012 with 40% of revolving debt (U.S. Census Bureau, Statistical Abstract of the United States:2012). In this study we will use credit card data from Turkey to study the policy response.

The rich data set allows to study the response in overall consumer spending, spending across specific categories, as well as whether the response was heterogeneous or homogeneous given the wide array of characteristics available in the data. We primarily focus on age, marital status, address, education, and past credit card debt.

The data was provided to us by a major commercial bank in Turkey, and our sample covers the spending behavior of more than a million customers across multiple categories from January 2010 to July 2013. The sample is ideal for studying the effect of the BRSA's policy on consumer spending, as it is covering the entire population of bank customers over the abovementioned horizon. As such we believe that this sample is very representative of the entire Turkish population, and that conclusion we derive from our empirical analyses will safely apply to a broad population of Turkish credit card users.

In the original sample provided by Bank there are 23 spending categories, however we merge the similar categories together as some of them have infrequent transactions and regression analysis does not yield reliable results. We end up with 8 categories that we use in our analysis, namely vehicle, travel, daily, services, products, construction, telecommunication, and other. Across all the categories we find consistent results in terms of the effect of the policy on consumer spending.

Our paper directly contributes to the vast literature on studying consumption response to various fiscal stimulus programs. Some recent studies include Shapiro and Slemrod (1995), Souleles (1999, 2000, 2002), Parker (1999), Browning and Collado (2001), Hsieh (2003), Stephens (2003, 2006, and 2008), Johnson, Parker and Souleles (2006), Parker, et al. (2013) and Gine and Kanz (2015). The literature finds mixed evidence; some studies find that consumption response is essentially zero, while other find that liquidity constrained consumers respond positively to the fiscal stimulus programs. Our work is more directly related to the work by Agarwal, Liu and Souleles (2007), Aaronson, Agarwal and French (2012), and Agarwal and Qian (2014) on the 2001 tax rebates, the minimum wage changes, and the fiscal policy changes in Singapore. The first study exploits the random timing of the 2001 tax rebates to identify the dynamic response of credit card payments, spending, and debt to the rebates. They find that consumers initially saved much of the rebates, on average, by increasing their credit card payments and thereby paying down debt. But spending did subsequently increase, offsetting the initial extra payments, so that eventually debt rose back to its original level. The second study looks at the spending and debt dynamics due to the changes in the minimum wage law changes. The third study looks at the fiscal policy experiment where the government of Singapore provided a onetime cash rebate to all Singaporeans and they show that consumers spend 90% of the rebate. However, the shortcoming of these studies is that they do not study the contractionary fiscal policy and its effect on spending.

Our work is also tangentially related to the literature on cross-border shopping due to tax differentials (i.e. income shocks) and the state sales tax holidays. Agarwal, Chomsisengphet and Qian (2013) find that Singaporeans households spend significantly less in Singapore due to the Value Added Taxes and potentially cross the border to shop. Agarwal and McGranahan, Consumption Response to State Sales Tax Holidays (2013) find that the spending in the states with a sales tax holidays is significantly higher than states without sales tax holidays. Finally, we also contribute to the broad literature that exploits the program design features of various government policies and studies the effectiveness of these programs (Agarwal , Bubna and Lipscomb (2013); Fu, Qian and Yeung (2012)).

The remaining part of this paper is organized as follows: Section 2 reviews the literature. Section 3 gives a brief description of consumer credit market in Turkey. Section 4, provides data description and empirical methodology. Section 5 provides results, falsification and robustness analysis and section 6 concludes the study with possible policy implications.

2. Literature Review

A number of papers have studied consumers' response to changes in a permanent predictable change in income, as a means of testing whether households smooth consumption as predicted by the rational expectation life-cycle permanent-income hypothesis.

Much of the previous literature on this topic uses aggregate data. For example, Wilcox (1989) finds that aggregate consumption rises in months when Social Security benefits per beneficiary rise. Because benefit increases are mandated by Congress, they are known well in advance. However, it is not clear if it is the increase in Social Security benefits or something else that causes consumption to rise.

More recent studies use micro data, which overcomes the problems associated with aggregate data. Shea (1995) tests whether consumption increases in response to income mandated years earlier in union contracts. Because he uses the Panel Study of Income Dynamics, he is forced to look at food consumption only. He finds that a 10% increase in income leads to almost a 10% increase in food consumption. Gross and Souleles (2002), use a unique data of credit card accounts and test the response to spending and debt to changes in credit limit. They interpret the change in credit limit as a permanent increase in income. They find an MPC of 13% and for accounts that had an increase in credit limit, they find that debt levels rise by as much as $350. Their results are consistent with models of liquidity constraint and buffer stocks.

More recently, two papers have exploited the end of debt contracts to identify predictable changes in disposable income. Coulibaly and Li (2006) find that when mortgages end, households do not alter their consumption on non-durable goods but increase their savings in durable goods such as furniture and entertainment equipment. Stephens (2008) uses the completion of vehicle loan payments and finds that a 10% increase in discretionary income leads to a 2 to 3% increase in non-durable consumption. Thus there is some contention about the size and composition of the spending change from this identification strategy.

Finally, Aaronson, Agarwal and French (2012) study the impact of a minimum wage hike on spending debt. Specifically, they find that following a minimum wage hike, households with minimum wage workers often buy vehicles. On average, vehicles spending increases more than income among impacted households. The size, timing, persistence, composition, and distribution of the spending response are inconsistent with the basic certainty equivalent life cycle model. However, the response is consistent with a model in which impacted households face collateral constraints.

There is perhaps even more disagreement over the consumption response to transitory income changes. This contention goes back to just after the publication of Friedman's (1957) PIH, when Bodkin (1959) used insurance dividends paid to WWII veterans to reject the PIH but Kreinin's (1961) study of restitution payments to certain Israelis could not reject the PIH. Among more recent studies, Paxson and Deaton (1994), Browning and Collado (2001), and Hsieh (2003) fail to reject, but Shea (1995), Parker (1999), and Souleles (1999) all reject the PIH.

A number of previous papers have also studied consumers' response to tax cuts and other windfalls. Modigliani and Steindel (1977), Blinder (1981), and Poterba (1988) studied the 1975 tax rebate. They found that consumption responded to the rebate, though they came to somewhat different conclusions regarding the relative magnitude of the initial versus lagged response. All three studies used aggregate time-series data, but there are a number of advantages to using micro-level data as well. First, it is difficult to analyze infrequent events like tax cuts using time-series data.[3] For example, time-series analysis of the 2001 rebate is complicated by the recession, changes in monetary policy, the September 11th tragedy, and

[3] Blinder and Deaton (1985) found smaller consumption responses when they considered jointly the 1975 rebate along with the 1968-70 tax surcharge. Nonetheless they found consumption to be too sensitive to the pre-announced changes in taxes in the later phases of the Reagan tax cuts. Overall they concluded that the time-series results are "probably not precise enough to persuade anyone to abandon strongly held a priori views".

other concurrent macro events. Second, with micro data one can investigate consumer heterogeneity in the cross-section, for instance by contrasting the response of potentially constrained and unconstrained households. Early papers using micro data include Bodkin (1959), who studied the insurance dividends the U.S. paid to WWII veterans, and Kreinin (1961), who studied restitution payments from Germany to Israelis. Among more recent related studies, Souleles (1999) found that consumption responds significantly to the federal income tax refunds that most taxpayers receive each spring. Gross and Souleles (2002) found that exogenous increases in credit-card limits (*i.e.*, windfall increases in liquidity) lead to significant increases in credit card spending and debt. Both of these papers found evidence of liquidity constraints.[4] Gine and Kanz (2015) find that stimulus program in India had no significant effect on consumption, but had a negative effect on credit allocation and led to severe loan defaults. This provides some evidence that government stimulus or restriction programs can have unwanted, sometimes opposite effects. There have been four recent studies, using micro data, by Shapiro and Slemrod (2003a and 2003b), Johnson, Parker and Souleles (2006) and Agarwal, Liu and Souleles (2007) on the 2001 tax rebates. As mentioned earlier, this paper directly builds on the results of the last of these four studies. Shapiro and Slemrod (2003a) found that only 21.8% of their survey respondents report they will mostly spend their rebate, a result they calculate is consistent with an average marginal propensity to consume of about one third. They found no significant evidence of liquidity constraints. Shapiro and Slemrod (2003b) used a novel follow-up survey in 2002 to try to determine whether there was a lagged response to the rebate. They found that, of respondents who said they initially mostly used the rebate to pay down debt, most report that they will "try to keep [down their] lower debt for at least a year". Johnson, Parker, and Souleles (2006) find that consumers spent only about a third of the rebate initially, within a quarter. But they also find evidence of a substantial lagged consumption response in the next two quarters. The consumption response was greatest for illiquid households, which is indicative of liquidity constraints. Agarwal, Liu, and Souleles (2007) find that consumers initially saved much of the rebates, on average, by increasing their credit card payments and thereby paying down debt. But soon afterwards spending temporarily increased, offsetting the initial extra payments, so that debt eventually rose back near its original level. For people whose most intensively used credit card account is in the sample, spending on that account rose by over

[4] Other related studies include Wilcox (1989, 1990), Parker (1999), Souleles (2000, 2002), Browning and Collado (2001), Hsieh (2003), and Stephens (2003), among others.

$200 in the nine months after rebate receipt, which represents over 40% of the average household rebate.

3. Consumer Credit in Turkey, Data and Methodology

3.1 Consumer Credit in Turkey

Turkey experienced a tremendous economic growth post 2001 with the newly elected government at the time. The country went through a financial crisis in 2001 and the election of new government as well as improving economic conditions provided a fresh outlook for future both domestically and internationally. As would later become apparent, most of this growth was fuelled by explosive credit growth, and a large chunk of it was sitting on consumers' shoulders. There were several factors that brought about such a situation in Turkey, traditionally a country were consumer credit was an exception and not the rule.

In the pre-2001 era Turkish banks relied heavily on funding the public deficit as the main source of their profit generation. However, with the new government, there were significant changes in the monetary and fiscal policy, as well as the general regulatory framework for the banking sector. This forced the banks to discover new venues for profit generation and consumer credit became the primary source of profits for Turkish banks in the post-2001 era.

Banks employed very aggressive marketing and spent lavishly on advertising in order to attract their customers. It was a common occurrence to sign up for a credit card at booths and stands that banks would set at the busy locations throughout many Turkish cities. Banks would grant credit cards limits higher than the income of the customer would normally allow, and many customers owned multiple credit cards, some up to a dozen. Many people with lower income started living beyond their means, and private debt started to soar at unprecedented levels. Other factor also contributed to the development of such a situation. Low inflation, low interest rates, low real wages and an abundance of low-wage and temporary jobs created a need to borrow for low income households.

The case of Turkey was not an unusual one, though. It was first the developed countries that initiated a trend of turning to household income as a source of profit. The developing countries followed suit, and Turkey's neighbor Greece is a well known example of how debt, both public and private, can cripple a country's economic standing. This situation did not only cause fierce competition between domestic banks in Turkey, but many foreign banks started entering the Turkish market. Consumer credit skyrocketed as a culmination of all the above mentioned factors.

BRSA's data show that the total number of loans increased on average 25% since 2007. Looking at our sample, average monthly growth in consumer loans is 2.12%, but around 1.75% for all banks in Turkey from January 2009 to November 2014, the latest month available in BRSA's database. The pattern is identical whether we look at housing loans, personal finance loans or credit cards. One interesting fact is that the bank from our sample is among the top four Turkish banks with the fastest growth in the size of consumer loan portfolio. The Central Bank of Republic of Turkey data show that the fastest growing group of banks increased their consumer loans 169% between 2010 and 2013. Between 2005 and 2013, they multiplied the amount of consumer credits extended 9 times. On the other hand, the figures for the remaining banks for the same periods are much lower. During our sample the remaining banks' consumer credits grew 89%, and between 2005 and 2013 their consumer credit portfolio increased 7.4 times.

For the sake of comparison, in Figure 1, we show commercial and consumer loans from January 2010 to November 2014, the last month of available data. The year-on-year consumer credit growth was hovering around 40% before suddenly dropping in the second half of 2011, which more or less parallels the initiation of the policy to curb the explosive credit growth.

Figure 2 show the ratio of non-performing loans to total loans. The highest incidence of bad loans is almost always for consumer loans; however we can see that both consumer and commercial loans move pretty much in tandem, peaking above 6% towards the end of 2009. Although BRSA's policy as well as certain regulatory moves by Central Bank helped somewhat stabilize and streamline the payment of existing consumer debt, it hardly curbed the growth of new debt being created. According to the data of Interbank Card Center, there were slightly less than 45 million credit cards in January 2010; but at the end of our sample, in August 2013, that number rose to 56.5 million cards, a 25% increase.

The explosive growth in consumer loans in Turkey (Figure 3) became alarming for the bank regulators, government and the central bank, leading to different policies and regulations. Numerous studies have shown that fast credit growth hurts financial stability and might event lead to financial crises. Mendoza and Terrones (2008) find that rapid credit expansion can make banking sector vulnerable and is associated with instances of financial crises, especially in developing countries. Schularick and Taylor (2012) conclude that extreme credit growth is a leading indicator of financial crises. With all these adverse developments in the consumer credit market in Turkey, the Central Bank also added financial stability, with special emphasis on credit growth as one of its primary objectives to deal with in the post global recession era (Kara and Tiryaki (2013)).

3.2 Data

The panel data we are using is provided by a major Turkish bank headquartered in Istanbul. It is in the top 10 largest banks by assets and number of employees in Turkey[5]. The Bank's capital ratio, banking and other fees are similar to the rest of the Turkish banking sector.

The original data set contains monthly spending behavior for 1,143,278 customers from January 2010 to August 2013 for a total of 50,304,232 observations. We have information on monthly customer spending across 23 spending categories as defined by the Bank. We reduce the number of spending groups to 8 by combining categories similar to each other or belonging to a broader spending sector. The spending groups we define are daily spending, vehicle purchase and maintenance, travel and transportation, services, products intended for long-term use, construction, telecommunication and other. The data is also rich in other consumer characteristics. For each consumer, besides monthly credit card statement information, we have credit card limit, number of different credit cards owned, spending segment, and demographic information including age, gender, education, occupation, marital status, address and the date of credit card initiation.

Table 1 contains the descriptive statistics for age, credit card limit and all spending variables for the entire sample. The average age of the Bank's customer population is slightly below 40, with the standard deviation of 10. This indicates that the large majority of customers are somewhere between 30 and 50 years of age. Credit card limit averages slightly above TL 4700; however there is a high level of dispersion in the distribution of credit card limit across customers, namely the standard deviation is TL 6818. The similar situation holds for all of the spending variables, where we have a high variation of monthly spending amounts across the Bank's customers.

[5] http://www.bddk.com.tr

Table 2 compares the average spending across the treatment and control groups, and provides relative distribution of consumers across different characteristics. Panel A shows that transactors on average have higher credit card limits and spend more on all goods and services compared to debtors. In Panel B we report the relative frequency distribution of customers based on their. Around 70% of all customers have high school or lower as their attained education level, whereas 29% have an undergraduate degree. The remaining small percentage of customers has some form of graduate education. Comparing across debtors and transactors, there seems to be a relatively higher proportion of customers with a university degree among transactors, while customers with less years of education seem to be those with higher amounts of debt. In the entire sample, almost 84% of consumers are male, and almost 83% are married.

In December 2010, Turkey's Banking Regulation and Supervision Agency released a decision in Official Gazette number 27788, by which it regulates minimum credit card payment, credit card limit, and cash withdrawals[6]. The regulation resulted as a government's effort to curb explosive credit growth in Turkey especially given the intensified global economic risks arising with the Great Recession. It stipulates the following: minimum payment on all credit cards will progressively rise in the three years following the regulation; cash withdrawals will be banned for all credit cards owners that have paid 50% or less of their monthly balance three or more times in a year; the same credit card owners will not be able to increase their credit card limit or make any cash withdrawals until the entire credit card balance has been paid off. Minimum payment rule started being implemented the day following the announcement in the Official Gazette. The cash withdrawal and credit card limit rules, on the other hand, were legally binding as of 9 months after, on September 17, 2011.

As of September 2011, there were over 18 million credit card users with almost 50 million credit cards in use in Turkey[7]. BRSA's regulation had the aim to curb credit card spending and issuance of new credit cards in the aftermath of global recession. Millions of Turkish consumers were to be significantly affected, especially if dependent on credit cards as means

[6] http://www.resmigazete.gov.tr/eskiler/2010/12/20101217-3.htm
[7] http://www.bkm.com.tr/istatistik/pos_atm_kart_sayisi.asp

of their purchases. The minimum payment rule was to be implemented in a progressive fashion over a longer time period; hence, we expect that it would not lead to any significant changes in the consumption pattern of Turkish credit card owners. However, credit card limit and cash withdrawal restrictions directly affect the purchasing power of consumers and, as such, have the potential to cause larger disruption in consumption behavior.

This specific policy is interesting in that it was announced 9 months before its becoming effective, so it was not unanticipated. In the month of September, almost all larger Turkish daily newspapers published articles on this issue, reminding the population of the policy going into effect. However, as per the same articles, many financial professionals in the banking sector claimed that the majority of their customers were not prepared to tackle the new rule, especially the ones that honored only the minimum payments every month and rolled over their debt. In that respect, if this policy came as a surprise to majority of the consumers we would see its effect only after September 2011. On the other hand, if most consumers were well aware of the policy and took early action to adjust the credit card spending we would see its effect earlier too, between December 2010 and September 2011.

In a survey conducted by Turkey's Interbank Card Center in November 2011 with 499 active credit card users, the results showed that average monthly credit card spending is 1050 Turkish Liras (TL) and that 58% of survey participants were not able to save any money and were hence dependent on their credit cards for their purchases[8]. Moreover, the survey also shows that 60% of the credit card users reduced their in-pocket cash holdings, while 40% had their cash holdings unchanged even after they started using a credit card. These results indicate that the policy could negatively influence spending patterns for more than a half of the credit card users, if they are forced to pay higher portion of their credit card balance and are completely restricted to withdraw cash from their accounts. There were exactly 2,295,033 point-of-sale (POS) devices in slightly more than 1.5 million locations, which means 86% credit card payment availability across all registered retail businesses in Turkey[9]. On the other side, Turkey has had a major issue with underground economy which constitutes 33% of its gross domestic product, indicating that the credit card is not an available payment option in many cases.

[8] http://www.bkm.com.tr/basin/ekonomik_katki_2011.pdf
[9] http://www.bkm.com.tr/istatistik/illere_gore_isyeri_sayisi.asp

The unique data set we use in this study gives us the opportunity to analyze the effect of credit restriction policy on customers of a well known bank in Turkey. The Bank has more than 300 branches all over Turkey and with more than a million customers with diverse demographic background we believe our sample is representative of a broader Turkish population[10]. In regards to the Bank's operations, the customers face similar conditions in terms of deposits, loans, and other banking transactions provided by the Bank; hence, the customer base is not in any way limited to a specific population. We have complete information on monthly spending for every customer as well as their demographic details which gives ample opportunity for rich analysis of consumer response to credit policy across various categories.

Given our goal to analyze the effect of credit restriction policy on the spending patterns of Turkish consumers we define two groups, "debtors" and "transactors". Transactors are consumers in the bottom 2 deciles by average credit card debt at the end of the month scaled by credit card limit. Debtors are consumers in the top tow deciles of average credit card debt at the end of the month, i.e. bank customers who use their credit cards as a primary means to pay for purchases. We use difference-in-difference approach to measure the consumers' response to credit card policy. In this approach, debtors are the treatment group, and transactors are the untreated group. Transactors have on average very little debt on their credit cards at the end of the month, i.e. they use their credit cards primarily as regular debit cards and hence, are assumed to have remained unaffected by the credit policy. On the other hand, we expect that the consumers that heavily depend on their credit cards for their purchases will be significantly affected by the BRSA's credit restriction policy. Specifically, our expectation is that the debtors' spending change will be significantly lower in comparison to transactors' spending change resulting from the BRSA's policy.

3.3 Methodology

Using monthly data on individual card spending we analyze the credit card spending response to Banking Regulation and Supervision Agency's policy to fight explosive credit growth in Turkey. We use the following specification to gauge the average response to policy:

[10] Bank's website

$$S_{i,t} = \alpha + \beta_{post} * 1_{post} + \beta * 1_{post} * 1_{treat} + \varepsilon_{i,t}$$

$S_{i,t}$, the response variable, depending on the regression is the amount of total credit card transaction value, total monthly spending, spending on each of the 8 consumption categories, amount paid, and amount left unpaid towards the credit card balance for individual i in month t. All the spending variables are level variables in this specification.

1_{post} is an indicator variable that has the value of one for period after the BRSA's policy implementation, i.e. months 2012:01 to 2013:07, and zero elsewhere. 1_{treat} is also an indicator variable that takes the value of one for treatment group, i.e. the debtors, and zero for the transactor group. β_{post} measures the average difference in spending comparing periods before and after the policy. In other words, it captures the overall trend in consumption spending over time. β on the other hand, measures the average monthly spending response of the debtors after the policy implementation relative to change in spending of the transactors, i.e. it captures the marginal effect of the policy on the spending of the treated group, assuming that the control group sees no effect of the policy.

Moreover, to analyze if the credit card users started responding to BRSA's policy after its initial announcement in December 2010, and before the actual implementation we specify the following regression model:

$$S_{i,t} = \alpha + \beta_{post} * 1_{post} + \beta_{announce} * 1_{announce} * 1_{treat} + \beta_{effect} * 1_{effect} * 1_{treat} + \varepsilon_{i,t}$$

We separate the post-policy period into announcement period which starts In December 2010, and implementation period which starts in December 2011. If the BRSA's policy was de facto unanticipated by majority of the consumers, even though it was announced in the Official Gazette in December 2011, $\beta_{announce}$ should be economically and/or statistically insignificant, otherwise it would show those consumers were responding to policy early on. $1_{announce}$ is an indicator variable equal to 1 for the months 2010:12 to 2011:12, and the 1_{effect} is an indicator variable with value of 1 for all subsequent months. The coefficients $\beta_{announce}$ and β_{effect} measure the respective average monthly spending response of the debtors during the policy announcement and after the policy implementation relative to change in the spending of the transactors.

We also run a distributed lag model to analyze the dynamics of the consumer spending response to the BRSA's policy:

$$S_{i,t} = \alpha + \sum_{m=-20}^{20} \beta_m * 1_{month\,m} * 1_{treat} + \varepsilon_{i,t}$$

The coefficients β_{-20} to β_{20} measure the average difference in credit card spending between the treatment and control groups 20 months before and 20 months after the policy, respectively. Coefficients β_1 to β_{20} capture the marginal spending responses for every month subsequent to the policy implementation. Adding these marginal coefficients up to month m will give the cumulative response of the policy up to that month. We expect to see significant spending response in the months following the policy, instead of a short and immediate response.

Finally, we study how different groups of individuals in terms of age, education, marital status and account related information in our sample respond to the BRSA's policy. The analysis of heterogeneity in spending response will be especially revealing if certain individuals were affected more than the others. We utilize the following regression:

$$S_{i,t} = \alpha + \sum_{m=-20}^{20} \beta_m * 1_{month\,m} * 1_{treat} + \sum_{m=-20}^{20} \beta_{g(1),m} * 1_{g(1)} * 1_{month\,m} * 1_{treat} + \cdots + \sum_{m=-20}^{20} \beta_{g(N-1),m} * 1_{g(N-1)} * 1_{month\,m} * 1_{treat}\ \varepsilon_{i,t},$$

where N is the number of subgroups of consumers used in the regression. $1_{g(n)}$ is an indicator variable that takes a value of one if the individual belongs to the nth group. All the regressions are performed using panel data regressions with fixed effects, and standard errors clustered at the individual level.

4. Empirical Results

We begin by estimating the average response of total credit card spending and spending in various subcategories to the BRSA's credit tightening policy. In further analysis we examine the dynamics of the consumer response to the policy employing distributed lag model and study response diversity across different characteristics of individuals. The main analysis is based on the full sample of Bank's customers. In the subsequent examination we use a matched sample to check if our results are driven by any of the observable customer characteristics.

4.1 Static regressions

Table 3, Panel A shows the average response for total credit card spending as well as spending categories by employing the difference-in-difference regression as specified in Equation (1). Post-policy dummy variable coefficients give average difference across credit card spending categories in the months before and after the Banking Regulation and Supervision Agency's (BRSA) policy implementation. Treatment group represents the top two deciles of number of months consumer has credit card debt scaled by his or her credit card limit. Similarly, the control group consists of the bottom two deciles of the same measure of consumer credit card indebtedness. Monthly credit card spending increased on average 848 Turkish Liras (TL) per month following the policy. Similarly, all spending sub-categories show statistically and economically significant increase over the same period. The highest surge in observed for the daily spending category which rose by a 375 TL in the months following policy implementation. Post-policy dummy coefficients, all positive, specify that there was an upward trend in spending across all consumers and all spending categories over the sample period. The average USD/TRY exchange rate over our sample was 1.70. Even in dollar terms the BRSA's policy had economically a very strong effect on spending of credit card holders in Turkey

The variable of our primary interest is the interaction term between treatment dummy and post-policy dummy variable, which shows the difference-in-difference effect, i.e. the marginal effect of policy on 'debtors' spending relative to change in spending of the 'transactors'. Our expectation is that debtors will have their relative spending curbed more than that of debtors following the BRSA's policy, since they would have to put aside more resources to honor the credit card payments compared to pre-policy period. Hence, their spending would increase less than that of the transactors. The negative coefficient on the interaction term confirms our intuition. Across all credit card spending variables the interaction term coefficient is negative and retains statistical and economic significance. The total credit card spending shows a coefficient of TL -794 in Table 3, which in economic terms is a non-trivial effect. The average salary from 2010 to 2013 across all industries in Turkey hovers around TL 1400[11]. The average difference of TL 794 between treated and control group in our study underlined the strong impact BRSA's policy had on spending of consumer with high credit card debt relative to their income. The highest marginal effect is for the "Daily" and "Telecommunications" subcategories with coefficients of TL -352 and TL -93, respectively. The smallest marginal effect of the policy is observed for construction spending category, a drop of mere TL 8. This makes perfect sense though; as construction related work is not a common spending activity that individual consumers engage in, and hence should not be significantly affected by policies such as BRSA's. It appears from our sample that the credit cards are used primarily for daily spending habits, primarily on groceries and other essential goods. Consumers with high credit card debt relative to income had to cut back their spending primarily for such items, as a result of a stricter credit card payment policy.

The coefficients on the post-policy dummy give a view of the overall increasing trend in the spending data, but the interaction terms shows that the majority of this increase in the post-policy is taken up by transactors. In other words, the burden of the policy is primarily shouldered by the debtors across all spending categories[12]. However, it is crucial to understand that the debtors are not necessarily being able to reduce their debt is the post-policy conditions. Table 3 shows that relative to transactors, debtors have a decrease in the total amount of debt paid, and similarly an increase in the amount left unpaid. The consumer spending habits seem difficult to change, leaving already highly indebted customers with more debt to pay off; at least in the short period we get to observe in our sample.

In Panel B of Table 3 we distinguish between policy announcement date and official implementation date. The consumers had exactly 9 months after the announcement to prepare and adjust their credit card spending according to new rules stipulated in the BRSA's policy. We augment the equation used in Panel A with an interaction term between the treatment

[11] Turkish Statistical Institute

[12] In unreported results we rerun the regressions defining debtors and transactors as the highest and lowest bin, respectively using 3, 7 and 10 bins. The results are very similar. We also repeat the same analysis using alternative days as a policy date. We test for September 2011, October 2011, November 2011, and January 2012 as the policy date across 3, 5, 7 or 10 bins, and we find that the results are qualitatively the same.

dummy and post-announcement dummy as show in Equation (2). Two interaction terms capture separately the announcement effect and the implementation effect (Agarwal and Qian (2014)). This type of analysis permits a clear test of the impact announcement of future income shock has on consumer spending. Life-cycle theory predicts that announcement itself should have a visible effect on consumer spending. The results of our test in Panel B indicate an economically significant adjustment in average spending in the 9 months prior to policy effective date. Average difference in total credit card spending between debtors and transactor in the 9-month window is TL -163. There is a significant difference between the announcement and implementation effect; the marginal effect of the policy implementation is more than four times higher than the announcement effect. It shows that there were some adjustments in credit card spending made by consumers, however, the actual enforcement of new policy rules brought about much bigger changes in credit card spending. The coefficients on the added interaction term are all negative, statistically and economically significant across all credit-card spending categories. Overall, this shows that consumers in the highest deciles of credit card debt relative to income started adjusting their spending habits in the anticipation of the policy enforcement date, relative to the consumers with little or no credit-card debt. To that end, it seems that the BRSA's policy to curb credit growth was a success. However, in short a sample we study here, it is not possible to analyse the long-term or permanent effects of this policy on consumer spending.

In summary, our results suggest two major findings. Similar to Agarwal and Qian (2014), we find that consumers with high credit card debt started adjusting their card spending upon announcement of the program. Second, enactment of the policy had a very strong effect of on credit card spending, increasing more than fourfold compare to the announcement window only. Whereas Agarwal and Qian (2014) find that announcement effect and disbursement effect are similar in magnitude in case of positive unanticipated income shock, we find that for a negative income shock the bulk of necessary adjustment in spending is delayed until the policy is legally enforced by the banks. Although this comparison between fiscal policies that cause a positive versus negative income shocks yields only suggestive conclusions, it is worth investigating this topic, as there might be systematic differences in terms of how consumers react to different fiscal policies.

4.2 Dynamic Regressions

Table 3 shows the average monthly response in credit card spending to the BRSA's policy. Debtors are substantially impacted by the policy lowering the average spending slightly less than TL 800 relative to the transactor group. To understand the evolution of the impact of BRSA's policy we study the dynamic progression of credit card spending response before and after the policy. In Figure 4 we show the cumulative coefficients for total credit card spending as well as spending categories. This type of analysis is akin to event study methodology, with the announcement and the event taking place in month -9 and month 0, respectively.

Figure 4 plots the paths of cumulative coefficients. We obtain cumulative coefficients as the sum of marginal coefficients of the current and all prior months in our sample Standard errors are calculated based on the marginal coefficient standard errors. All standard errors are clustered at the individual level. We don't show the confidence intervals on the plots; the standard errors are small, and hence upper and lower confidence level bounds fall very close to the coefficient line. For the ease of disposition, cleaner cumulative coefficient plots, we decide to exclude them. Figure 4 contains the plots for total credit card spending and transaction values as well the seven spending categories.

Consistent with what we see in Table 3, the difference in cumulative credit card spending between the treatment and control group starts to change after the policy announcements, and diverges almost exponentially after the policy implementation. The total cumulative difference in credit card spending between debtors and transactors is around TL -24000 from the announcement month to the end of the sample in August 2013. This result is statistically significant at 1%.

We observe the similar pattern for all 7 spending categories. For all 7 categories both the policy announcement and implementation effects are statistically significant, although not economically strong for construction spending. The daily spending category is the most interesting one; from the magnitude and the path of the cumulative coefficients it seems that the daily spending drives the results we observe for the total spending. The plot indicates that the announcement effect if economically relatively small. It is the policy enactment that really drives the divergence in credit card spending between transactors and debtors. This results makes perfect sense in the context of Turkish economy and the characteristics of highly indebted credit card holders. In other words, credit card holders with highest debt relative to income are usually low-income consumers that utilize credit cards primarily on grocery spending and other necessity purchases. As such, we observe the smallest relative announcement effect for daily spending category, since consumers are trying to delay as much as possible the inevitable drop in the purchasing power until the policy in actually enforced. All other categories show a higher relative announcement effect; it is easier for consumers to eliminate spending on non-essential products and services than on necessity items. The results overall demonstrate that BRSA's policy reached its intended goal. However, the negative side-effect is that the biggest relative burden of the policy is taken up by the consumers that use credit cards primarily for essential purchases, i.e. the consumers with the lowest income. In other words, policy does curb credit card spending, but does so at the expense of the class of population most dependent on the use of credit cards for their livelihood.

We note that this policy was not a surprise policy; it was announced 9 month prior to its official enactment leaving consumers with ample time to adjust their spending and prepare for higher credit card payments. We find an economically significant announcement effect. It could well the case that the large proportion of consumers was not fully unaware of this announcement in the Official Gazette. As in Agarwal and Qian (2014) we have an announcement effect, however this effect is much smaller than the adjustment in spending that comes after policy is given a start. It is unclear whether we should expect an announcement effect, and how large it should be. However, the results in this paper as well as Agarwal and Qian (2014) tell us a compelling story. We analyse a fiscal policy with contractionary effects on spending, and the latter paper studies a policy with expansionary effect, however both suggest that consumers have propensity to spend now, instead of save for the future. This propensity is either observed as current consumption of future income, or delay in payments until absolutely necessary to maintain the current consumption habits as long as possible

In the months after the policy implementation, we see a strong and consistent response that persists for months following. All the spending categories indicate that the debtors had a significant decrease in their spending relative to the transactors as a result of the policy. Furthermore, the policy effect lasts many months following the policy date, and what is particularly interesting is that the spending difference between the debtors and the transactors grows wider in the subsequent months. The effect we observe could be an initial sign of a successful policy that aimed to curb explosive credit spending. However, we have seen that the highest difference occurs in the category "Daily", which combines spending for daily and weekly purchased products and services, primarily spending for groceries, food etc. This in itself is an important result, indirectly showing that the burden of the policy, at least in the first year of its implementation, weighs heavily on the consumer with significant amount of debt relative to their income and consumers that use credit card for their basic, non-durable household purchases. This fact is observable again in Figure 4, in the plots that report coefficients for "Amount Paid" and "Amount Unpaid" variables. Given the higher monthly minimum payment on the credit card balance as a result of BRSA's policy, the existing debt, and spending habits of high debt consumers that developed before the policy, we see an increase in the Amount Unpaid, and similarly a decrease in Amount Paid relative to the transactor group. All the results indicate that the debtors are severely affected by the credit restriction, and have to balance between honouring the minimum monthly payment as well as trying to adjust their spending accordingly. Looking at the opposite side of the coin, the transactors significantly increased their spending relative to the debtors. From Table 3, looking at the intercept, we know that over the full sample there was a positive trend is overall spending as well as all the spending subgroups. Given that, it might be the case that the policy actually backfired, putting greater pressure on the debtors, but encouraging consumers with low amount of debt to increase their credit card expenditure. In other words, it might well be the case that now faced with a higher monthly minimum payment requirement, transactors transferred some of their traditionally cash purchases to credit card purchases, balancing therefore the minimum payment requirement with the ability to spread payment on credit card over extended period of time. 1_{post} x $1_{treatment}$ x1_{new}

4.3 Heterogeneity

We next analyze the heterogeneity in responses to BRSA's policy. Our data contains rich demographic information about credit card holders allowing us to examine the dynamics in consumer spending in greater depth. We focus on the differences in average credit card spending based on age, gender, marital status, address, education, date when credit card account is open, and whether card holder was monitored by bank due to lack of payment of previous balances. The results are shown in Table 4. We run regressions similar to what we have in Table 3, with the addition of a triple interaction term that measures marginal difference in spending response across the above mentioned demographic and account-related information as a result of BRSA's policy. This analysis will show what types of consumers carry the highest amount of credit card debt relative to their income, and hence are bearing the weight of the policy in terms of reduced consumption after its implementation.

First of all, we focus our attention on the coefficient of the interaction variable between the treatment dummy and post-policy dummy. If the findings obtained above hold across all customers, we will observe the same negative sign and economically and statistically significant magnitude of the coefficient on this interaction. Otherwise, it might be the case that a subset of consumers is responsible for the results we found previously. This possibility might hold particularly because some demographic and account-related information is missing for certain customers, hence focusing on specific consumer characteristics will reveal if the effect of policy we find is a pervasive phenomenon or a peculiar case for only certain consumers.

In line with the results obtained using the full sample of consumers, we see economically and statistically significant negative coefficients across the board on the 1_{Post} x $1_{treatment}$ interaction terms. This confirms that there was not a group that the BRSA's policy was broad and far-reaching, attaining its primary goals to curb credit growth in the economy. Next we focus on the individual consumer characteristics to gauge if any groups were impacted more by the policy, resulting on large adjustments to credit card spending relative to other consumers.

We direct our attention to the triple interaction term in Table 4. Statistically and economically significant magnitudes make it is apparent that certain consumers were affected more than the others by the policy. The biggest relative decrease in total credit card spending in experienced by consumers that are male, young, married, less educated, live in less urban areas, are long-time credit card holders, and have been monitored by the bank in the past due to unpaid balances. One surprising finding here is that male consumers decreased their credit card spending much more than their female counterparts. Our prior was that either there should be no significant difference or that female consumers would be more impacted by the policy. However, the fact that slightly more than 80% of consumers in our sample are recorded as male is a probable cause of the result we observe here. The credit card spending response across other consumer features is not surprising. We expect that consumers that are young, married, lack university education, live in rural areas are have previous records of high indebtedness, have higher amounts of credit card debt relative to their income, and therefore experience a more acute response of credit card spending following BRSA's policy.

There is a high proportion of young population in Turkey, among the highest in Europe according to Eurostat 2014 statistics. They have to rely on credit card for the purchases as they have low or no savings and low discretionary income. Married consumers have higher spending outlays, which is true especially for families with children; hence it is expected that on average they will have higher levels of debt relative to their income. Finally, the higher number of debtors among consumers with no university education or consumers that live in non-urban areas is predictable. Such individuals will have less opportunity to find high paying jobs, leaving them with less discretionary income, and more debt on average relative to their earnings. Finally, we have consumers with previous credit card debt issues that banks closely monitor to prevent future non-payments of their credit card balances. We expect these credit card holders to be hit the hardest by the BRSA's policy. i.e. experiencing the largest drop in post-policy spending relative to other consumers.

Analysis of heterogeneity in consumer response to BRSA's policy uncovers some important results. First, across gender and education dimension of consumer characteristics, the daily spending category is not the one with the highest marginal change post policy implementation, which is the case across the full sample. For high-debt consumers that are male and have no tertiary education, the highest drop in spending relative to low-debt female and university educated consumers is in the telecom and vehicle spending categories. This result most likely reflects the cultural landscape of mainly patriarchal Turkish society where there exists a high proportion of females that are housewives, unemployed or unaccounted for in the labor force if they live in the rural areas.[13] Males are usually the owners of any vehicles and have much higher demand for telecommunication services as primary job-holders in the household. Similar hold for university educated population relative to consumer with high school education or less. Second interesting result is that the average vehicle and telecommunication services spending increased for certain groups after the policy, but at the same time their essential good purchases dropped relative to other consumers For example, consumers that live in urban areas experience such changes in marginal spending relative to non-urban consumers; their vehicle and telecommunication spending coefficients are positive, but daily spending coefficient is negative. Similar situations holds for consumers that are older in age relative to young consumers. Their marginal daily spending decreased as a result of policy, but all other categories experienced a rise.

In summary, our rich heterogeneity results confirm our overall results of a significant impact of BRSA's policy on consumers' credit card spending, primarily in the daily spending category. Consumers that are male, young, married, live in rural areas, and are senior credit

[13] TurkStat Population and Housing Census 2011 shows that female labor participation in Turkey is the lowest in Europe and is one third of that for male population

card holders experience highest drop in their credit card spending relative to their female, older, single, urban consumers, and new credit card holders, respectively. Finally, the policy does not seem to have a one-direction impact on consumers' spending habits. There are instances where we see both a rise and a drop in marginal spending for different items for the same consumer groups. The richness in the demographic information of our data indeed portrays a picture of diverse effects of the BRSA's policy across different consumer characteristics and for different spending categories.

4.4 Falsification tests

In the previous sections we provide statistically and economically strong evidence that the BRSA's credit restriction policy had affected consumers spending. In what follows, we test the robustness of these results. As a first robustness check we randomly assign individuals to treatment and control groups and repeat the same empirical exercise as in Table 3. If the consumer spending was genuinely due to BRSA's policy, and not some other, potentially unobservable factor, we expect that the results will yield coefficients that are statistically and economically insignificant. Otherwise, our claim that the BRSA's policy lead to a change in consumer spending does not hold. Either there were other events in the economy that triggered such a change, or the consumption trend of the debtors and transactors was not parallel prior to policy, rendering the difference-in-difference analysis inappropriate for our study.

The results are reported in Table 6. We find exactly as predicted that none of the coefficients on the interaction terms between post-policy dummy and rand treatment assignment dummy are significant. The magnitude of coefficients is around TL 2 or less, where some are positive, and the others negative. Coefficients on all spending categories are indistinguishable from zero, indicating that indeed that BRSA's policy had a strong effect on credit card spending of debtors, the consumers with high debt balances. Transactors maintained their spending patterns even after the policy, whereas debtors had to significantly lower their spending after the policy enactment. Findings in Table 6 are crucial for the overall results in this paper, as they confirm that the difference-in-difference methodology used here is the appropriate empirical tool to implement. Had our results been obtained by chance or as a results of unobservable events, other than BRSA's policy there would be a high likelihood of finding significant result in Table 6. These results therefore strengthen the view that difference-in-difference analysis is warranted in this case as a method of choice to study the effects of fiscal policy on consumer spending. Our overall results indicate that the policy was a success, at least in the short term we get to observe in our sample, but also not without some negative consequences. Consumers with highest amount of credit card debt relative to income are forced to decrease their credit card spending most relative to other consumers, however, this reduction takes its toll primarily on the purchase of essentially daily purchases.

Difference-in-difference analysis gives us quite intuitive results about the consumer response to BRSA's policy. However, we need to test further whether difference-in-difference analysis is warranted for our study. It is crucial that we make sure our results are not due to observable factors or consumer characteristics that might be driving the policy effect between debtors and transactor s we find in this study. For this test, we create a matched sample based on age, education level, gender, address, marital status and account related information of consumers in our sample. Matched sample generation is based on nearest neighbour propensity score matching. Our estimators are based on bias-corrected and heteroscedasticity consistent standard errors. We utilize the matched sample and perform the same difference-in-difference analysis as in Table 3. If the results we obtain are not driven by any of the observable demographic or account related features of consumers the matched sample analysis should yield results similar to those we get with the full sample.

We report the results in Table 7. As expected, we find that the coefficients on interaction term between post-policy and treatment dummies are statistically and economically significant for all spending variables. Moreover the coefficient magnitudes even larger than those reported in Table 3, where we employ full sample of consumers. The only exception is the construction spending variable, where the coefficient is positive instead of negative, but it lack statistical significance. All other spending categories have the expected negative sign, indicating that the debtors had to significantly decrease their spending relative to transactors even after accounting for all the observable consumer characteristics. Although our examination of heterogeneity in consumer response to BRSA's policy uncovered significant difference in spending across various dimensions, the effect of policy is not driven by them. Our definition of debtors and transactors as the extreme top and bottom two deciles of credit card debt relative to income is a valid and reliable measure that captures well the dynamic of credit-restraining fiscal policy as implemented in Turkey.. Therefore, together with the previous results we safely conclude that the difference-in-difference methodology is warranted for the type of analysis and conclusions reached in our study.

5. Conclusion

This paper uses a unique, new panel dataset of more than a million credit cards accounts in Turkey to analyze how consumers respond to a fiscal policy shock on spending. Turkey's Banking Regulation and Supervision Agency enacted a credit tightening policy in 2011 with the goal to curb explosive credit growth for traditionally not very indebted consumer population in Turkey. We use difference-in-difference methodology to analyze the marginal effect of policy on spending changes between consumers with very high and very low amounts of credit card debt.

Our findings are summarized as follows. First, the credit tightening policy has an immediate and economically strong effect on consumer spending. Consumers with high credit card debt are forced to decrease their spending on average by TL 794 in terms of credit card transaction value relative to the change in spending of low-debt consumers. The same patter consistently hold across different spending categories, with Daily and Telecommunication spending showing the largest coefficients, TL 352 and TL 93, respectively. The fact that the biggest drop in spending is for the Daily category, agrees with the fact that a big majority of Turkish consumers were using credit card for the purchase of groceries and other necessities. Hence, this policy had the most adverse effect on those in biggest need of available credit card balance.

Second, BRSA's policy was announced exactly 9 months prior to the official starting date. Our results show that there was economically and statistically significant adjustment in consumer spending between the announcement and effective date of the policy. It might be the case that the certain percentage of consumers were aware and willing to react early and adjust their spending, while others did not. On the other hand, it is possible that announcement effect of future negative income shock does not have to bear similar magnitude as the actual policy effect, contrary to what is predicted by life-cycle spending hypothesis. Analysis of dynamics of consumers' response to BRSA's policy reveals results consistent with those obtained in basic difference-in-difference egressions. The adjustments to consumer spending start immediately following the policy announcement, and the marginal difference between spending of debtors and transactors grows exponentially in the months following policy enactment. Overall, the policy did tighten the credit card spending, as it had to do by construction, but the negative side effect is that biggest squeeze in spending is observed in purchases of essential and necessity goods and services.

We also found significant heterogeneity in the response to the policy implementation. Across different consumer characteristics we find a similar pattern of spending response to the policy. In other words, there was not any specific category of consumers that was not affected by the policy, at least using the demographic and account-related information available in our dataset. However, the response was not unilateral in magnitude across the different consumer characteristics. The highest burden of the credit tightening policy was experienced by consumers that are young, married, male, live in rural areas, and are monitored by banks due to prior credit card debt problems. This result comes natural as the above mentioned categories have lowest discretionary income or highest purchase need and are, hence, in the biggest need of credit as means to maintain their spending habits.

Our results are robust to changes of the definition of debtors and transactors, and are not an artefact of pure chance or driven by other events or observable features of consumers in our sample. Difference-in-difference analysis is shown be the proper methodology for this type of study, and we find that debtors experienced large downward swing relative to transactors who maintained their pre-policy spending trend. Overall, this paper finds that a fiscal policy that aims to restrain credit growth is likely to be successful if the following tools are employed: increase in interest rates, increase in minimum monthly payments, and limit to number of credit cards and individual can hold. The policy examined here has a negative shock for future income, contrary to a number of previous papers. It is worthwhile engaging in further research to test if there are systematic differences between policies that cause a positive versus a negative shock to future income.

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Figure 1: Commercial and Consumer Loans (Source: CBRT)

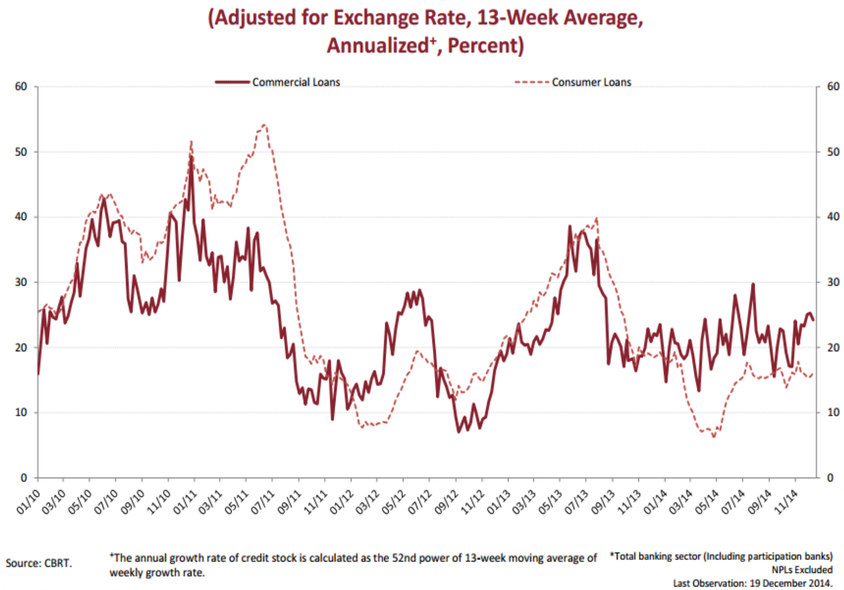


Figure 2: Non-Performing Loans (Source: CBRT)

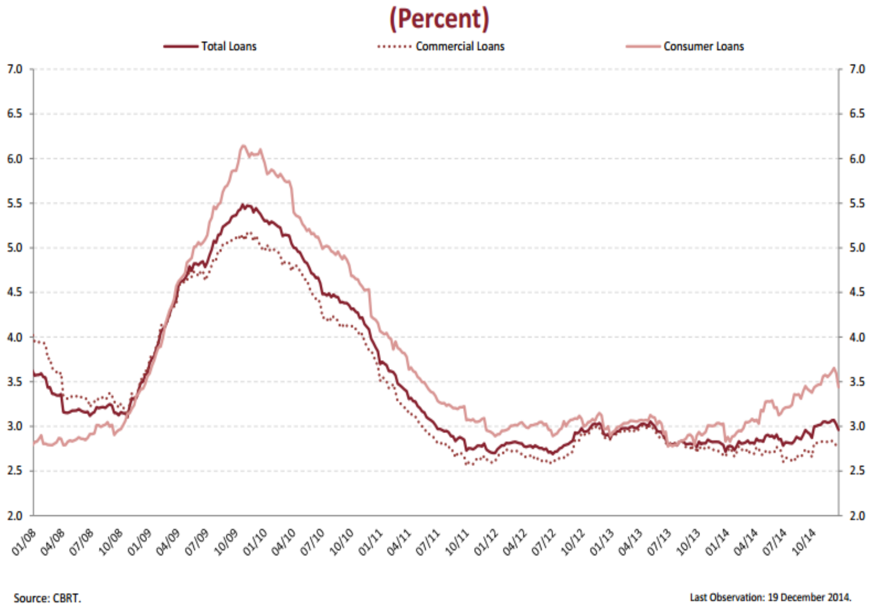


Figure 3: Consumer Loans: Unadjusted raw data (Source: BRSA)

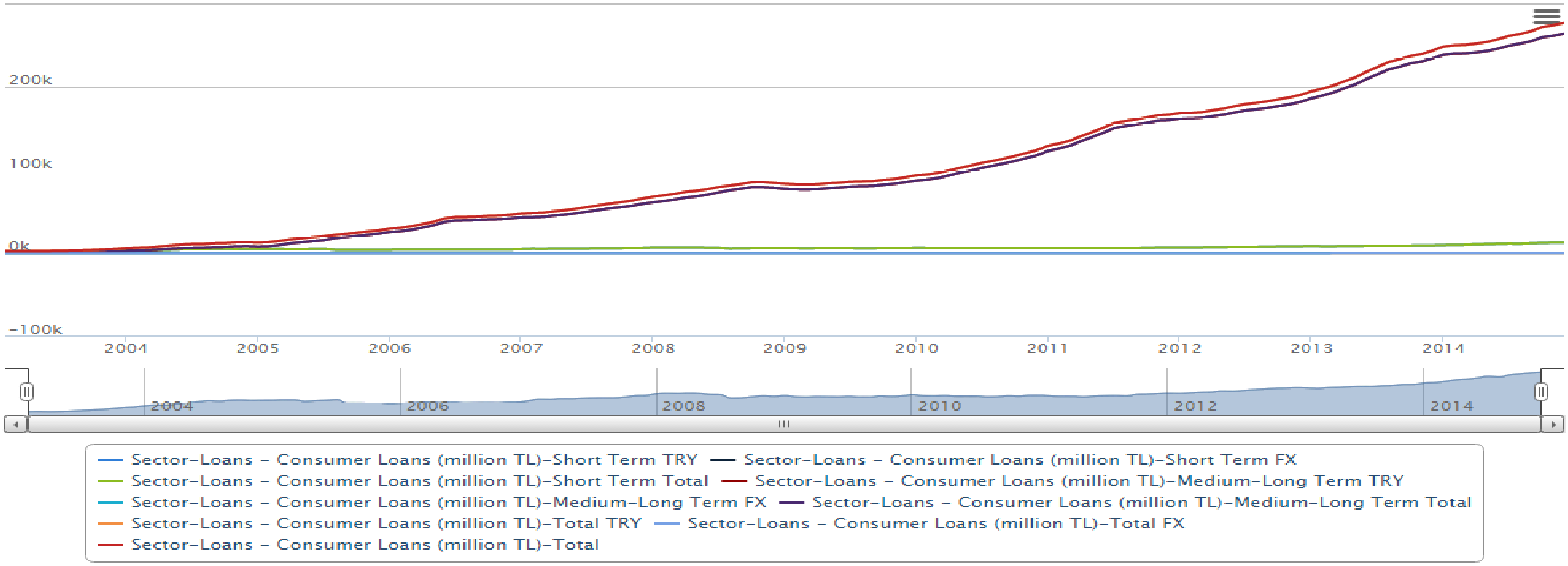
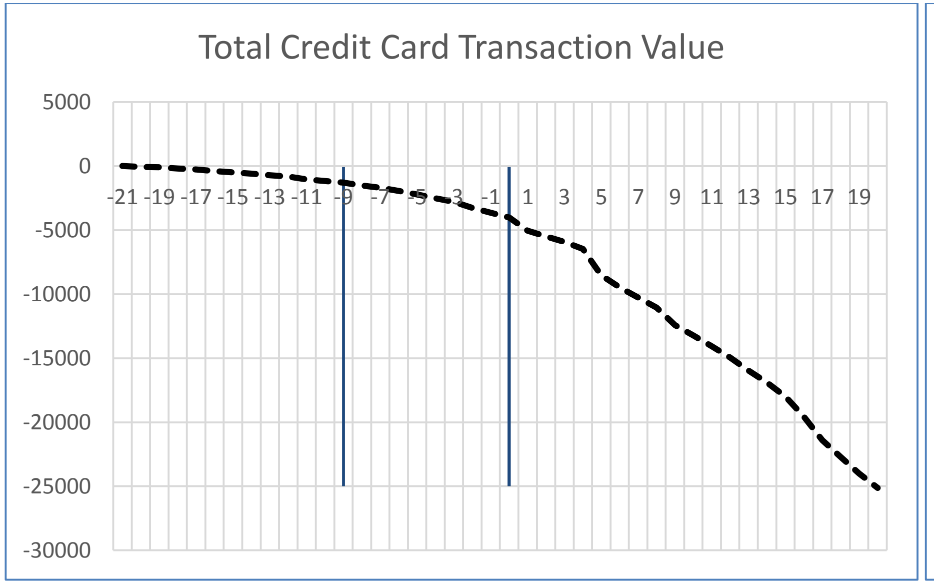
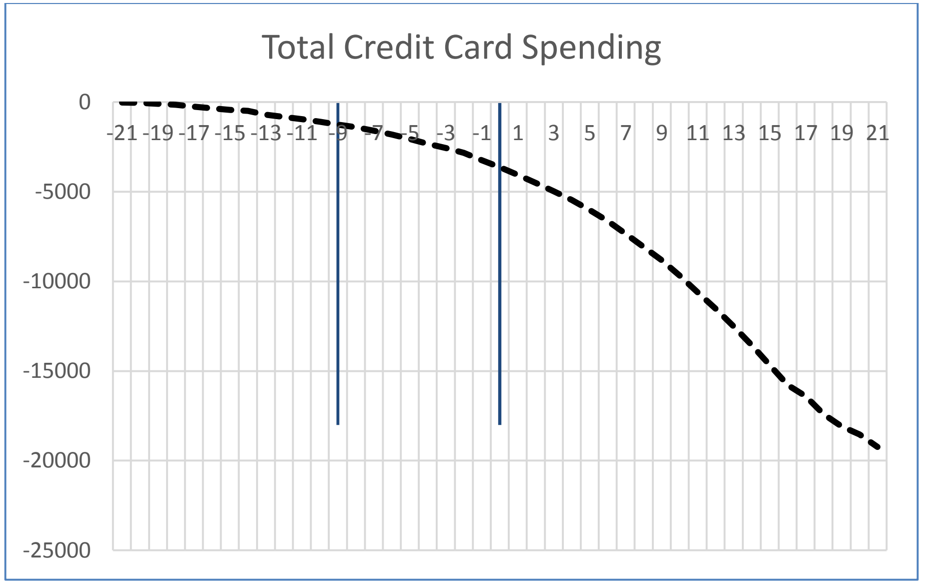
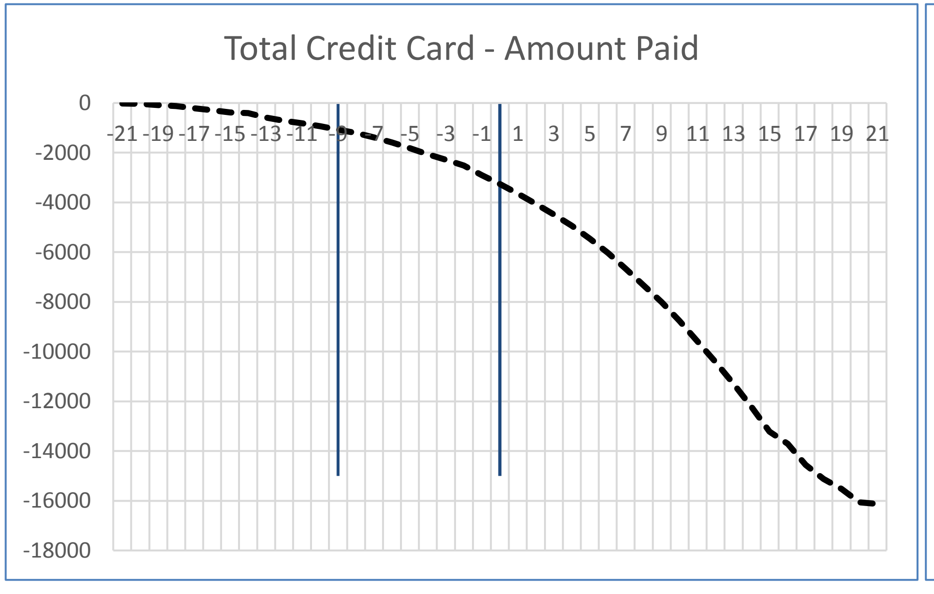


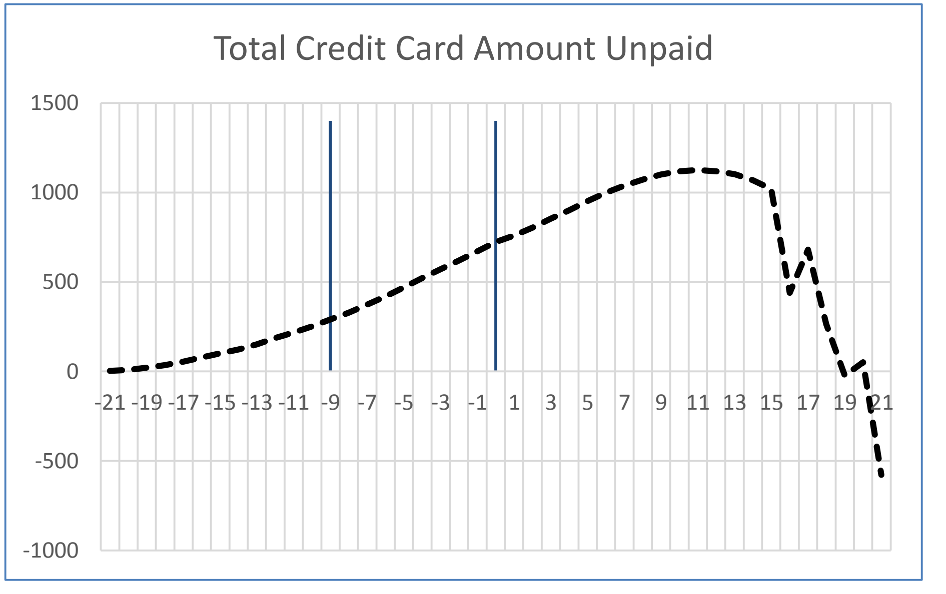
Figure 4: Dynamic results – all spending categories

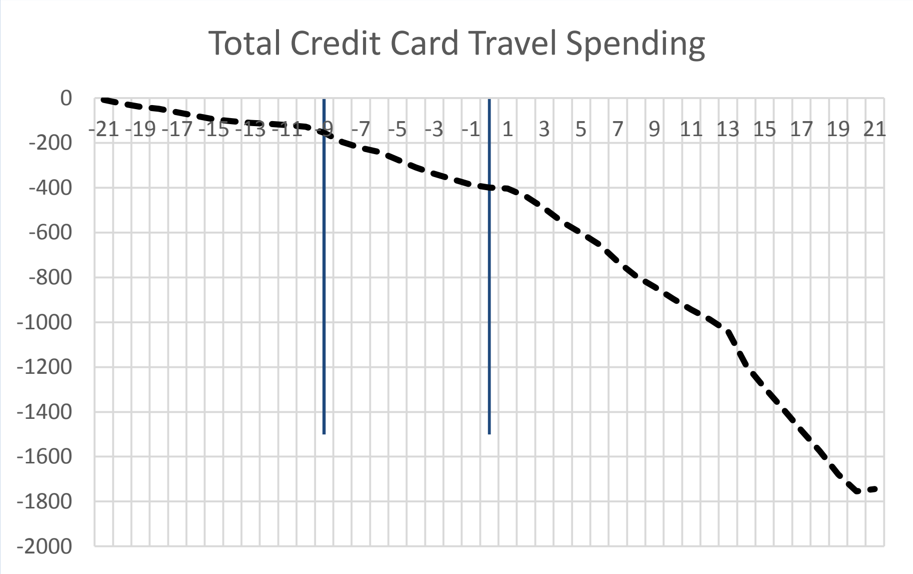
These figures provide cumulative coefficients from distributed lag model for different spending categories in the data. Reported is the cumulative coefficient line.. Confidence interval calculations are based on robust standard errors, clustered on individual consumer level.

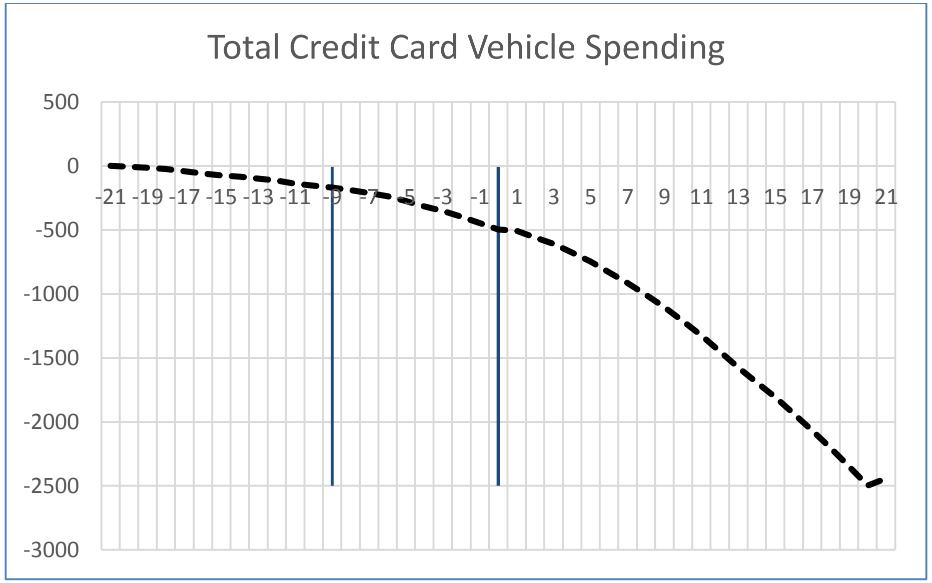

Total Credit Card Transaction Value
5000
0
-5000
-10000
-15000
-20000
-25000
-30000
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19


Total Credit Card Spending
0
-5000
-10000
-15000
-20000
-25000
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19 21


Total Credit Card - Amount Paid
0
-2000
-4000
-6000
-8000
-10000
-12000
-14000
-16000
-18000
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19 21


Total Credit Card Amount Unpaid
1500
1000
500
0
-500
-1000
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19 21


Total Credit Card Travel Spending
0
-200
-400
-600
-800
-1000
-1200
-1400
-1600
-1800
-2000
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19 21


Total Credit Card Vehicle Spending
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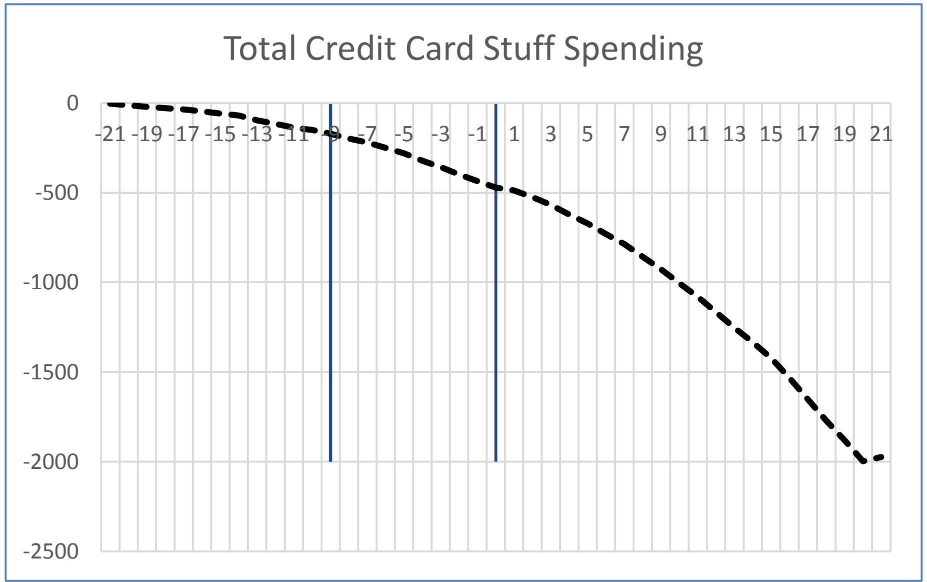
0
-500
-1000
-1500
-2000
-2500
-3000
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19 21


Total Credit Card Stuff Spending
0
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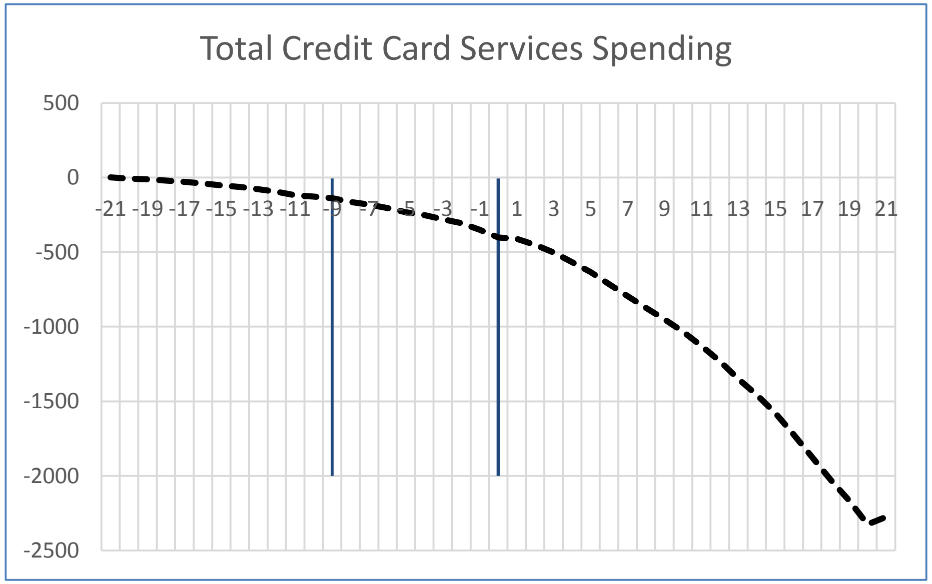
-1000
-1500
-2000
-2500
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19 21


Total Credit Card Services Spending
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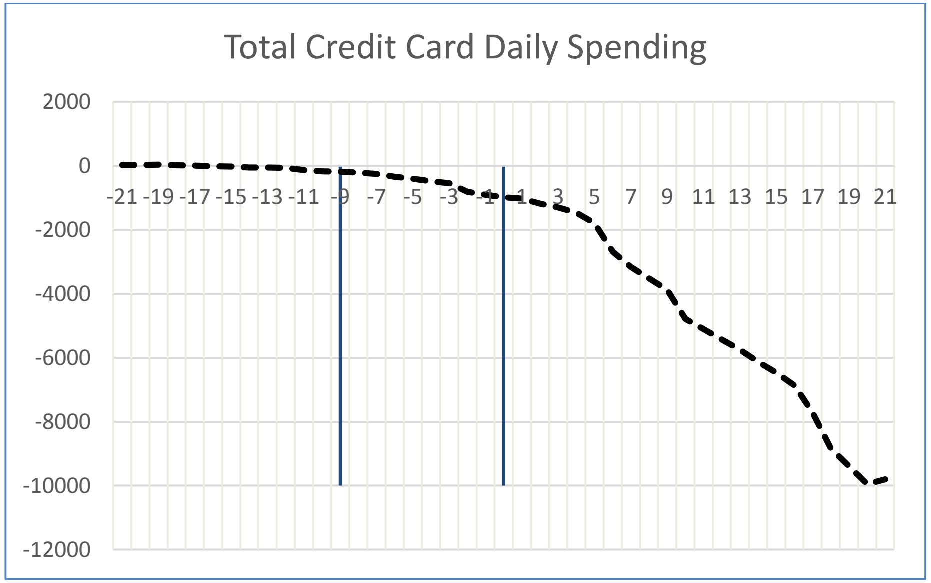
0
-500
-1000
-1500
-2000
-2500
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19 21


Total Credit Card Daily Spending
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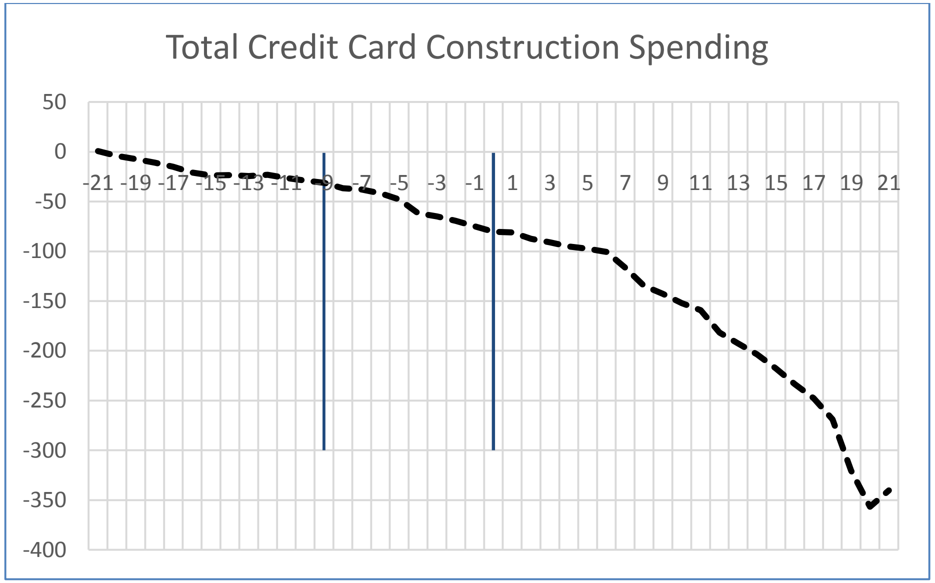
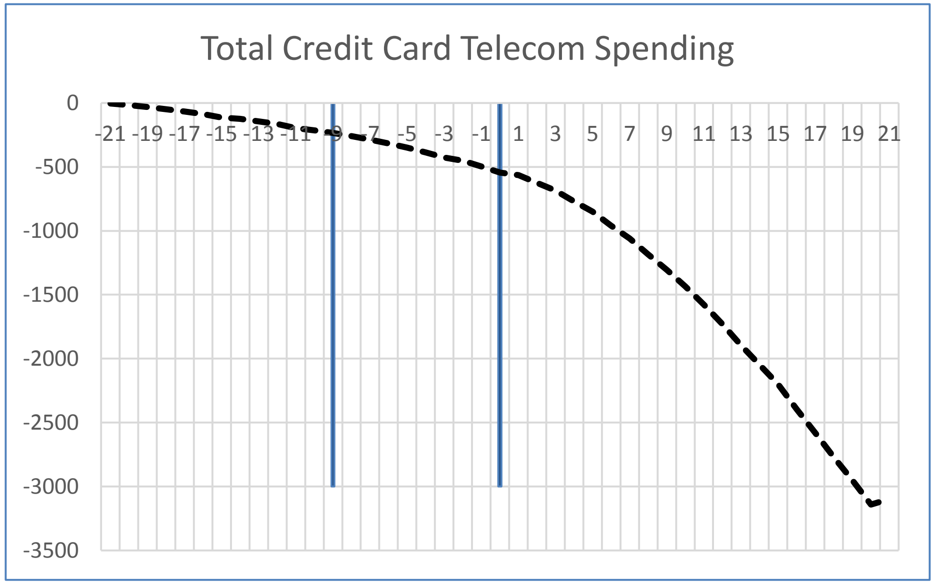
0
-2000
-4000
-6000
-8000
-10000
-12000
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19 21


Total Credit Card Construction Spending
50
0
-50
-100
-150
-200
-250
-300
-350
-400
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19 21


Total Credit Card Telecom Spending
0
-500
-1000
-1500
-2000
-2500
-3000
-3500
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19 21

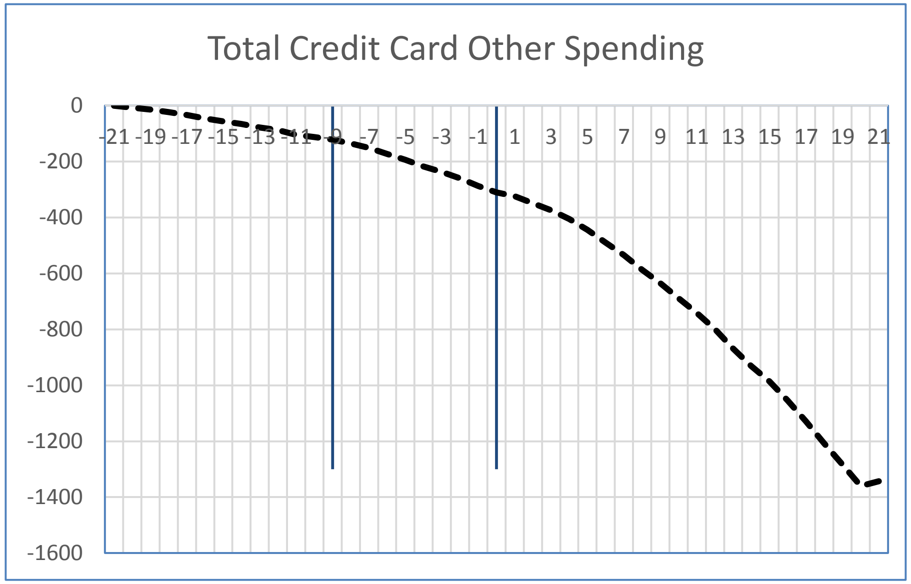

Total Credit Card Other Spending
0
-200
-400
-600
-800
-1000
-1200
-1400
-1600
-21 -19 -17 -15 -13 -11 -9 -7 -5 -3 -1 1 3 5 7 9 11 13 15 17 19 21

Table 1: Descriptive Statistics

This table reports the basic descriptive statistics for age, credit card limit and all credit card spending variables. Reported are the number of observations, average, standard deviation, minimum and maximum value.

Panel A: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Age	38212196	39.80806	10.31816	17	97
CC Limit	38212196	4737.722	6818.894	0	570000
Transaction value	38212196	536.9972	1896.479	0	1852419
Spending Amount	38212196	482.3256	1543.31	0	398952
Advance Payments	38212196	124.3371	1007.955	0	1852419
Instalment Payments	38212196	412.6601	1545.71	0	699206.8
Amount Paid	38212196	425.8068	1418.807	-182872	485782.8
Amount Unpaid	38212196	167.0585	809.6659	-365744	365744.1
Travel	38212196	29.02345	368.3488	0	425823
Daily	38212196	192.6649	1075.564	0	1852419
Vehicle	38212196	66.24312	561.2339	0	160250
Service	38212196	68.42594	543.4408	0	289361.8
Products	38212196	38.90078	396.2961	0	195738.5
Construction	38212196	10.8157	277.1447	0	378024.4
Telecom	38212196	55.78875	533.914	0	150000

Other	38212196	22.58251	382.425	0	699000

Table 2: Spending variables by groups

Panel A reports differences in age, credit card limit and all the spending variables between debtors and transactors. Transactors are classified as consumers in lowest quintile of consumers having debt on CC. Debtors are the top quintile of consumers based on number of months with debt. Panel B reports the distribution of consumers in the treatment and control group across gender, education and marital status characteristics.

Panel A: Average spending by groups - full sample				Panel B: Distribution across gender, education, marital status			
Consumer group	Transactor	Debtor	Total		Transactor	Debtor	Total
Age	42.3364	38.2926	40.09641	Male	89.56%	79.06%	83.75%
CC Limit	11925.9	1573.6	6191.383	Female	10.44%	20.94%	16.25%
Transaction value	1156.55	163.219	606.3092	Total	100%	100%	100%
Spending Amount	996.016	151.904	528.4318				
Advance Payments	342.68	27.3607	168.0131	PhD	1.19%	0.27%	0.73%
Instalment Payments	813.873	135.858	438.2961	Masters	3.91%	1.26%	2.58%
Amount Paid	897.086	137.072	476.0867	Bachelors	39.61%	18.29%	28.96%
Amount Unpaid	82.154	163.692	127.3208	Vocational	4.84%	3.96%	4.40%
Travel	58.9922	10.0128	31.86073	High School	37.27%	48.04%	42.65%
Daily	430.463	60.2982	225.4155	Middle School	5.12%	11.63%	8.37%
Vehicle	131.975	22.1877	71.15998	Primary School	7.97%	16.43%	12.20%
Service	125.371	24.0924	69.26927	No Education	9.00%	12.00%	4.40%
Products	78.1552	9.97689	40.38877	Total	100%	100%	100%

Construction	26.6723	2.61841	13.34796
Telecom	126.81	13.8543	64.23962
Other	52.6813	4.6207	26.05881

Single	9.93%	23.16%	17.28%
Married	90.07%	76.84%	82.72%
Total	100%	100%	100%

Table 3: Total Spending Response by Spending Category

This table reports average difference in response to CC spending tightening policy between 'debtors' and 'transactors', shown across different spending subcategories. These are the results of difference-in-difference estimation where post-policy period covers months between September 2011 and August 2013. Transactors are classified as consumers in two bottom deciles of number of months with credit card debt scaled by credit card limit. Debtors comprise the top two deciles of the same measure. Panel A reports the results for the difference-in-difference regressions as defined in Equation(1). Panel B includes also the announcement effect, as specified in Equation (2). Robust standard errors are reported, clustered on an individual consumer level. ** 1% level of significance. * 5% level of significance.

Panel A	Transaction value	Spending Amount	Amount Paid	Amount Unpaid	Travel	Vehicle	Products	Service	Daily	Construt.	Telecom	Other
1_{Post}	848.130**	604.888**	480.630**	122.956**	45.506**	72.711**	52.734**	74.139**	375.030**	8.242**	97.626**	35.779**
	(171.77)	(140.56)	(125.51)	(92.33)	(66.44)	(45.59)	(61.72)	(51.27)	(154.85)	(11.96)	(67.49)	(36.00)
1_{Post} x $1_{treatment}$	-794.035**	-578.586**	-471.239**	-81.509**	-42.863**	-70.026**	-49.614**	-71.097**	-352.025**	-8.455**	-93.455**	-34.729**
	(-159.10)	(-132.87)	(-121.26)	(-59.36)	(-61.99)	(-42.76)	(-57.28)	(-48.80)	(-144.31)	(-12.16)	(-64.16)	(-34.77)
Constant	392.887**	379.775**	361.299**	86.650**	20.485**	53.429**	27.189**	51.101**	131.308**	11.488**	40.269**	17.412**
	(335.71)	(371.68)	(395.64)	(266.35)	(126.41)	(138.00)	(133.65)	(149.84)	(229.98)	(70.52)	(118.11)	(74.57)
Obs.	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128
Clusters	371,162	371,162	371,162	371,162	371,162	371,162	371,162	371,162	371,162	371,162	371,162	371,162
Adj. R	0.022	0.022	0.016	0.003	0.001	0.002	0.002	0.002	0.009	0.000	0.003	0.001

	Transaction	Spending	Amount	Amount	Travel	Vehicle	Products	Service	Daily	Construction	Telecom	Other

Panel B	value	Amount	Paid	Unpaid								
1_{Post}	747.740**	524.920**	406.694**	123.920**	35.348**	62.029**	41.722**	66.983**	334.120**	6.594**	90.207**	30.634**
	(156.98)	(125.93)	(109.11)	(93.62)	(46.00)	(39.47)	(45.92)	(45.66)	(136.75)	(8.95)	(62.06)	(30.45)
$1_{\text{Post Announce}}$	175.682**	139.943**	129.388**	-1.687**	17.776**	18.692**	19.271**	12.524**	71.593**	2.883**	12.983**	9.004**
	(66.28)	(55.31)	(54.43)	(-2.85)	(32.03)	(16.77)	(27.64)	(12.55)	(49.35)	(5.08)	(14.94)	(13.19)
1_{Post} x $1_{\text{treatment}}$	-701.095**	-505.967**	-402.114**	-96.621**	-33.223**	-60.147**	-39.547**	-64.912**	-315.304**	-6.979**	-86.571**	-29.797**
	(-145.87)	(-120.34)	(-106.76)	(-70.05)	(-42.78)	(-37.88)	(-42.98)	(-43.93)	(-128.10)	(-9.38)	(-59.17)	(-29.46)
$1_{\text{Post Announce}}$ x $1_{\text{treatment}}$	-162.645**	-127.085**	-120.968**	26.445**	-16.869**	-17.289**	-17.617**	-10.824**	-64.262**	-2.584**	-12.048**	-8.631**
	(-59.97)	(-48.88)	(-47.68)	(34.77)	(-29.94)	(-13.99)	(-25.04)	(-10.75)	(-43.93)	(-4.52)	(-13.75)	(-12.58)
Constant	356.207**	349.969**	334.565**	81.095**	16.871**	49.522**	23.113**	48.304**	115.881**	10.866**	37.565**	15.602**
	(252.97)	(278.31)	(289.36)	(211.90)	(88.47)	(95.23)	(90.79)	(115.45)	(172.49)	(53.33)	(93.07)	(54.55)
Obs.	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128
Clusters	371,162	371,162	371,162	371,162	371,162	371,162	371,162	371,162	371,162	371,162	371,162	371,162
Adj. R	0.022	0.023	0.016	0.004	0.001	0.002	0.002	0.002	0.009	0.000	0.003	0.001

Table 4: Total Spending Response by Spending Category - Heterogeneity

This table reports average difference in response to CC spending tightening policy between 'debtors' and 'transactors', shown for different groups of consumer 10 months before the policy date and 20 months after the policy date. We only show results for the total monthly credit card transaction value and the daily spending subcategory. Month 201001 is absorbed. Coefficient are for the variable that is a triple interaction, e.g. post policy*treatment*male Transactors are classified as consumers in the lowest quintile of consumers having debt on CC. Debtors are the top quintile of consumers based on number of months with debt. Robust standard errors are reported, clustered on an individual consumer level. ** 1% level of significance. * 5% level of significance

GENDER	Transaction value	Spending Amount	Amount Paid	Amount Unpaid	Travel	Vehicle	Products	Service	Daily	Construct.	Telecom	Other
1_{Post}	598.217***	412.435***	314.040***	97.477***	34.107***	26.814***	32.088***	61.360***	340.517***	4.335***	43.430***	15.158***
	(60.77)	(48.63)	(43.10)	(33.08)	(25.21)	(10.80)	(16.78)	(16.24)	(63.20)	(4.08)	(18.34)	(13.92)
1_{Post} x $1_{treatment}$	-552.704***	-387.283***	-303.206***	-54.162***	-31.672***	-25.217***	-29.531***	-57.858***	-319.136***	-4.616***	-40.724***	-14.529***
	(-55.92)	(-45.49)	(-41.38)	(-17.96)	(-23.26)	(-10.13)	(-15.42)	(-15.29)	(-58.98)	(-4.27)	(-17.15)	(-13.28)
1_{Post} x 1_{male}	279.168***	214.983***	186.087***	28.466***	12.738***	51.278***	23.067***	14.279***	38.583***	4.364***	60.500***	23.036***
	(24.81)	(22.11)	(22.08)	(8.65)	(8.22)	(16.79)	(10.83)	(3.49)	(6.42)	(3.33)	(21.13)	(14.78)
1_{post} x $1_{treatment}$ x 1_{male}	-268.291***	-213.525***	-187.912***	-30.835***	-12.473***	-49.902***	-22.354***	-14.862***	-36.524***	-4.279***	-58.644***	-22.502***
	(-23.69)	(-21.81)	(-22.09)	(-9.13)	(-7.98)	(-16.12)	(-10.44)	(-3.62)	(-6.05)	(-3.21)	(-20.39)	(-14.36)
Constant	392.864***	379.752***	361.275***	86.652***	20.484***	53.425***	27.189***	51.092***	131.301***	11.488***	40.265***	17.412***
	(332.15)	(367.65)	(391.34)	(263.34)	(124.97)	(136.44)	(132.14)	(148.10)	(227.34)	(69.71)	(116.85)	(73.73)
Obs.	16,330,424	16,330,424	16,330,424	16,330,424	16,330,424	16,330,424	16,330,424	16,330,424	16,330,424	16,330,424	16,330,424	16,330,424

Adj. R^2	0.413	0.539	0.523	0.120	0.104	0.378	0.181	0.286	0.198	0.129	0.295	0.218

AGE	Transaction value	Spending Amount	Amount Paid	Amount Unpaid	Travel	Vehicle	Products	Service	Daily	Construction	Telecom	Other
1_{Post}	892.942***	640.877***	513.938***	113.676***	45.477***	78.643***	63.420***	88.638***	358.464***	8.776***	105.560***	40.556***
	(124.04)	(102.91)	(93.91)	(67.53)	(43.79)	(35.01)	(46.48)	(40.80)	(107.48)	(8.29)	(48.61)	(28.94)
1_{Post} x $1_{treatment}$	-838.634***	-609.599***	-499.032***	-65.450***	-43.121***	-75.245***	-60.053***	-85.090***	-336.239***	-9.397***	-101.608***	-39.390***
	(-115.89)	(-97.35)	(-90.56)	(-37.75)	(-41.32)	(-33.31)	(-43.84)	(-38.93)	(-100.35)	(-8.85)	(-46.61)	(-28.00)
1_{post} x 1_{old}	-77.429***	-62.185***	-57.553***	16.035***	0.050	-10.250***	-18.464***	-25.052***	28.625***	-0.923	-13.709***	-8.253***
	(-7.79)	(-7.19)	(-7.50)	(6.17)	(0.04)	(-3.22)	(-10.48)	(-8.54)	(5.95)	(-0.66)	(-4.67)	(-4.16)
1_{post} x $1_{treatment}$ x 1_{old}	76.902***	49.856***	43.889***	-32.827***	0.661	8.482**	17.851***	23.800***	-26.692***	1.932	14.251***	7.965***
	(7.63)	(5.68)	(5.61)	(-12.19)	(0.47)	(2.56)	(9.96)	(8.05)	(-5.50)	(1.36)	(4.82)	(3.99)
Constant	392.887***	379.775***	361.299***	86.650***	20.485***	53.429***	27.189***	51.101***	131.308***	11.488***	40.269***	17.412***
	(331.93)	(367.49)	(391.19)	(263.37)	(124.96)	(136.42)	(132.17)	(148.16)	(227.37)	(69.71)	(116.77)	(73.73)
Obs.	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128
Adj. R^2	0.413	0.538	0.523	0.120	0.104	0.378	0.181	0.286	0.198	0.129	0.295	0.218

ADDRESS	Transaction value	Spending Amount	Amount Paid	Amount Unpaid	Travel	Vehicle	Products	Service	Daily	Construct.	Telecom	Other
1_{Post}	862.659***	615.756***	500.625***	116.000***	42.750***	87.119***	51.405***	67.803***	349.291***	7.300***	112.422***	41.226***
	(124.88)	(101.93)	(92.35)	(72.42)	(47.64)	(34.87)	(43.69)	(35.18)	(112.11)	(6.76)	(53.33)	(26.32)
1_{Post} x $1_{treatment}$	-806.560***	-589.520***	-491.102***	-75.200***	-39.999***	-84.344***	-48.251***	-65.514***	-325.737***	-7.650***	-107.937***	-39.882***
	(-115.21)	(-96.06)	(-88.89)	(-45.03)	(-44.12)	(-32.60)	(-40.64)	(-33.60)	(-103.67)	(-7.05)	(-50.82)	(-25.37)
1_{post} x 1_{urban}	-30.345***	-22.699***	-41.762***	14.529***	5.756***	-30.093***	2.776	13.235***	53.758***	1.966	-30.903***	-11.375***
	(-3.03)	(-2.61)	(-5.39)	(5.33)	(4.13)	(-9.43)	(1.60)	(4.50)	(10.89)	(1.42)	(-10.59)	(-5.72)
1_{post} x $1_{treatment}$ x 1_{urban}	26.219***	22.834***	41.489***	-13.196***	-5.979***	29.907***	-2.847	-11.683***	-54.888***	-1.686	30.255***	10.770***
	(2.59)	(2.59)	(5.28)	(-4.70)	(-4.25)	(9.13)	(-1.62)	(-3.95)	(-11.04)	(-1.21)	(10.30)	(5.39)
Constant	392.887***	379.775***	361.299***	86.650***	20.485***	53.429***	27.189***	51.101***	131.308***	11.488***	40.269***	17.412***
	(331.88)	(367.44)	(391.16)	(263.33)	(124.97)	(136.45)	(132.12)	(148.14)	(227.43)	(69.71)	(116.80)	(73.73)
Obs.	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128
Adj. R^2	0.413	0.538	0.523	0.120	0.104	0.378	0.181	0.286	0.198	0.129	0.295	0.218

DATE OF CC START	Transaction value	Spending Amount	Amount Paid	Amount Unpaid	Travel	Vehicle	Products	Service	Daily	Construct.	Telecom	Other
1_{Post}	853.282***	595.362***	465.328***	122.467***	40.021***	69.354***	50.614***	70.078***	392.384***	4.907***	104.287***	34.681***
	(127.08)	(101.13)	(88.98)	(67.76)	(42.71)	(31.19)	(42.66)	(33.60)	(120.52)	(4.79)	(51.19)	(25.37)
1_{Post} x $1_{treatment}$	-830.137***	-588.592***	-475.790***	-86.846***	-39.737***	-69.512***	-49.122***	-70.483***	-380.982***	-5.953***	-102.711***	-34.466***
	(-122.90)	(-99.25)	(-90.14)	(-46.96)	(-42.21)	(-30.67)	(-41.01)	(-33.66)	(-116.62)	(-5.78)	(-50.31)	(-25.15)
1_{post} x 1_{new}	-15.013	27.760***	44.591***	1.426	15.984***	9.781***	6.177***	11.835***	-50.570***	9.717***	-19.412***	3.201*
	(-1.57)	(3.35)	(6.04)	(0.55)	(12.14)	(3.27)	(3.84)	(4.61)	(-10.61)	(8.44)	(-7.27)	(1.69)
1_{post} x $1_{treatment}$ x1_{new}	180.646***	76.765***	61.655***	29.752***	-3.359**	5.430*	2.531	6.613**	112.669***	-5.262***	33.297***	1.266
	(18.35)	(9.03)	(8.10)	(11.06)	(-2.47)	(1.76)	(1.54)	(2.52)	(23.08)	(-4.45)	(12.01)	(0.66)
Constant	392.887***	379.775***	361.299***	86.650***	20.485***	53.429***	27.189***	51.101***	131.308***	11.488***	40.269***	17.412***
	(332.08)	(367.56)	(391.32)	(263.38)	(125.03)	(136.43)	(132.13)	(148.15)	(227.50)	(69.72)	(116.78)	(73.72)
Obs.	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128
Adj. R^2	0.413	0.539	0.523	0.120	0.104	0.378	0.181	0.286	0.198	0.129	0.295	0.218

MARITAL STATUS	Transaction value	Spending Amount	Amount Paid	Amount Unpaid	Travel	Vehicle	Products	Service	Daily	Construct.	Telecom	Other
1_{Post}	730.019***	536.297***	426.357***	99.650***	38.012***	61.904***	61.808***	75.319***	271.546***	5.264***	85.895***	34.837***
	(59.60)	(49.84)	(44.27)	(34.72)	(23.67)	(15.52)	(23.36)	(21.02)	(48.18)	(3.96)	(22.91)	(15.73)
1_{Post} x $1_{treatment}$	-679.882***	-503.730***	-410.970***	-51.681***	-35.564***	-58.588***	-57.877***	-71.403***	-253.111***	-6.193***	-82.357***	-33.811***
	(-55.35)	(-46.67)	(-42.51)	(-17.58)	(-22.06)	(-14.65)	(-21.82)	(-19.87)	(-44.81)	(-4.65)	(-21.90)	(-15.25)
1_{Post} x $1_{married}$	134.656***	78.199***	61.875***	26.571***	8.544***	12.321***	-10.346***	-1.345	117.981***	3.394**	13.374***	1.074
	(10.05)	(6.65)	(5.89)	(8.23)	(4.81)	(2.83)	(-3.70)	(-0.34)	(18.91)	(2.21)	(3.29)	(0.43)
1_{post} x $1_{treatment}$ x$1_{married}$	-129.401***	-86.519***	-69.838***	-35.232***	-8.285***	-13.160***	9.268***	0.184	-111.913***	-2.445	-12.535***	-1.043
	(-9.61)	(-7.32)	(-6.60)	(-10.62)	(-4.64)	(-2.99)	(3.30)	(0.05)	(-17.87)	(-1.58)	(-3.07)	(-0.42)
Constant	392.887***	379.775***	361.299***	86.650***	20.485***	53.429***	27.189***	51.101***	131.308***	11.488***	40.269***	17.412***
	(331.95)	(367.47)	(391.16)	(263.35)	(124.97)	(136.42)	(132.13)	(148.13)	(227.52)	(69.71)	(116.77)	(73.72)
Obs.	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128
Adj. R^2	0.413	0.538	0.523	0.120	0.104	0.378	0.181	0.286	0.198	0.129	0.295	0.218

EDUCATION	Transaction value	Spending Amount	Amount Paid	Amount Unpaid	Travel	Vehicle	Products	Service	Daily	Construction	Telecom	Other
1_{Post}	921.847***	676.060***	547.863***	132.057***	44.707***	88.190***	58.315***	74.907***	368.796***	8.629***	128.942***	41.551***
	(137.64)	(115.59)	(104.29)	(80.75)	(51.07)	(39.04)	(49.41)	(39.54)	(116.71)	(10.45)	(59.98)	(33.12)

1_{Post} x $1_{treatment}$	-873.762***	-651.377***	-540.259***	-88.703***	-42.788***	-85.696***	-55.469***	-72.333***	-349.696***	-9.097***	-124.856***	-40.619***
	(-129.60)	(-110.52)	(-101.88)	(-52.93)	(-48.62)	(-37.30)	(-46.57)	(-38.06)	(-110.20)	(-10.95)	(-57.86)	(-32.27)
1_{Post} x $1_{university}$	-200.391***	-193.473***	-182.766***	-24.741***	2.173	-42.078***	-15.173***	-2.087	16.947***	-1.054	-85.129***	-15.689***
	(-20.42)	(-22.67)	(-24.29)	(-8.65)	(1.52)	(-13.84)	(-9.07)	(-0.70)	(3.40)	(-0.70)	(-32.84)	(-7.48)
1_{post} x $1_{treatment}$ x$1_{university}$	246.184***	205.800***	196.378***	10.205***	3.343**	43.528***	17.258***	5.656*	12.807**	2.991*	85.772***	16.593***
	(24.40)	(23.51)	(25.29)	(3.38)	(2.24)	(13.79)	(10.14)	(1.82)	(2.50)	(1.93)	(32.53)	(7.83)
Constant	392.887***	379.775***	361.299***	86.650***	20.485***	53.429***	27.189***	51.101***	131.308***	11.488***	40.269***	17.412***
	(332.26)	(367.93)	(391.72)	(263.38)	(124.97)	(136.48)	(132.15)	(148.13)	(227.37)	(69.71)	(117.04)	(73.73)
Obs.	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128
Adj. R^2	0.413	0.539	0.523	0.120	0.104	0.378	0.181	0.286	0.198	0.129	0.295	0.218

BANK MONIITORING	Transaction value	Spending Amount	Amount Paid	Amount Unpaid	Travel	Vehicle	Products	Service	Daily	Construction	Telecom	Other
1_{Post}	843.351***	600.757***	477.973***	117.997***	45.226***	72.505***	52.436***	73.600***	372.602***	7.953***	97.202***	35.512***
	(168.43)	(137.77)	(123.12)	(92.06)	(64.99)	(44.72)	(60.52)	(49.99)	(152.05)	(11.34)	(66.40)	(35.10)
1_{Post} x $1_{treatment}$	-784.424***	-572.226***	-463.888***	-79.072***	-42.263***	-69.467***	-49.084***	-70.002***	-347.343***	-7.973***	-92.645***	-34.301***
	(-154.50)	(-129.22)	(-117.29)	(-59.51)	(-60.02)	(-41.38)	(-55.64)	(-47.10)	(-140.44)	(-11.25)	(-62.71)	(-33.69)
1_{Post} x $1_{monitor}$	552.078***	477.290***	306.975***	572.947***	32.351***	23.695	34.402***	62.270***	280.572***	33.325***	48.943**	30.849***

	(8.81)	(8.25)	(6.09)	(11.60)	(4.42)	(1.49)	(3.12)	(5.82)	(7.80)	(5.34)	(2.26)	(3.73)
1_{post} x $1_{treatment}$ x$1_{monitor}$	-586.468***	-493.159***	-340.382***	-555.003***	-34.627***	-26.212*	-36.056***	-66.226***	-296.609***	-34.706***	-51.693**	-31.999***
	(-9.36)	(-8.52)	(-6.75)	(-11.23)	(-4.73)	(-1.65)	(-3.27)	(-6.19)	(-8.25)	(-5.55)	(-2.38)	(-3.86)
Constant	392.887***	379.775***	361.299***	86.650***	20.485***	53.429***	27.189***	51.101***	131.308***	11.488***	40.269***	17.412***
	(331.98)	(367.54)	(391.20)	(264.49)	(124.97)	(136.42)	(132.13)	(148.13)	(227.43)	(69.71)	(116.77)	(73.72)
Obs.	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128	16,331,128
Adj. R^2	0.413	0.539	0.523	0.121	0.104	0.378	0.181	0.286	0.198	0.129	0.295	0.218

Table 6: Random Treatment Assignment

. Reported are the results for the difference-in-difference regressions as defined in Equation (1). Standard errors are robust, clustered on an individual consumer level

This table reports the spending responses to BRSA's policy between the treatment and control group shown across different spending subcategories, where treatment is assigned randomly for every observation. These are the results of difference-in-difference estimation where post-policy period covers months between September 2011 and August 2013. Reported are the results for the difference-in-difference regressions as defined in Equation(1). Robust standard errors are shown, clustered on an individual consumer level. ** 1% level of significance. * 5% level of significance.

	Transaction value	Spending Amount	Amount Paid	Amount Unpaid	Travel	Vehicle	Products	Service	Daily	Construction	Telecom	Other
1_{Post}	315.770**	228.816**	162.338**	109.027**	16.838**	27.354**	22.576**	29.665**	131.150**	0.961**	34.702**	12.384**
	(1.592)	(164.06)	(131.61)	(156.00)	(70.42)	(54.76)	(77.20)	(63.94)	(173.84)	(4.31)	(75.44)	(47.01)
1_{Post} x $1_{treatment}$	2.415	2.465	1.351	-0.475	0.255	0.126	-0.334	1.122	1.415	-0.119	-0.057	-0.117
	(2.299)	(1.23)	(0.76)	(-0.49)	(0.75)	(0.18)	(-0.81)	(1.65)	(1.29)	(-0.40)	(-0.09)	(-0.27)
Constant	371.304**	362.073**	340.595**	110.191**	20.155**	51.912**	27.187**	52.626**	123.739**	10.344**	37.664**	16.139**
	(0.601)	(690.34)	(734.70)	(434.18)	(226.80)	(278.64)	(253.64)	(296.67)	(429.99)	(133.55)	(222.44)	(142.64)
Obs.	38,212,196	38,212,196	38,212,196	38,212,196	38,212,196	38,212,196	38,212,196	38,212,196	38,212,196	38,212,196	38,212,196	38,212,196
Clusters	868,459	868,459	868,459	868,459	868,459	868,459	868,459	868,459	868,459	868,459	868,459	868,459
Adj. R^2	0.012	0.012	0.007	0.006	0.001	0.001	0.001	0.001	0.005	0.000	0.001	0.000

Table 7: Falsification – Nearest Neighbor Matched Sample

This table reports average difference in response to CC spending tightening policy between 'debtors' and 'transactors', shown across different spending subcategories. To define treatment and control groups, we employ propensity score matching based on nearest neighbour based on age, gender, martial status, education, date of credit card initiation and previous credit card debt situation. These are the results of difference-in-difference estimation where post-policy period covers months between September 2011 and August 2013. Reported are the results for the difference-in-difference regressions as defined in Equation(1). Robust standard errors are shown, clustered on an individual consumer level. ** 1% level of significance. * 5% level of significance..

	Transaction value	Spending Amount	Amount Paid	Amount Unpaid	Travel	Vehicle	Products	Service	Daily	Construction	Telecom	Other
1_{Post}	899.685**	619.806**	465.439**	165.624**	34.892**	55.579*	62.219*	64.370**	430.494**	-5.411	102.367**	36.137**
	(11.49)	(8.14)	(6.52)	(11.73)	(2.81)	(2.21)	(2.17)	(5.56)	(8.70)	(-0.64)	(5.07)	(3.71)
1_{Post} x $1_{treatment}$	-835.594**	-588.700**	-451.856**	-126.555**	-31.154*	-52.305*	-58.487*	-60.268**	-403.225**	5.546	-97.253**	-34.674**
	(-10.67)	(-7.73)	(-6.33)	(-8.96)	(-2.51)	(-2.08)	(-2.04)	(-5.21)	(-8.15)	(0.65)	(-4.82)	(-3.56)
Constant	727.144**	702.943**	670.396**	86.105**	36.293**	116.107**	65.970**	75.128**	251.460**	22.556**	70.283**	27.170**
	(35.54)	(35.31)	(35.93)	(23.33)	(11.20)	(17.63)	(8.79)	(24.84)	(19.44)	(10.15)	(13.32)	(10.67)
Obs.	11,981,112	11,981,112	11,981,112	11,981,112	11,981,112	11,981,112	11,981,112	11,981,112	11,981,112	11,981,112	11,981,112	11,981,112
Clusters	138,719	138,719	138,719	138,719	138,719	138,719	138,719	138,719	138,719	138,719	138,719	138,719
Adj. R^2	0.018	0.015	0.009	0.005	0.001	0.001	0.001	0.002	0.010	0.000	0.003	0.001