Federal Reserve Bank of Chicago

Tax Credits and the Debt Position of US Households

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This paper investigates the effect of tax credit receipt on the outstanding indebtedness of households. In particular, we use data on zip code level indebtedness to explore whether debt levels and past due amounts change more dramatically during tax refund season in those zip codes where households receive greater Earned Income Tax Credit (EITC) and Additional Child Tax Credit (ACTC) refunds. We see a substantial decline in debt past due in high tax credit zip codes during tax refund season indicating that some recipient households use tax refunds to repair their balance sheets. At the same time, we see increases in both auto and credit card debt during tax refund season showing a link between tax refunds and asset accumulation and consumption.

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1. Introduction

The refundable portion of the Earned Income Tax Credit (EITC), combined with the similarly targeted Additional Child Tax Credit (ACTC), transferred over $85 Billion to households in 2014 (IRS 2015a). These programs, which we label "tax credits", provide cash benefits primarily to low income working families with children. Funds are delivered through the tax code in the form of a single annual payment as part as the household's tax refund. Due to these tax credits, for many low income households with children, tax refunds represent the single largest incoming transaction each year. Among households receiving the EITC, the EITC refund alone represents over six weeks of Adjusted Gross Income (AGI) on average (IRS 2015a). The large single payment allows households an opportunity to alleviate financial stress, fund pressing consumption needs, and improve their overall financial position. The goal of this paper is to see how the financial position of low income households changes once they receive their EITC and ACTC. In particular, we explore how household indebtedness responds to this single large payment using zip code level data on refunds and debt and by exploiting the unique timing of tax refunds.

Previewing our results, we find that household indebtedness *increases* in high tax credit zip codes in the period surrounding tax refund receipt. In particular, we find substantial jumps in both credit card and auto debt in high tax credit zip codes after refunds have been received. At the same time, we observe substantial declines in delinquent debt indicating that households also use tax credit funds to repair their balance sheets.

The paper proceeds as follows. In section 2, we provide background information on the EITC and ACTC programs. Section 3 discusses previous investigations into household responses to tax refunds in general and to the EITC and ACTC in particular. Section 4 follows with an extended introduction to the numerous different data sources we use and presentation of how we combine them to measure tax credit and financial status variables. We then introduce the methodology we use and report results in section 5. The final section offers conclusions.

2. Background information on tax refunds and credits

As mentioned above, federal income tax refunds represent the single largest incoming transaction for many households each year. In 2014 (for tax year 2013), 73% of returns received a refund averaging $2762 (IRS 2016). Households receive a single refund each year shortly after filing taxes that derives from a few different sources. In aggregate, the single largest source of tax refunds is overpayment refunds. These most commonly arise when households over-withhold payroll taxes usually by claiming too few allowances on their W-4 forms.

The second largest source of refunds is the EITC. The EITC is an income support program targeted towards low income working households with children and is the second largest income support program in the United States, following the Supplemental Nutritional Assistance Program (SNAP). The EITC matches a percent of earnings up to a maximum amount, levels out at a "plateau" amount for a range of incomes, and then phases out at higher earnings levels. It gives more generous benefits to households with more children – up to three. The EITC has grown in generosity since it was first introduced in 1975. In 2014 (for tax year 2013), the maximum credit of $6,044 was received by households with three or more children earning between $13,430 and $17,530. (Tax Policy Center 2016). The EITC is claimed via a schedule attached to the household's tax return. The EITC is refundable so that funds remaining after household tax liability is reduced to zero are refunded to the household as part of the annual tax refund. The great majority of EITC dollars are refunded. For tax year 2013, $59 Billion of total EITC spending of $68 Billion was refunded. (IRS 2015a)

The third largest source of refunds is the Additional Child Tax Credit (ACTC). The ACTC is given to households that do not receive their entire non-refundable Child Tax Credit (CTC). The CTC gives households a per child tax credit, set at $1000 per child since 2010, that phases out at higher income levels. The CTC is non-refundable so that credit amounts remaining after tax liability is reduced to zero are not refunded. However, if a household's tax liability is less than the value of their CTC benefit, they may be eligible for the ACTC. The ACTC is a refundable credit. A household is eligible for an ACTC credit equal to 15% of their earned income above $3,000 up to the value of their unused CTC. The CTC did not exist prior to 1997 and broad refundability via the ACTC began for tax year 2001. (See Crandall-Hollick 2014 and

CPBB 2015). For tax year 2013, the CTC reduced tax liability by $27B, while the ACTC refunded $28B.[1]

Other short term policies, such as First-Time Homebuyer Tax Credit (2008-2010) also contribute to tax refunds, but are smaller in size and shorter in duration. Due to the targeted nature of the EITC and ACTC, tax refunds represent a particularly large share of income for low income households with children.

3. Household Responses to Income Shocks

Tax refunds could be thought of as sizeable, but largely expected, income shock. A broad literature investigates economic responses to income shocks. The majority of this research focuses on the consumption response to these income shocks. Much of it has the goal of investigating the implications of the Life Cycle/Permanent Income Hypothesis (PIH). The PIH predicts that in the absence of credit constraints, households should not increase their consumption in response to an anticipated increase in income. The theory also predicts that the consumption response to an unexpected increase in income should be sustained, reflecting a transition to a higher consumption path. In contrast to these predictions, much of the existing empirical research finds short terms bursts in consumption following both anticipated and unanticipated increases in income. Researchers have attributed this pattern of consumption behavior to liquidity constraints, myopia and mental accounting.

Tax refunds and rebates are one of the primary sources of income shocks investigated in the literature. This probably derives from the fact that these refunds are more measurable, identifiable and widespread than many other short term changes in income. In addition, refunds and rebates are a popular type of fiscal policy and the efficacy of the policies hinges on their ability to induce consumption. In his 1999 paper investigating the consumption responses to tax refunds reported in the Consumer Expenditure Survey, Souleles finds excess sensitivity to refunds especially among liquidity constrained households. Subsequent papers using micro-data have varied in either the particular refund or rebate that was studied or in the data set used to measure consumption responses. Across most data sets and refunds, researchers confirm that

[1] The interplay among the EITC and CTC is such that the CTC reduces tax liability to zero before the EITC is applied. As a result, among households receiving the ACTC, all EITC dollars are refunded.

household consumption responds to refunds. (For example Johnson, Parker and Souleles 2006 and Parker et al 2013). In a recent paper, Baugh, Ben-David and Park (2014) evaluate the consumption response to the revelation of tax refund amounts and to the receipt of refunds. They find that households respond to the receipt of the refund rather than to the revelation of its magnitude and that responses are largest among lower income households. Their results support a portrayal of households as myopic and responsive to cash on hand rather than to knowledge of their overall financial situation. In a largely descriptive paper Cole, Thompson and Tufano (2008) document how H&R Block clients who received their refunds via a stored value card spend down their refunds and document the speed with which refunds are spent. They find that households spent their refunds relatively quickly with nearly half of the accounts empty after a month. They find that 56% of the funds are withdrawn as cash, with most of the remainder used to purchase items from merchants.

There is less of a literature documenting the response of aspects of household financial well being other than consumption to tax refunds. This may partly be due to data limitations, partly due to the fiscal policy relevance of consumption, and partly due to the fact that the PIH has clear and testable implications for consumption given assumptions about when households know the magnitude of their payment. Theoretical predictions concerning the response of other measuring of financial status, such as debt, net worth and savings, to refunds are less clear cut. As Browing and Lusardi (1996) point out, savings is a residual defined as the difference between income and consumption. As a result, predictions about changes in savings in response to an income shock would hinge on the difference between the income shock and the consumption response. Predictions about debt levels (the financial measure we are investigating here) are even more difficult to formulate because savings are the combination of increases in assets and declines in liabilities, and by looking only at changes in liabilities, we have an incomplete picture of savings. In this paper, we only have data on debt which is just one part of net savings. In light of this we treat the effect of refunds on household indebtedness as an empirical question and discuss suggestive theoretical implications in light of the findings.

There is limited empirical research on the effect of tax refunds or other income shocks on debt. Agarwal, Liu and Souleles (2007) investigate credit card debt and other responses to the 2001 tax rebates. They find an initial decline in credit card debt following rebate receipt, but a subsequent increase as higher spending offsets the initial decline in debt. By nine months after the rebate, debt increases are insignificantly positive. They find larger initial debt declines for better off individuals. Agarwal and Qian (2013) perform a similar exercise for stimulus payments to Singaporeans which yields a broadly consistent set of results. In particular, they find a modest decrease in credit card debt in the months after the receipt of a stimulus payment. However debt subsequently increased and returned to pre-treatment levels. Aaronson, Agarwal and French (2012) find that debt increases following minimum wage hikes which they attribute to increases in collateralized debt particularly for autos. This debt increase persists for a number of quarters following the minimum wage increase. Combined these papers find short lived decreases in credit card debt and longer lived increases in auto debt following positive income shocks.

While the debt response to tax refunds and other income shocks is investigated in a fairly limited empirical literature, there is a larger descriptive literature that asks individuals how they spend tax refunds which touches on the subject of debt. Particularly relevant for this paper, a number of studies use questionnaires to ask EITC recipient families what they do with their tax refunds. These studies find that reducing household debt burdens is one of the primary uses of refunds. For example, in their survey of 237 rural working mothers, Mammen and Lawrence (2006) found that 44% of interviewees say they use their refund to pay current or past due bills. This was the single greatest reported use of EITC dollars. Halpern-Meeken et al (2015) find that about a quarter of refunded dollars went to pay debts and bills; about the same amount that went for day to day expenses among the Boston area families they surveyed. They further find that among households using refunds to pay off debts, households reduced their debt burden by about fifty percent. Relatedly, when Tach and Green (2014) asked 194 EITC recipient families how they manage their household debt, they found that the single most popular answer was through the use of their EITC refunds. Across these studies using questionnaires, researcher consistently find high reported debt repayments following EITC receipt. We supplement this research and ask whether this pattern of debt payoffs is present in a large national data set.

4. Data

We estimate the relationship between debt and tax credits using quarterly zip code level data on refunds and debt. For this paper, we use four data sources – quarterly data on consumer credit by zip code, annual data on the distribution of refunds across zip codes, monthly national data on the timing of refund disbursements, and annual data on zip code demographics. In this section, we present each of these data sources individually and then report how we combine them to create the data set we use for our analysis.

4.1 Debt Data

To measure quarterly debt at the zip code level, we use the RADAR Consumer Credit Panel (CCP) from the Federal Reserve Bank of New York. These data are derived from a five percent random sample of the Equifax credit reports of individuals who have both credit reports and social security numbers. The data set provides quarterly credit variables for sampled individuals that measure credit aggregates as of the end of the quarter. For each sampled individual we know their zip code of residence and numerous credit measures including the number of different types of credit accounts, the status of those accounts, such as whether they are current or past due, as well as the balances in those accounts. For our analysis, we measure the total debt amounts of the sampled households from a zip code. These totals can be multiplied by twenty to approximate total indebtedness in the zip code. We use quarterly data from 1999 to 2014 and calculate total past due amounts and auto, credit card, other personal debt outstanding. An observation in the data is a quarter-zip code combination.

We define past due as at least 30 days late. We investigate auto, credit card and other personal debt because these types of debt can be adjusted within a quarter. We do not investigate housing or student loan debt. Mortgage and home equity debt is fairly uncommon among low income households and is slower to adjust than other debt.[2] We do not look at student loan debt because our identification comes from quarterly debt patterns and the quarterly pattern of student loan growth is driven by the academic calendar. Other personal debt includes sales financing and personal loans and retail loans from clothing, department stores and gas retailers.[3]

Variable means, presented as the average across zip codes of indebtedness per sampled credit record are presented in Table 1. In the table, the means are weighted by the number of credit

[2] According to Tach and Greene, 13% of the EITC recipients they surveyed had mortgage debt. 60% had credit card debt and 42% had car loans.

[3] Medical and utility debt are excluded from most of the variables in the underlying data set unless such payments go to collections.

records in the data set per zip code so they represent the average per sampled individual. Across the quarters of the sample, the average sampled individual had $2,623 in debt past due, $3,320 in auto debt, $3,355 credit card debt and $1,904 in other personal debt. These debt measures capture a snapshot of household indebtedness at a point in time. For credit card debt, which we also label bank card debt, this combines revolving balances and transactional balance. In other words, a household that pays off balances in full every month will be listed as having a debt equal to the value of its unpaid transactions. The average sampled individual lives in a zip code where there are 1072 credit reports while the average zip code in the sample (based on an unweighted mean) has 260 credit records.

4.2 The Distribution of Refunds

Our second data set measures the amount of total refunds, EITC refunds and ACTC refunds received by taxpayers in each zip code. These amounts are available annually, by tax year, from two sources: the IRS Statistics of Income Tax Stats – Individual Income Tax Statistics – ZIP Code Data (SOI) and the Brookings Institution's EITC interactive (Brookings). These data report aggregate tax related measures by the zip code reported on tax returns. The available variables differ by year and across the two sources, but in all years a large selection of tax related measures is available. We use data for tax years 1998 to 2013 which reflect refunds paid out in calendar years 1999 to 2014.[4]

As explained earlier, for the EITC, the refunded amounts are only part of total programmatic spending because some of the credit serves to reduce tax liability while the remainder of the credit is refunded to the tax unit. Over the years covered in our sample, approximately 90% of the value of the credit has been refunded because most EITC households have limited tax liability. This percent has been fairly stable over the years covered in this paper.

The ACTC operates somewhat differently because the non-refundable CTC and the refundable ACTC are separate programs. Due to changing program parameters the percent of spending on the combined CTC and ACTC that is the refundable ACTC has been increasing over time from less than 5% prior to tax year 2001 to approximately 50% since tax year 2009.

[4] Refunds are paid after taxes are filed which is in the calendar year following the tax year.

In Table 2, panel a, we show variable means by year, calculated as the amount per return, averaged across zip codes, for the refund and tax credit related variables available in the SOI data. In particular, we show average total refunds, EITC refunds and ACTC refunds.[5] We also show total EITC per return, CTC per return, and total taxes due. Total taxes due is a measure of the amount due from households in the zip code at filing. While some households receive refunds, other households have remaining tax liability and owe the Federal Government money when they file their taxes. The SOI data are administrative totals generated from the IRS's Individual Master File. The zip code is based on the zip code reported on the tax return. Some zip codes are omitted, including those with less than 100 returns. (For details see IRS 2015c). We note that not all variables are available in all years, none of our desired variables is available in some years, and there are no data files in other years.

In Table 2, panel b, we show relevant available tax refund and tax credit averages by tax year from the Brookings data. The Brookings data are tabulated by the Brookings Institution based on data provided by the IRS. (See Brookings 2014). Starting in tax year 2009, the Brookings data are part year and only cover returns filed between January and June. While this is not a problem for the total EITC and ACTC variables because about 99% of benefits are paid out in the first half of the year, it is a problem for the data on the number of tax returns, total refunds received and taxes due at filing because sizeable payments occur throughout the year. As a result, we set the total refund and taxes due variables equal to missing for tax years 2009 and after.[6]

The values for the EITC and CTC variables are nearly identical when they are reported in both data sets. Insofar as sample means differ for the EITC and CTC variables, it is largely because a slightly wider set of zip codes is covered in the Brookings data because Brookings imputes suppressed values. The data on taxes due is also comparable across the data sets. The total refund amounts differ more substantially across zip codes probably due to the deletion of some returns from the SOI data and definitional differences between variables. Each of these sources has advantages. The principal advantage of the Brookings data set is that it covers a

[5] According to the SOI documentation, their measure of the refundable EITC for a household is (EITC – total income tax) if the EITC is greater than total income tax and zero otherwise. They note that no other refundable credits are taken into account for this calculation. They are assuming that the EITC goes first in reducing tax liability to zero after the non-refundable credits have been applied (including the CTC).

[6] We use the total number of tax returns reported in the SOI data for 2009-2012 analysis.

consistent time series with EITC measures for every year between 1998 and 2013. The main advantage of the SOI dataset is that it has two separate EITC variables in most years it covers. In particular it has data on both the refundable portion of the EITC and on the total value of the EITC, while the Brookings data set only has information on the total value of the EITC. Both data sets have information on the non-refundable CTC and the ACTC for some years.

We combine the data from these two sources to generate estimates of most of the desired tax related variables for most tax years between 1998 and 2013. We use the SOI data when it is available and supplement it with values from the Brookings data when a value is not available in the SOI data set. For any zip code – tax year observation, if data on total EITC spending is available, but data on the refundable EITC is not available, we estimate refundable EITC spending by multiplying the national percent of the EITC that is refunded by the zip code total EITC. Similarly, when ACTC data is unavailable, but CTC data is available we estimate the ACTC by multiplying the zip code level information on the non-refundable CTC by the ratio of the refundable ACTC to non-refundable CTC at the national level.[7] For tax years 1998-2000, we assume that the ACTC is zero for all zip codes because the credit was non-refundable for the vast majority of households.[8] (National data on the refundable total EITC and total CTC and ACTC is available from the IRS for all years (IRS 2015a)). Finally we estimate overpayment refunds as equal to total refunds minus our estimates of the refundable EITC and ACTC. Due to this calculation, our measure of overpayments includes other small refunds such as the first-time homebuyer credit and the refundable education credit, but these are tiny relative to overpayment refunds. Table 2c displays zip code means by tax year for variables measuring refunds and taxes due at filing from the combined data set.

From this table, we see that on average, across zip codes, overpayments are larger than EITC and ACTC refunds. We also see the growth over time in the refundable EITC and the ACTC, especially around the passage of the American Reinvestment and Recovery Act in 2009 which increased the generosity of both programs beginning in tax year 2009. We also note that while

[7] We can evaluate this estimation using the years with data on the refundable EITC and ACTC. In those years, the correlation between the actual and estimated refundable EITC is 0.99. The correlation between the actual and estimated ACTC is 0.75. While the ACTC correlation is lower, we only estimate the ACTC for one year while we rely on this estimate for 9 years for the EITC.

[8] In TY2000, the CTC was $20 Billion while the ACTC was just under $1 Billion. In TY2001, the CTC was $22 Billion while the ACTC was $5 Billion.

the average ACTC refund is less than half the size of the average EITC refund, it is a substantial fraction of combined tax credits. Due to the similarity in the eligibility for the two programs, per-return zip code EITC and ACTC refunds are highly correlated (about 0.8) across zip codes particularly in the more recent tax years. Average tax payments due at filing are smaller than average total refunds consistent with the fact that that during tax season, the IRS pays out more than it takes in.

These means mask substantial heterogeneity in refund related variables across zip codes. In Figure 1, we show a zip code heat map for tax year 2013 of average combined EITC refund and ACTC per return. Average tax credit amounts vary substantial across space. The highest tax credit amounts are in Appalachia and the deep south – areas characterized by above average poverty levels.

The pattern in the map combined with the targeted nature of the tax credit programs suggests that the heterogeneity in refunds across zip codes partly derives from differences in income across the zip codes. We further display this by showing refunds per return and refunds as a share of AGI by zip code-AGI category for tax year 2013 in Figure 2a and 2b. Zip code AGI is measured based on AGI per return in the SOI data. While refunds levels are largest in the wealthiest zip codes (2a), refunds are a far larger share of AGI in the poorest zip codes (2b). This latter difference becomes even more pronounced if we take into account taxes due at filing and measure net refunds in a zip code (see Figure 2c). At tax filing time, some households in a zip code receive refunds, while other households owe money. In Figure 2c, we show average total refunds, taxes due at filing and net tax refunds (defined as refunds minus taxes due for all returns in the zip code) as a share of AGI. We observe that in the wealthier zip codes, taxes due among some households nearly or completely offset the refunds received by other households. In the poorer zip codes, taxes due are small and as a result net refunds are a large share of AGI. These graphs show that tax time has a very different meaning in low income zip codes than it does in high income zip codes.

4.3 Refund Timing

The third data source we use is information from the Monthly Treasury Statement (MTS) on the timing within a year of tax refunds and final tax payments. We need this information as we will use the timing of refunds within the year as a source of identification. In Table 3 we display average total monthly refunds and refunds broken down into four sources: overpayments, EITC, ACTC and miscellaneous other refunds paid on average for 1999-2014. Miscellaneous refunds represent payments from an assortment of programs that used the tax code to spur demand during the Great Recession – such as Making Work Pay. As discussed earlier, the largest source of refunds is overpayment refunds, followed by the EITC and the ACTC. Miscellaneous refunds are small on average, but were relatively large in some years of the sample due to policies designed to alleviate the effects of the Great Recession on households. We also show total taxes paid, taxes paid broken into amounts withheld from wages and other income sources, amounts not withheld, and net taxes. Most individual income taxes are withheld. Within non-withheld taxes, the MTS does not provide a breakdown between final payments (those due at filing) and estimated payments (those paid prior to filing but not via withholding). This is in contrast to the zip code data that captured final payments but did not have a measure of zip code level withholding or estimated payments. Taxes paid are much higher than refunds, but non-withheld individual income taxes are of a similar magnitude to refunds.

There are vast differences in the magnitude of refunds and payments made across the months of the year. In Figure 3a, we graph the annual share of total, overpayment, EITC and ACTC refunds paid out by the Treasury in each month of the year in 2014 (reflecting tax year 2013). The vast majority of EITC refunds and ACTC refunds were paid out in February (73%), over payments also peaked in February (29%) with a substantial amount in March (24%) and April (25%) as well. This pattern derives from the fact that the lower income families that are eligible for the EITC and ACTC file their taxes soon after the tax window opens (on January 31 in 2014) while many of the middle income families who receive overpayment refunds wait until the tax filing deadline on April 15. The patterns in other years closely parallel those in 2014, although overpayment refunds peaked in April rather than February prior to 2012. Combining these, we see that total refunds are highest in February, followed by March and April. In Figure 3b, we display the fraction of gross taxes paid and withheld and non-withheld taxes paid in each month of 2014. Tax payments peak in April due to final payments, but are also high in the months when estimated payments are due (January, April, June, and September) and in December when holiday bonuses increase withholding. In Figure 3c, we graph the dollar amount of total refunds, total taxes paid and taxes paid net of refunds by month of 2014. From this graph, we see that February is the only month in which the government refunds more than it receives. The government has high net receipts in January, April, June, September, and December.

We can combine the data on the timing of different types of refunds from the MTS and the data on the distribution of refunds across zip codes from the merged SOI and Brookings data to create estimates of the monthly and quarterly amount of refunds for each zip code. In particular, we allocate annual refunds in the zip code for each tax year for each type of refund (overpayment, EITC, ACTC) across the months of the following calendar year according to the pattern for that refund type in the calendar year's MTS. We then sum across the months of the quarter to create quarterly estimates. This combination leads to the finding that individuals in low income zip codes receive large tax refunds at the start of the year – particularly in February while higher income tax payers receive more modest refunds, especially relative to income, later in the year. We cannot perform a similar exercise for tax payments because the timing data covers the sum of estimated and final payments while the zip code data covers only final payments.

4.4 Census Demographics

Our fourth data set contains Census zip code tabulation area (ZCTA) demographic information from the US Census Bureau from the decennial Census and the American Community Survey. These data are available at most annually. We interpolate and extrapolate for years where the data is unavailable. In Table 4, we show average measures across zip codes and years for these Census demographics.

4.5 Merging Data

We merge these four data sets together to create a quarterly data set that includes debt variables, estimated quarterly refunds received, and demographics at the zip code level. We delete a number of observations from this merged data set. First off, we only include zip codes that are present in all three zip code level data sets. Most zip codes lost due to this requirement are absent from the Census data set.[9] These tend to be places with few tax returns and credit

[9] Some postal zip codes do not have corresponding Census Zip Code Tabulation Areas (ZCTAs). Census blocks are assigned to ZCTAs based on the most prevalent postal zip Code in the block. Some small zip codes do not dominate any census block. See U.S. Census Bureau 2015 for more details.

records. To insure that the zip codes are defined in a comparable manner across sources and over time, we also delete zip codes that fail a series of comparability tests. In particular, we delete the zip codes in the bottom percentile of the distributions of the number of returns, census population, and number of credit reports. We do this because we would like the census, tax return and credit report data to cover the same population and we believe this will be least true in the least populated zip codes. We also delete zip codes with big changes in the number of credit reports from quarter to quarter because we are concerned that the coverage of the CCP data is changing. We further restrict the sample to zip codes where the number of tax returns reported in the zip is less than twice the represented CCP population and the reported Census population. In this case, we are concerned about zip codes that are used as mailing addresses for tax returns, but where fewer people live. Because the filing of tax returns is not mandatory, we do not delete the bottom of the tax return to population distribution. Additionally, we delete zip codes where the population represented by the CCP and the Census total population diverge dramatically. We also delete zip codes that had dramatic changes in their geography or changed drastically in how much per capita EITC and ACTC residents received relative to other zip codes across the years of the sample. Finally, we use a balanced panel of zip codes – zip codes must meet our requirements every quarter of the sample period. Through these processes, we keep 70% of the zip codes in the Census sample representing 90% of the Census population.[10] The first columns of Table 5 present variable means (across zip code-quarters) for the merged quarterly sample. We definite the debt and tax variables in per capita terms using Census population rather in per tax return or per debt record terms to maximize the comparability across the data sources. In the average zip code-quarter, households receive $50 per capita from tax credits, with a standard deviation of $88.

The later columns of Table 5 display variable means separately for zip codes in the highest tax credit per capita quintile in 2007 and in all other zip codes. Tax credit amounts in high tax credit zip codes are 2.5 times as high as in other zip codes. High tax credit zip codes have higher debt past due amounts per capita, but lower levels of other types of debt, particularly credit card debt.

4. Empirical Approach

[10] These tabulations are based on 2005:Q1.

We use this combined data set to investigate whether household indebtedness adjusts in response to refundable tax credits. In particular, we ask whether there are differential debt changes in high refundable tax credit zip codes during the period when EITC and ACTC refunds are received as compared to low refundable tax credit zip codes. Initially, we concentrate on the targeted credits and will expand our analysis to overpayment refunds later. We begin with a simple diff-in-diff approach that asks whether the quarterly pattern of indebtedness in high tax credit zip codes is different from the pattern in other zip codes. We define a high tax credit zip code as one in the top quintile of (population weighted) combined refundable EITC and ACTC per capita in tax year 2007. In 2007, about 40 percent of EITC/ACTC payments were made to households in the top tax credit quintile. We choose 2007 because it is close to the midpoint of our sample and is a year in which we have actual refundable EITC data (from SOI) and actual ACTC data (from Brookings). We fix the zip codes we define as high tax credit to be constant over time to downplay changes in tax credit amounts within a zip code. The zip codes receiving the highest average tax credit amounts are fairly consistent over time. We are interested in seeing whether the change in indebtedness that occurs during the first quarter of the calendar year (when nearly all tax credits are received) is different in high tax credit zip codes.

In our initial specification we estimate:

$$Debt_{it} - Debt_{it-1} = \alpha + \gamma_q HighTC_i \times Quarter_t + time + time^2 + time^3 + qtr_t + \lambda_i + \varepsilon_{it} \quad (1.1)$$

We are asking about changes in debt controlling for a cubic time trend in debt growth, for zip code specific fixed effects, the quarter of the observation (1 through 4), and the quarter interacted with a dummy for being a high tax credit zip code in 2007. Debt is defined as per capita debt in the zip code. The coefficients of interest are the γ_q, which indicate whether debt growth is higher or lower in different quarters of the year in high tax credit zip codes. Recall that debt is measured as of the end of each quarter. Differential patterns of debt growth in the first quarter of the year in high tax credit zip codes would be indicative of tax credits influencing debt patterns. We are investigating the effects of the tax credit on debt by exploiting the unique timing of tax credit refunds.

We estimate this equation for total debt past due, auto debt, bank card debt, and other personal debt. Recall that other personal debt includes store and gas credit cards, sales financing and personal loans. Results for changes in debt in quarters relative to the third quarter (the γ_q) are presented in Table 6 and displayed graphically in Figure 4. The finally row of the table displays the first quarter coefficient estimate divided by the standard deviation of the dependent variable in the high tax credit zip codes to provide a sense of the magnitudes.

We find that debt past due declines substantially in the first quarter in high tax credit zip codes relative to other zip codes. Debt declines by an additionally $71 this represents a 0.1 standard deviation drop in debt growth. Households appear to be paying off their delinquent debt in the wake of receiving their tax credits. Debt past due also declines more in the second and fourth quarters in high tax credit zip codes relative to the omitted third quarter, but these declines are more modest than the decline in the first quarter.

The results for changes in outstanding auto, bank card and other personal debt are shown in columns (2)-(4). For all three debt types, outstanding debt grows more dramatically in the first quarter in high tax credit zip codes. In the first quarter of the year, per capita auto debt grew by $32 more in high tax credit zip codes than in other zip codes relative to the omitted third quarter, controlling for average zip code level debt growth and average first quarter debt growth. Bank card debt grew by $47 per capita and personal debt grew by $17. We note that there are also statistically significant differences in the other quarters of the year. In particular, there are also larger auto debt increases in high tax credit zip codes in the second quarter (relative to the omitted third quarter).

These results show that after tax credits have been received, we see a relative increase in household auto, credit card and personal debt in high tax credit zip codes. This could be due to increases in debt issuance or decreases in the rate of paying off loans. For auto loans, while we do not distinguish between debt increases due to new car loan issuance in the zip code and those due to a decline in the rate of paying off preexisting car loans, the auto finding is consistent with other research that shows that households respond to income windfalls by purchasing cars.[11] For credit card loans, as noted earlier, our measure of indebtedness includes both revolving and transactional balances. In light of this, increases in credit card debt could occur because households are purchasing more items with their credit card and so have higher transactional

[11] We are working on ways to distinguish between new and preexisting loans in the CCP/Equifax micodata. Parker et al 2013 and Aaronson, Agarwal and French 2012 both find this pattern.

balances or because they are paying off prior purchases more slowly so that revolving balances are increasing. While we cannot distinguish between these two options, the finding that outstanding debt increases is consistent with higher credit card sponsored consumption during refund season. Our pattern of results is consistent with higher levels of debt spending for both cars and other goods during refund season. This is in sharp contrast to the result that past due debt declines.

One concern with these results is that they could be driven by different quarterly borrowing and repayment patterns among the households targeted by the credits rather than by the credits themselves. For instance households with kids may have different quarterly spending patterns than households without kids due to factors like school or holiday shopping. We address this possibility by allowing different types of households to have different quarterly debt patterns by adding a series of quarter - demographic interactions into the regression. In particular, we interact the quarter dummies with the percent of households with kids in the zip code in 2007 and with the percent of the over 25 population with a high school degree in 2007 (A similar adjustment is made in Barrow and McGranahan 2000). Households with kids are explicitly targeted by the tax credit programs while households with more education are less likely to be lower income and lower income households are also prime beneficiaries. As with the tax credits, we fix the demographics in 2007 because they do not vary dramatically over time and we want to pick up the effect of the different quarters rather than evolving within zip code demographics. The model we estimate is:

$$\begin{aligned} Debt_{it} - Debt_{it-1} &= \alpha + \gamma_q HighTC_i \times Quarter + \gamma_{q_d} Demog_i \times Quarter + \\ & time + time^2 + time^3 + qtr_t + \lambda_i + \varepsilon_{it} \end{aligned} \quad (1.2)$$

Results for the γ_q are presented in Table 7 and Figure 5. The results for past due debt, auto debt and other personal debt are substantively unchanged. There is a more pronounced change for bank cards. The first quarter – tax credit interaction falls and second quarter estimate increases so the debt changes in high tax credit zip codes in these two quarters become similar. Upon further investigation, we find this alteration in the estimates to be driven by higher first quarter debt growth in less educated zip codes, not just those receiving high amounts of tax credits.

In the remainder of this section, we perform a series of regressions where we create a number of different versions of the variables measuring the interaction between the quarter and the tax credit amount.

For our first additional specification, we replace the high tax credit-quarter terms in equation 1.2 with a variable that is equal to the percent of annual combined EITC/ACTC benefits received that quarter interacted with the high tax credit dummy. Instead of four quarter-high tax credit interactions, we have one variable measuring the percent of annual tax credits in each quarter interacted with the high tax credit indicator. We estimate equation (1.3). We maintain the demographic quarter interactions.[12]

$$\begin{aligned}&Debt_{it} - Debt_{it-1} = \alpha + \gamma HighTC_i \times TC\_Share_t + \gamma_{q_d} Demog_i \times Quarter + \\ &time + time^2 + time^3 + qtr_t + \lambda_i + \varepsilon_{it}\end{aligned} \tag{1.3}$$

The results are presented in Table 8. The coefficient estimate for the parameter γ tells us how much extra debt growth we would expect to see in high tax credit zip codes, relative to other zip codes, in a quarter when 100% of the year's tax credits were paid out. The final column of the table shows the coefficient γ divided by the standard deviation of the dependent variable in high tax credit zip codes. These results confirm the earlier finding that there are larger increases in indebtedness in high tax credit zip codes in those quarters when more tax credits are received and larger declines in past due debt.

As a robustness check on the results in Table 8, we add interactions between the quarterly tax credit share and each of the five (2007) tax credit quintile indicators. We are investigating whether the response to tax credit shares is unique to the highest tax credit zip codes or is broad based. We present the results graphically in Figure 6.[13] The quarterly share of tax credits has the most negative effect on the change in debt past due for the highest tax credit quintile zip codes. The coefficient increases (becomes less negative) as the tax credit quintile falls. We observe the opposite pattern with the measures of outstanding debt. For auto debt, bank card debt and other

[12] We do not add a variable measuring the quarterly share of annual tax credit share because it is close to co-linear with the quarter dummies. Adding such a variable does not substantively alter the results.

[13] We drop the quarter dummies from this regression because the tax credit shares are fairly consistent across time so including quarter dummies would be identifying results off of the differences over time in the distribution of tax credits across quarters. Regressions with quarter dummies yield consistent results.

person debt, the largest increases in response to quarterly tax credit shares are in the highest tax credit zip codes. These graphs show that the largest responses to tax credit timing are in those places receiving the largest tax credit amounts.

We next replace the high tax credit dummy in equation 1.2 with the amount of tax credits per capita in 2007. We are exploiting the fact that we have information on tax credit amount, not just on whether a zip code is in the top tax credit quintile. The equation we estimate is

$$\begin{aligned} & Debt_{it} - Debt_{it-1} = \alpha + \gamma_q Credits2007_i \times Quarter + \gamma_{q_d} Demog_i \times Quarter + \\ & time + time^2 + time^3 + qtr_t + \lambda_i + \varepsilon_{it} \end{aligned} \quad (1.4)$$

We are allowing the annual tax credit amount from 2007 to have a different effect on changes in indebtedness each quarter of the year. We would anticipate that the tax credit amount would have the largest impact in the first quarter when nearly all credits are paid out. We present the coefficient of interest, the γ_q, in Table 9. The coefficient on the tax credit x quarter variable indicates how much debt changes each quarter of the year in response to a \$1 annual increase in tax credits relative to the omitted third quarter. In all four regressions, the first quarter of the year is the outlier. Auto indebtedness increases by \$0.11 more in the first quarter than in the omitted third quarter in zip codes where household receive an extra \$1 per capita in average tax credits. Zip codes where households receive more tax credits also increase credit card and other personal debt more in the first quarter. There are statistically significant increases in other quarters of the year but they are far more modest. We continue to see the opposite pattern for debt past due. Debt past due falls more dramatically in the first quarter of the year in response to tax credit amounts than in the omitted third quarter.

We next use our estimate of quarterly tax credits paid out to households in the zip code. As noted earlier, we estimate quarterly tax credits by allocating the annual tax credits paid to households in the zip code across the quarters of the year based on the timing data in the MTS. In doing so, we are assuming that the quarterly pattern of payouts is identical across all zip codes. Here, the estimated amount of tax credits paid out in each quarter is as a continuous variable. We no longer use the 2007 tax credit amounts, but now use the annual tax credits from every year of the sample. The equation we estimate is;

$$Debt_{it} - Debt_{it-1} = \alpha + \gamma QuarterlyCredits + \gamma_{q_d} Demog_i \times Quarter + time + time^2 + time^3 + qtr_t + \lambda_i + \varepsilon_{it} \quad (1.5)$$

Results are presented in Table 10. The coefficient γ tell us what happens to debt growth in response to an extra dollar of per capita tax credits. We find that in a quarter when households receive an extra dollar of tax credits, auto debt increases by \$0.30, bank card debt by \$0.16 and personal debt by \$0.14. In keeping with the prior pattern of results, past due debt falls by \$0.40.

Across all of these specifications our findings point to a pattern of increasing auto, credit card, and personal indebtedness and declining debt past due in response to tax credit receipt. Households appear to use their tax credits to pay off delinquent debt to repair their balance sheet while at the same time increasing the levels of non-past due auto and credit card debt.

Until this point, we have only looked at debt responses to tax credits. For most of the years in our sample, we also have information on overpayment refunds for each zip code. We create a measure of quarterly overpayments received by households in each zip code in the same way that we generated the quarterly tax credit measure. In particular, we divide annual overpayments paid to a zip code across quarters of the year according to the pattern in which annual overpayments are paid out according to the MTS. As is the case with tax credits, we are assuming overpayment refunds are paid out in the same way across all zip codes. We add this estimate of quarterly overpayment refunds to our debt regressions by estimating equation (1.6):

$$Debt_{it} - Debt_{it-1} = \alpha + \gamma_{TC} TaxCredits_{it} + \gamma_{OP} OverPayments_{it} + \gamma_{q_d} Demog_i \times Quarter + time + time^2 + time^3 + qtr_t + \lambda_i + \varepsilon_{it} \quad (1.6)$$

We present estimates of the coefficients on tax credit and overpayment refunds in Table 11. The coefficients on the overpayment variable are far smaller than on the tax credit variables. Household overpayment refunds do not seem to influence indebtedness to nearly as great an extent as tax credits. A one dollar increase in tax credit refund amounts leads to a \$0.35 reduction in debt past due, while a one dollar increase in overpayment refunds leads to a \$0.02 reduction in debt past due. For auto debt, we find large increases in debt in response to tax credits and modest increases in response to overpayments. The pattern of results for credit cards is different. In contrast to the increases in credit card debt we find in response to tax credits, we estimate that there are modest declines in debt in response to overpayment refunds. This is consistent with prior research (in particular Agarwal, Liu and Souleles (2007)) that finds a drop credit card debt following the receipt of refunds. This is suggestive of different responses by the lower income households that receive tax credits and the higher income households that receive overpayment refunds. In the next two rows of the table, we adjust for the fact that overpayments are larger on average than tax credits. In particular, we rescale the coefficients by multiplying them by the standard deviation of the relevant refund amount. Even with this adjustment, we continue to see far larger responses to tax credits than to overpayments.

4. Interpretation

The results are consistent across a range of specifications. We find that auto, credit card, and personal debt increase in high tax credit quarters in those zip codes that receive large EITC and ACTC payments. At the same time, we find that debt past due declines by a substantial amount during tax refund season in high tax credit zip codes.

The decline in debt past due is consistent with a depiction of households using the large tax credit payment to put their financial house back in order.

The result that credit card and auto debt increase during tax refund season runs counter to the notion that the EITC and ACTC would serve to reduce household indebtedness because they have more funds to pay off debt. We evaluate the implications of this finding concerning credit card and auto debt in the context of the overall household balance sheet and in light of the nature of our data. We know that the increase in savings in a quarter, defined as the change in assets minus the change in liabilities, is equal to income minus consumption. In the quarter in which tax credits are received, after tax income goes up quite substantially among recipient households. Previous research has shown that consumption increases in response to tax credits, but by an amount less than the increase in income. (Barrow and McGranahan 2000; Goodman-Bacon and McGranahan 2008). This implies that there is some additional savings in tax credit quarters. In other words, the increase in assets must be greater than the increase in liabilities. If we assume that our finding that liabilities increase in response to tax credits is correct, household assets must increase more than household liabilities. Households must then use their tax refunds to increase their asset position. The most commonly held assets among low income households are transaction accounts, autos, and homes. (Federal Reserve Board, 2014) If the tax credit alleviated liquidity constraints, low income households may choose the first quarter to invest in durable goods. The tax credit may be sufficient for a down payment on either a home or auto.

Other facts concerning auto debt are particularly consistent with this story. Refinancing of auto loans is rare due to the rapid depreciation of autos. As a result, increases in auto debt are likely associated with car purchases. In addition, most auto lenders require substantial down payments from low income borrowers. If a household is using its tax credits to cover the down payment for a car, at tax time, the household's debt balance would increase by the amount of the car purchase that was financed. The household's asset position would increase by the total value of the car. However, our data do not incorporate the corresponding increase in assets. Assuming that the car is worth something close to what the household paid for it, after the tax credit induced car purchase, the household balance sheet is stronger. As further support for this narrative, Figure 7 shows new and used car retail sales by month for 2013. While new car sales peak in the summer months, sales of used cars peak in February—a pattern which is suggestive of a tax credit effect. Future research could investigate how assets change in the period surrounding refund receipt.

Potential explanations for the increase in refund season for credit card and other personal debt hinges on the nature of the information in the data set. As mentioned earlier, our measure of credit card balances does not distinguish between transactional and revolving balances. In light of this, credit card balances could increase because either of these balances increases. Increasing revolving balances would indicate that households are paying off less of their preexisting balances. This seems unlikely given that household income increases so dramatically when refunds are received. Conversely, increases in transactional balances would indicate that households are spending more on their credit cards. This could arise if households are spending more in general in response to their increase in income and choosing to use their credit cards to fund these transactions. In short, it is possible that the increase in our measure of credit card debt is a sign of increased consumption rather than a sign of an increase in debt.

Combing our results, we conclude that households use their tax credit refunds to pay past due debts, purchase cars and fund consumption on their credit cards.

Table 1: Zip code means of quarterly credit aggregates, 1999-2014

	Obs.	Mean	Std. Dev	Description
Average Debt Past Due	2930813	2622.72	2087.97	Payments that are late by 30 days or more
Average Auto Debt	2930813	3319.96	1268.33	Auto loans from banks or dealers
Average Bank Card Debt	2930813	3355.18	1300.40	Revolving Accounts/Credit Cards
Other Personal Debt	2930813	1903.79	1305.34	Retail store and gas cards, sales financing, personal loans
Year	2930813	2006.63	4.58	
Quarter	2930813	2.50	1.12	
Observations Per Zip Code	2930813	1071.54	699.5	Number of records per zip
Obs. Per Zip Code (unweighted)	2930813	259.64	459.1	Number of records per zip

Source: Author's tabulations from Equifax/FRBNY CCP and Haver Analytics.

Notes: Each observation is a zip code-quarter combination and is the average debt per sampled household. Amounts are in 2013 Dollars. Data are weighted by the number of records per zip code.

Table 2a: Average refund and tax amounts per tax return by zip code, IRS-SOI zip code data

Tax Year	Total Refund Per Return	EITC Per Return	Refundable EITC per Return	CTC (Non-Refundable) per Return	ACTC (Refundable) per Return	Taxes Due at Filing Per Return
1998	NA	0.394	NA	NA	NA	NA
1999	--No Data File------------------------------------					
2000	--No Data File------------------------------------					
2001	NA	NA	NA	NA	NA	NA
2002	NA	NA	NA	NA	NA	NA
2003	--No Data File------------------------------------					
2004	NA	0.388	NA	NA	NA	NA
2005	NA	0.381	NA	NA	NA	NA
2006	NA	0.372	NA	NA	NA	NA
2007	1.634	0.347	0.307	0.212	NA	0.750
2008	2.297	0.399	0.349	0.233	NA	0.658
2009	2.442	0.466	0.406	0.223	0.197	0.689
2010	2.565	0.439	0.380	0.217	0.184	0.782
2011	2.164	0.434	0.380	0.207	0.179	0.828
2012	2.052	0.436	0.382	0.197	0.171	0.863
2013	2.080	0.441	0.375	0.189	0.163	0.879

Source: Author's calculations from IRS 2015b and Haver Analytics.

Notes: Amounts are in thousands of 2013 dollars and deflated by the deflator for year following the tax year. (For example tax year 2000 data is assumed to be in 2001 nominal dollars). Data are not weighted by number of returns per zip code. "NA" indicates that the listed variable is not available in the SOI data set in that tax year. There are no data files for 1999, 2000 and 2003.

Table 2b: Average refund and tax amounts per tax return by zip code, Brookings Zip Code data

Tax Year	Total Refund Per Return	EITC Per Return	Refundable EITC per Return	CTC (Non-Refundable) per Return	ACTC (Refundable) per Return	Taxes Due at Filing Per Return
1998	NA	0.363	NA	NA	NA	NA
1999	NA	0.363	NA	NA	NA	NA
2000	1.980	0.356	NA	NA	NA	1.357
2001	2.415	0.387	NA	NA	NA	0.957
2002	2.346	0.403	NA	NA	NA	0.794
2003	2.427	0.400	NA	0.206	NA	0.741
2004	2.367	0.394	NA	0.280	0.130	0.915
2005	2.334	0.392	NA	0.264	0.127	1.070
2006	2.529	0.381	NA	0.248	0.122	1.060
2007	2.268	0.342	NA	0.212	0.104	0.951
2008	2.927	0.395	NA	0.226	0.141	0.872
2009	PY	0.456	NA	0.215	0.189	PY
2010	PY	0.432	NA	0.210	0.179	PY
2011	PY	0.426	NA	0.200	0.176	PY
2012	PY	0.428	NA	0.194	0.170	PY
2013	PY	0.435	NA	0.187	0.168	PY

Source: Author's Calculations from Brookings, 2015 and Haver Analytics.

Notes: Amounts are in thousands of 2013 Dollars and deflated by the deflator for year following the tax year. (Tax year 2000 data assumed to be in 2001 nominal dollars). " NA" indicates that the listed variable is not available in the Brookings data set in that tax year. Brookings data become part year in 2009 and only cover returns filed January-June. The great majority of returns (over 90%) are filed in the first half of the year, but many high income filers with large balances and overpayments file late. As a result we treat the 2009-2012 data on total refunds and taxes due as missing and label these variables "PY". The per return variables for 2009-2012 are divided by the number of returns filed January-June. Data are not weighted by number of returns per zip code.

Table 2c: Combined and estimated data on refunds and taxes due per tax return

Tax Year	Total Refund Per Return	Overpayment Refund Per Return	Refundable EITC per Return	Additional CTC per Return	Taxes Due Per Return
1998	NA	NA	0.310	0.000	NA
1999	NA	NA	0.314	0.000	NA
2000	1.980	1.674	0.306	0.000	1.357
2001	2.415	NA	0.337	NA	0.957
2002	2.346	NA	0.356	NA	0.794
2003	2.427	1.993	0.352	0.082	0.741
2004	2.367	1.905	0.332	0.130	0.915
2005	2.334	1.876	0.331	0.127	1.070
2006	2.529	2.086	0.321	0.122	1.060
2007	1.807	1.366	0.294	0.104	0.762
2008	2.548	2.061	0.346	0.141	0.763
2009	2.442	1.838	0.406	0.197	0.689
2010	2.565	2.000	0.380	0.184	0.782
2011	2.164	1.605	0.380	0.179	0.828
2012	2.052	1.498	0.382	0.171	0.863
2013	2.080	1.542	0.375	0.163	0.879

Source: Author's Calculations from IRS 2015b, Brookings, 2015 and Haver Analytics.

Notes: Amounts are in thousands of 2013 dollars and deflated by the deflator for year following the tax year. (Tax year 2000 data assumed to be in 2001 nominal dollars). We assume the ACTC was zero prior to Tax year 2001 because the CTC was not initially broadly refundable. We calculate overpayments as total refunds minus the refundable EITC and ACTC.

Table 3: Average Monthly Refund Amounts, 1999-2014

		Average 1999-2014	
Total Refunds		**$**	**25,309.54**
	Overpayment Refunds	$	19,858.11
	Refundable Earned Income Credit	$	3,813.57
	Additional (Refundable) Child Tax Credit	$	1,350.09
	Misc. Refunds (e.g. Making Work Pay)	$	287.77
Gross Ind. Income Taxes Paid (Final, Withholding, Estimated)		**$**	**118,617.20**
	Withheld	$	84,613.82
	Nonwithheld (Final and Estimated)	$	33,998.39
Taxes Paid Net of Refunds		**$**	**93,314.15**

Source: U.S. Department of the Treasury and Haver Analytics.

Note: Amounts in millions of 2013 dollars. Deflated by CPI for month in which refunds were paid.

Table 4: Zip code demographics, 1999-2014

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Population	496880	9472.63	13610.87	0	118917.6
Percent High School Grad	496880	82.93	11.38	0	100
Percent of Households Containing Kids	496880	32.89	11.32	0	100
Year	496880	2006.50	4.61	1999	2014

Source: U.S. Census Bureau

Note: Data are annual and are based on Census zip code tabulation areas (ZCTAs). Values are interpolated between available years and extrapolated out of sample. Zip codes are only included if they are available in the 2000 Census and in the 2011, 2012, 2013 and 2014 5-year ACS. These 31,067 zip codes represent about 97% of the US population.

Table 5: Variable Means from the Merged Sample

		Total Population		Top Tax Credit Quintile		Not Top Tax Credit Quintile	
	Observations	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Debt Variables							
Past Due Debt Per Capita	1383168	1674.67	1435.22	1918.13	1485.89	1630.12	1421.25
Auto Debt Per Capita	1383168	2590.37	1136.06	2418.34	1175.07	2621.85	1125.93
Bank Card Debt Per Capita	1383168	2479.88	1211.57	1718.82	948.25	2619.14	1202.74
Other Personal Debt Per Capita	1383168	1778.50	1495.50	1773.59	1583.98	1779.40	1478.73
Tax Variables							
Refundable EITC Per Capita	1383168	36.60	67.10	77.23	119.43	29.17	48.57
Refundable ACTC Per Capita	1210272	12.78	24.48	22.23	40.84	11.05	19.61
Refundable EITC+ACTC Per Capita	1210272	49.86	88.20	100.41	153.35	40.61	65.92
Overpayment Refund Per Capita	1037376	191.87	235.66	149.27	148.62	199.67	247.51
Total Refund Per Capita	1210272	243.97	282.03	250.22	241.10	242.83	288.88
2007 Tax Credits Per Capita Quintile	1383168	2.94	1.31	5.00	0.00	2.57	1.06
Census Variables							
Population	1383168	12288.03	14426.12	16041.02	18143.63	11601.28	13524.36
Percent High School Grad	1383168	83.37	10.09	71.60	10.77	85.52	8.31
Percent of Households Containing Kids	1383168	33.45	8.74	38.09	9.82	32.60	8.25
Year	1383168	2006.50	4.61	2006.50	4.61	2006.50	4.61
Quarter	1383168	2.50	1.12	2.50	1.12	2.50	1.12

Source: Author's tabulations based on data from Equifax/FRBNY CCP, IRS 2015c, Brookings 2015, U.S. Census Bureau, U.S. Department of the Treasury and Haver Analytics.

Note: Data are quarterly. Dollar amounts are in 2013 dollars.

Table 6: Quarterly patterns of indebtedness in high tax credit zip codes compared to other zip codes

	(1)	(2)	(3)	(4)
VARIABLES	past due	auto	bank card	other personal
Q1 x High Tax Credit Zip	-70.56***	32.28***	46.54***	16.54***
	(5.080)	(2.484)	(2.319)	(4.107)
Q2 x High Tax Credit Zip	-15.76***	14.21***	-4.924**	-4.836
	(4.998)	(2.443)	(2.281)	(4.041)
Q4 x High Tax Credit Zip	-21.49***	-0.702	-6.841***	0.450
	(4.998)	(2.443)	(2.281)	(4.041)
Observations	1,361,556	1,361,556	1,361,556	1,361,556
R-squared	0.005	0.019	0.022	0.003
Q1 Effect/ St Dev of Dep. Var. in High TC Zip	-0.105	0.0907	0.144	0.0274
Standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Source: Author's tabulations based on data from Equifax/FRBNY CCP, IRS 2015c, Brookings 2015, U.S. Census Bureau, U.S. Department of the Treasury and Haver Analytics.

Note: Each column represents a separate regression where the dependent variable is the quarterly change in per capita debt of the type listed in the column heading. Third quarter is omitted.

Table 7: Quarterly patterns of indebtedness in high tax credit zip codes compared to other zip codes, including demographic x quarter controls

	(1)	(2)	(3)	(4)
VARIABLES	past due	auto	bank card	other personal
Q1 x High Tax Credit Zip	-62.76***	19.88***	13.15***	12.63***
	(6.021)	(2.943)	(2.746)	(4.868)
Q2 x High Tax Credit Zip	-27.45***	5.435*	13.76***	-0.569
	(5.923)	(2.895)	(2.702)	(4.789)
Q4 x High Tax Credit Zip	-28.30***	-0.489	3.642	-6.203
	(5.923)	(2.895)	(2.702)	(4.789)
Observations	1,361,556	1,361,556	1,361,556	1,361,556
R-squared	0.006	0.020	0.024	0.004
Q1 Effect/ St Dev of Dep. Var. in High TC Zip	-0.0933	0.0558	0.0408	0.0209
Standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Source: Author's tabulations based on data from Equifax/FRBNY CCP, IRS 2015c, Brookings 2015, U.S. Census Bureau, U.S. Department of the Treasury and Haver Analytics.

Note: Each column represents a separate regression where the dependent variable is the quarterly change in per capita debt of the type listed in the column heading. Third quarter is omitted.

Table 8: Quarterly share of tax credits in high tax credit zip codes compared to other zip codes, including demographic x quarter controls

	(1)	(2)	(3)	(4)
VARIABLES	past due	auto	bank card	other personal
Quarterly Share of Tax Credits x High Tax Credit Zip	-60.80***	21.45***	11.04***	17.47***
	(6.362)	(3.109)	(2.902)	(5.144)
Observations	1,361,556	1,361,556	1,361,556	1,361,556
R-squared	0.006	0.020	0.024	0.004
Coefficient on Quarterly Share x High Tax Credit /St. Dev. of Dep. Var. in High TC Zip	-0.0904	0.0603	0.0343	0.0289
Standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Source: Author's tabulations based on data from Equifax/FRBNY CCP, IRS 2015c, Brookings 2015, U.S. Census Bureau, U.S. Department of the Treasury and Haver Analytics.

Note: Each column represents a separate regression where the dependent variable is the quarterly change in per capita debt of the type listed in the column heading. Third quarter is omitted

Table 9: Quarterly effects of annual tax credits per capita, including demographic x quarter controls

	(1)	(2)	(3)	(4)
VARIABLES	past due	auto	bankcard	other personal
Q1 x Tax Credits Per Capita	-0.353***	0.105***	0.150***	0.114**
	(0.0292)	(0.0167)	(0.0186)	(0.0441)
Q2 x Tax Credits Per Capita	-0.0551**	0.0543***	0.0139	-0.0276
	(0.0267)	(0.0152)	(0.0126)	(0.0355)
Q4 x Tax Credits Per Capita	-0.137***	-0.0254*	-0.0237	-0.0221
	(0.0305)	(0.0137)	(0.0196)	(0.0453)
Observations	1,361,556	1,361,556	1,361,556	1,361,556
R-squared	0.006	0.020	0.024	0.004
Standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Source: Author's tabulations based on data from Equifax/FRBNY CCP, IRS 2015c, Brookings 2015, U.S. Census Bureau, U.S. Department of the Treasury and Haver Analytics.

Note: Each column represents a separate regression where the dependent variable is the quarterly change in per capita debt of the type listed in the column heading.

Table 10: Quarterly tax credits per capita and zip code debt growth

	(1)	(2)	(3)	(4)
VARIABLES	past due	auto	bankcard	other personal
Quarterly Tax Credits Per Capita	-0.404***	0.299***	0.164***	0.140***
	(0.0193)	(0.00910)	(0.00851)	(0.0145)
Observations	1,188,660	1,188,660	1,188,660	1,188,660
R-squared	0.007	0.023	0.027	0.006
Standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Source: Author's tabulations based on data from Equifax/FRBNY CCP, IRS 2015c, Brookings 2015, U.S. Census Bureau, U.S. Department of the Treasury and Haver Analytics.

Note: Each column represents a separate regression where the dependent variable is the quarterly change in per capita debt of the type listed in the column heading.

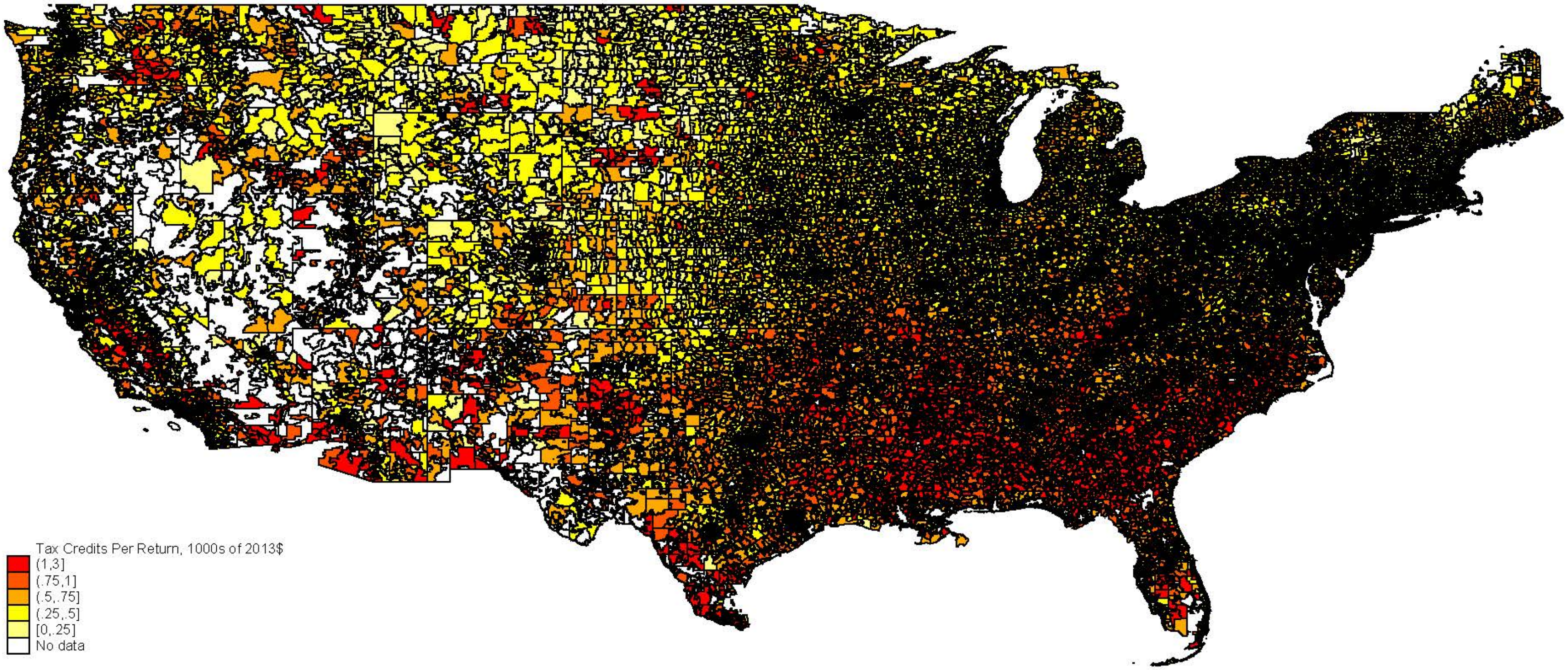
Table 11: Quarterly tax credits and overpayment refunds and zip code debt growth, including demographic-quarter controls

	(1)	(2)	(3)	(4)
VARIABLES	past due	auto	bankcard	other personal
Quarterly Tax Credits Per Capita	-0.348***	0.360***	0.229***	0.155***
	(0.0212)	(0.00942)	(0.00890)	(0.0142)
Quarterly Overpayments Per Capita	-0.0191***	0.0151***	-0.0361***	0.00171
	(0.00543)	(0.00241)	(0.00228)	(0.00363)
Effect of Standard Deviation Increase in Tax Credits	-30.68	31.79	20.23	13.70
Effect of Standard Deviation Increase in Overpayments	-4.494	3.559	-8.501	0.403
Observations	1,037,376	1,037,376	1,037,376	1,037,376
R-squared	0.008	0.026	0.028	0.008
Standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Source: Author's tabulations based on data from Equifax/FRBNY CCP, IRS 2015c, Brookings 2015, U.S. Census Bureau, U.S. Department of the Treasury and Haver Analytics.

Note: Each column represents a separate regression where the dependent variable is the quarterly change in per capita debt of the type listed in the column heading.

Figure 1: Average Combined EITC and ACTC Refund per Return, Tax Year 2013

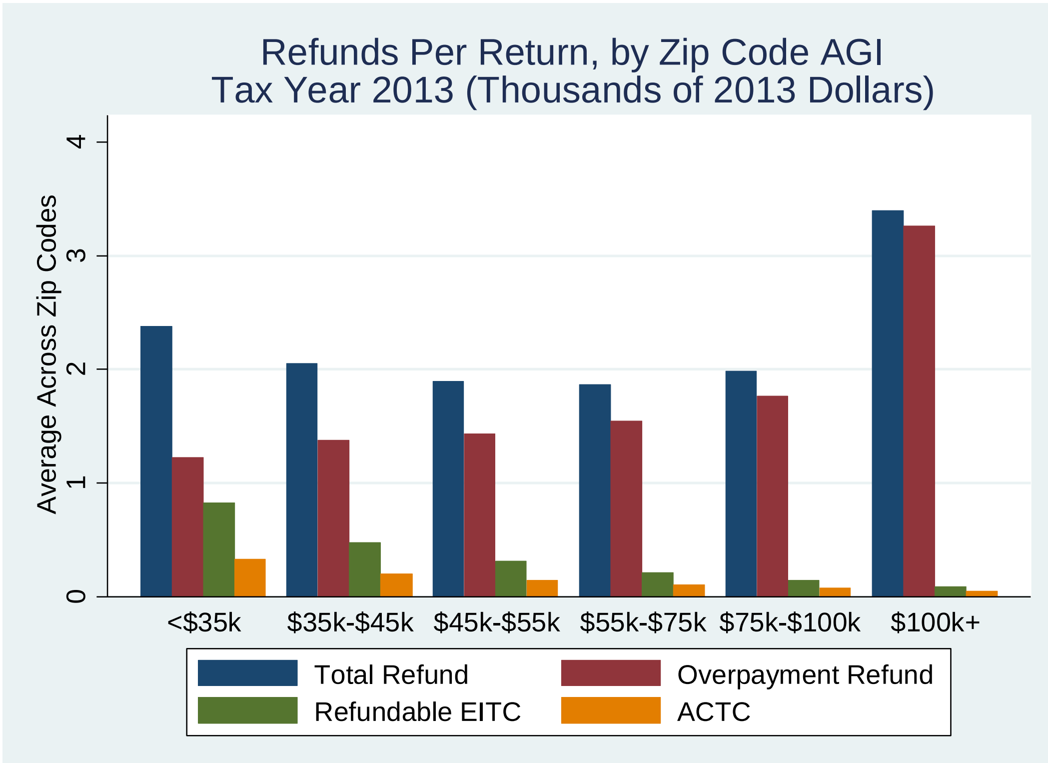


Source: IRS 2015c, Brookings 2015, U.S. Census Bureau, and Haver Analytics.

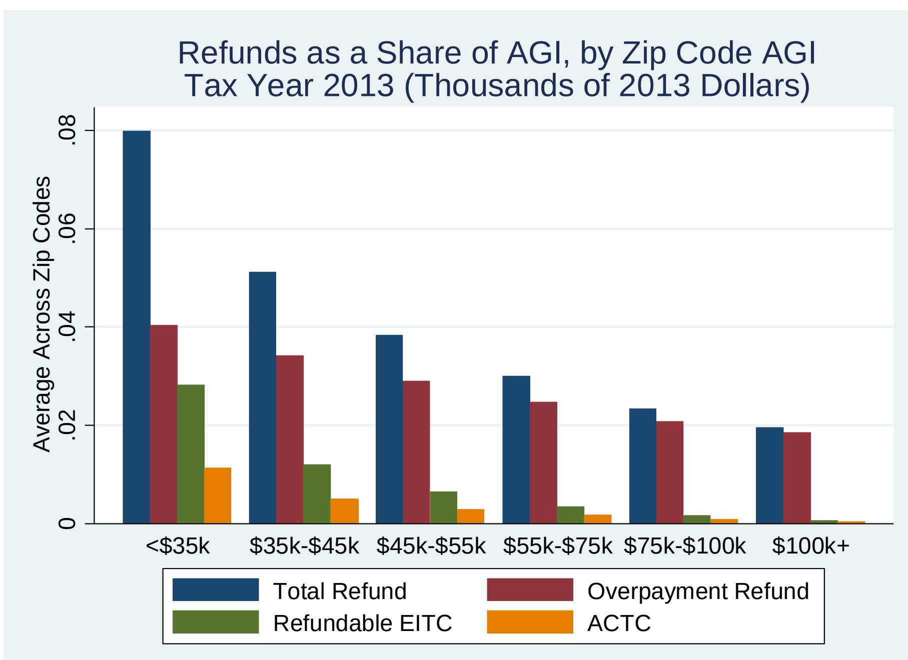
Note: There are blank spaces on the map because unpopulated areas and large water bodies are not included in the Census zip code shapefile and because tax credit data is missing for some zip codes.

Figure 2: Refunds by AGI Category

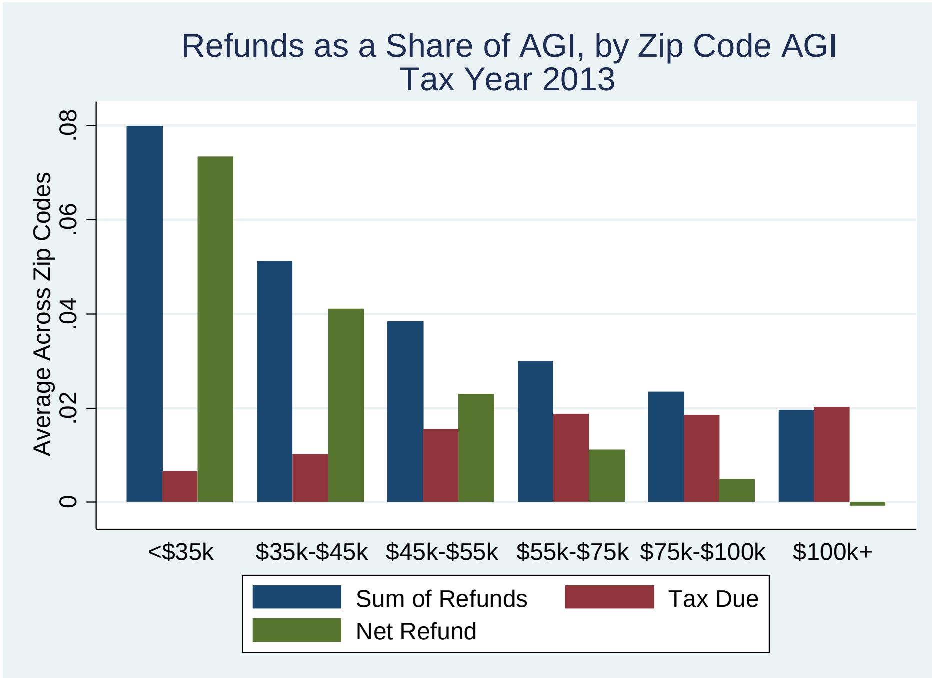
Panel a: Average Refund per Return by Zip Code, 2013



Panel b: Average Refund as a Share of AGI, 2013.



Panel C: Average Refunds, Taxes Due and Net Refunds, 2013

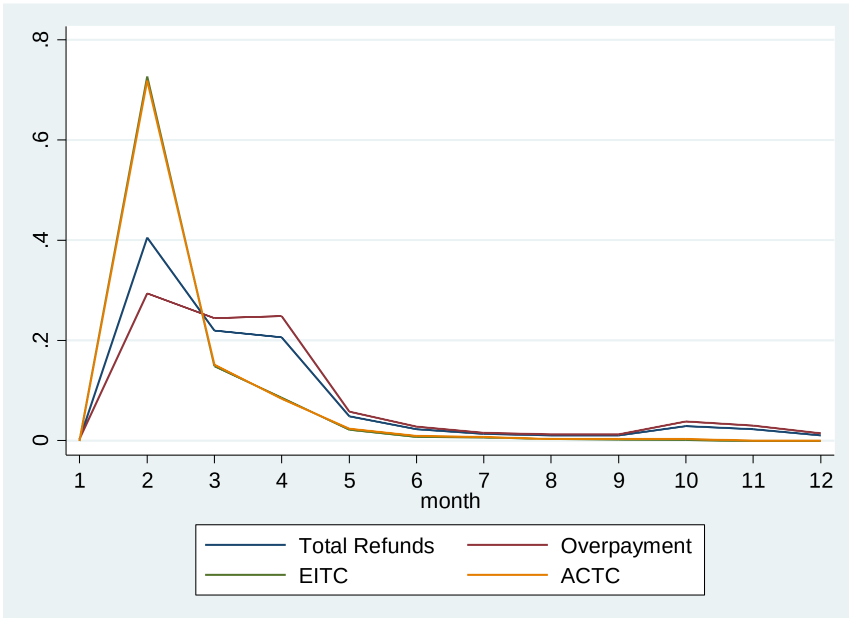


Source: Author's tabulations based on data IRS 2015c, Brookings 2015, and Haver Analytics.

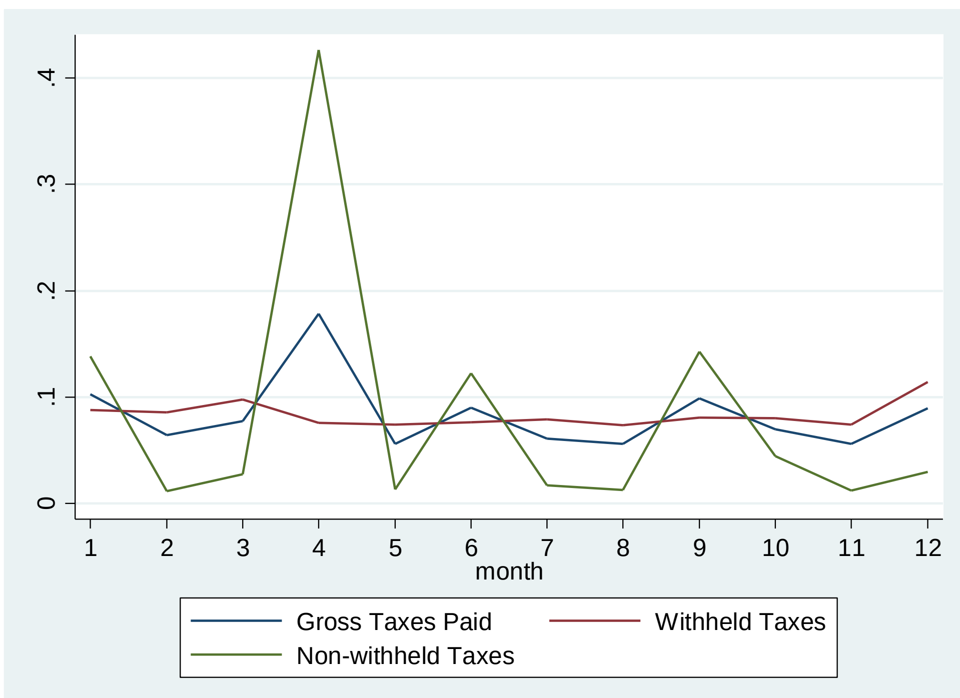
Note: Zip code AGI is average real AGI per return in the zip code. The percent of zip codes in each category are 11% (under $35k), 31% ($35k-$45k), 27% (45k-55k), 20% (55k-75k), 7% (75k-100k) and 6% ($100k+). All dollar amounts are in 2013 dollars.

Figure 3: Refund and Tax Payments by Month, 2014

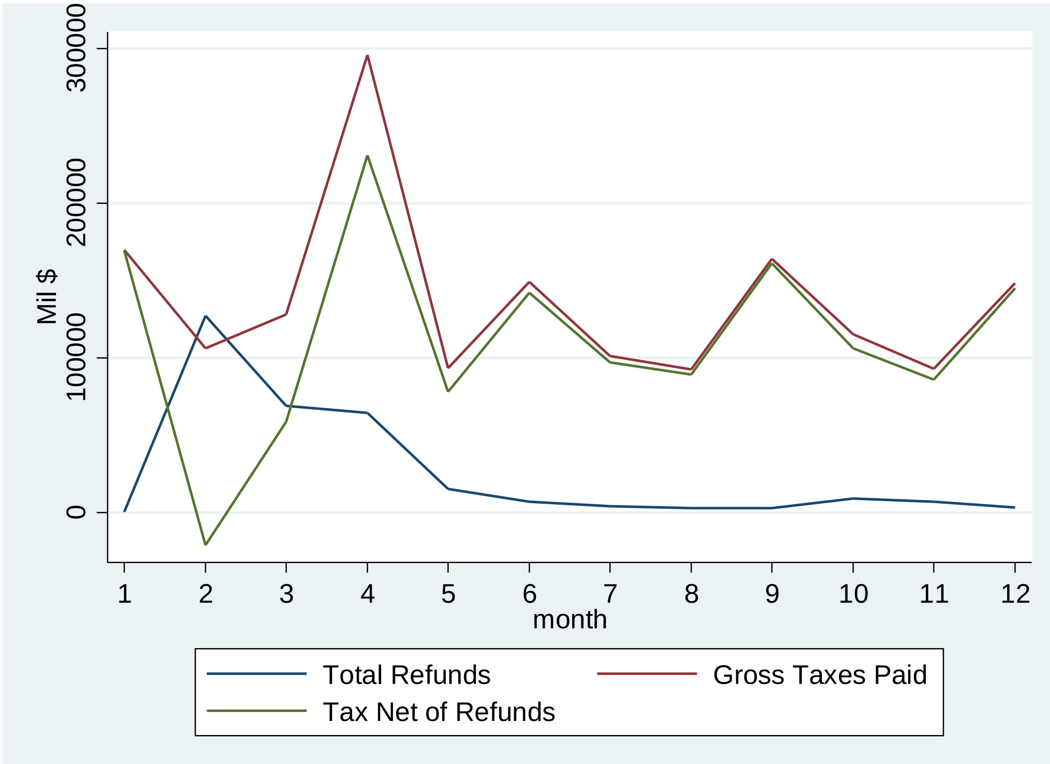
Panel a: Share of Annual Refunds paid Each Month, By Refund Type



Panel b: Share of Annual Taxes Paid Each Month By Tax Payment Type

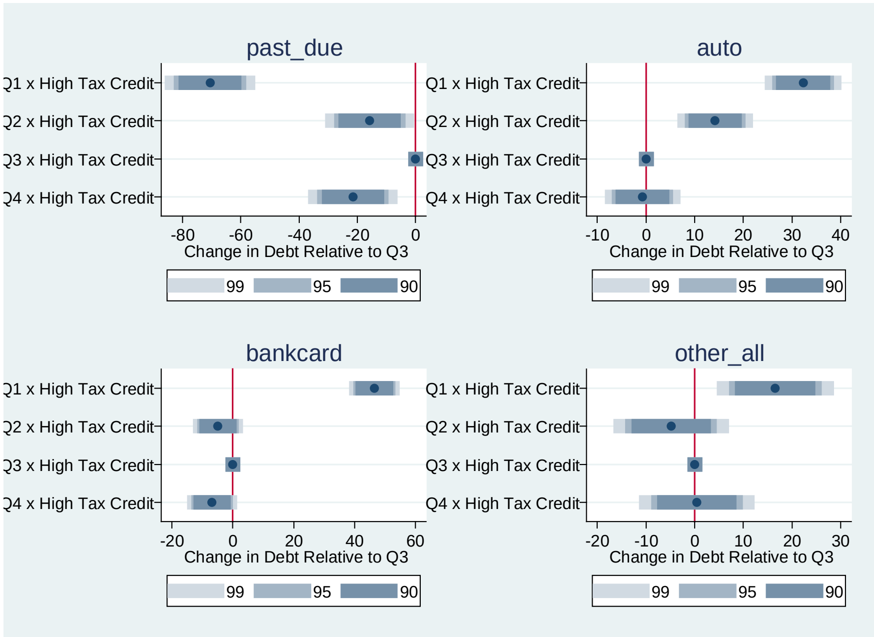


Panel c: Monthly Timing of Gross and Net Taxes



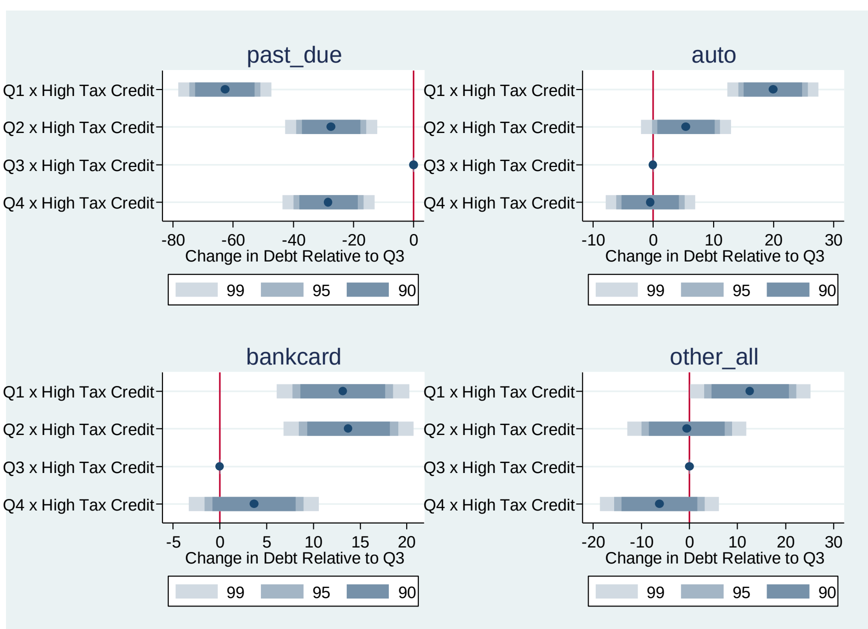
Source: Author's Tabulations from US Department of the Treasury, Monthly Treasury Statement and Haver Analytics.

Figure 4: Coefficient Estimates of changes in indebtedness by quarter, Baseline



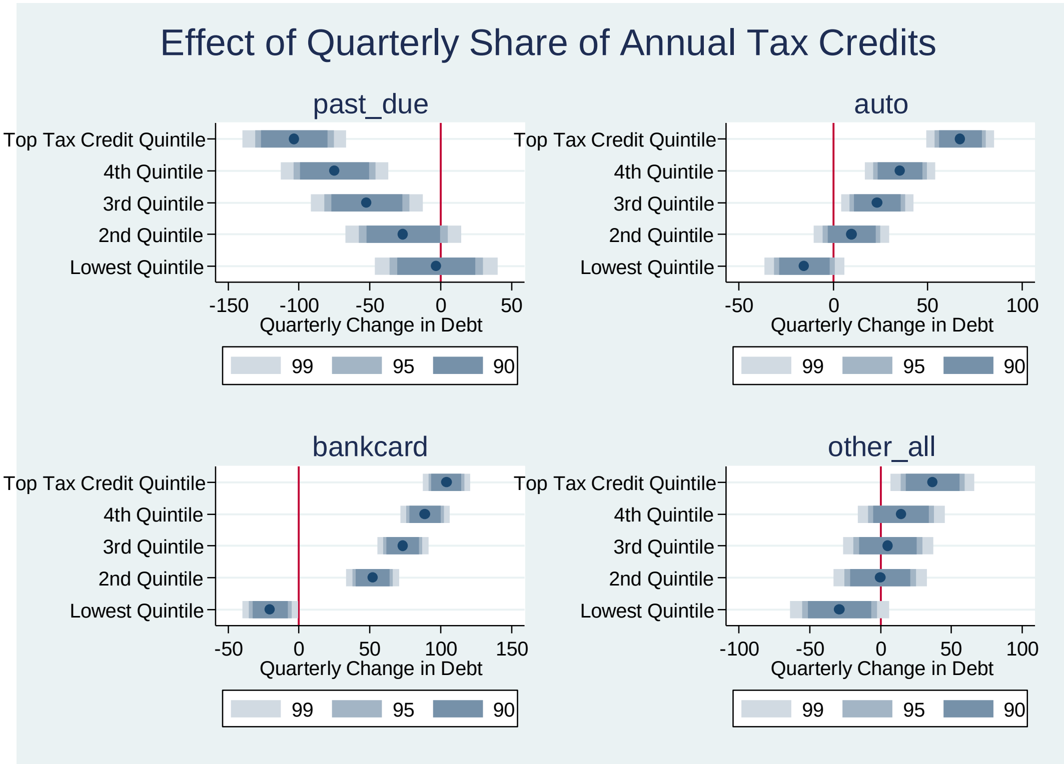
Source: Author's tabulations based on data from Equifax/FRBNY CCP, IRS 2015c, Brookings 2015, U.S. Census Bureau, U.S. Department of the Treasury and Haver Analytics.

Figure 5: Coefficient Estimates of changes in indebtedness by quarter, with demographics x quarter controls



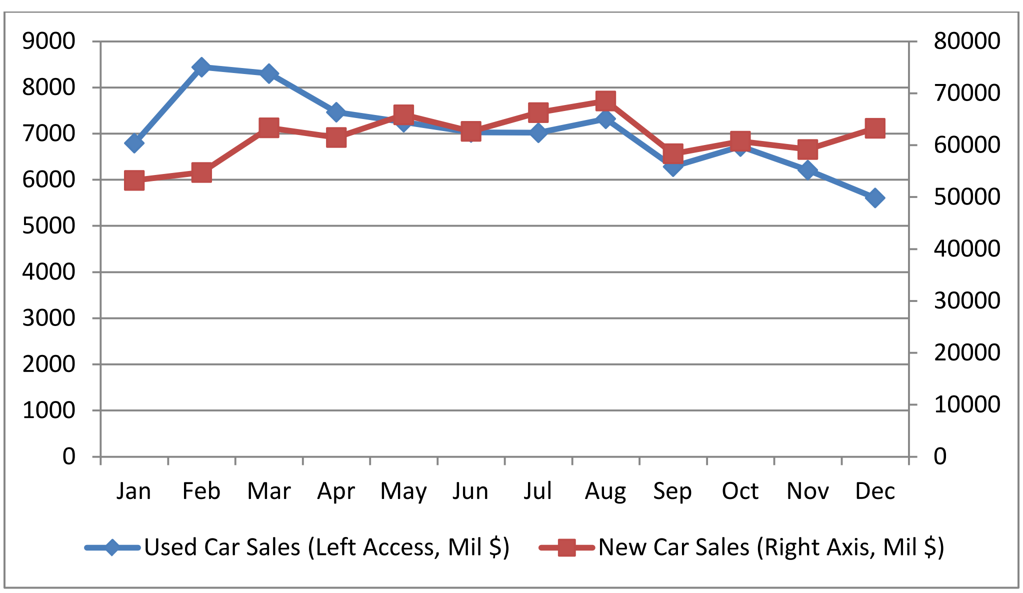
Source: Author's tabulations based on data from Equifax/FRBNY CCP, IRS 2015c, Brookings 2015, U.S. Census Bureau, U.S. Department of the Treasury and Haver Analytics.

Figure 6: Effect of quarterly share of tax credits, by tax credit quintile



Source: Author's tabulations based on data from Equifax/FRBNY CCP, IRS 2015c, Brookings 2015, U.S. Census Bureau, U.S. Department of the Treasury and Haver Analytics.

Figure 7: Retail Sales of Used and New Car Sales by Month, 2013



Source: U.S. Census Bureau and Haver Analytics

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