Timing is Money: Does Lump-Sum Payment of Tax Credits Induce High-Cost Borrowing?

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PRELIMINARY: Please do not cite

Abstract

Since the advent of welfare reform in 1996, spending on tax credits targeted towards low-income families has far surpassed spending on traditional welfare. As of 2011, spending on welfare was around 30 billion dollars nationally, while the two largest tax credits for low-income families, the Earned Income Tax Credit (EITC) and the Child Tax Credit (CTC), were each worth nearly 60 billion dollars. The shift away from delivery of transfer income through the welfare system to delivery through the tax code means that, instead of receiving a consistent, monthly welfare check, many families receive a lump-sum payment when they file their taxes each year. While lump-sum delivery of benefits can be a helpful savings mechanism to allow families to purchase large items that would be otherwise unaffordable (Tach and Halpern-Meekin 2014), it may also induce families to take on costly debt throughout the year in anticipation of tax refunds come tax time. In this paper, we investigate the extent to which the once-a-year timing of benefit payments induces families to take on additional unsecured debt. Using the Survey of Income and Program Participation (SIPP) wealth topical modules from 1990 to 2008, we use a simulated instruments approach to estimate the impact of tax credit program expansions on household credit card debt. Preliminary evidence suggests increases in tax credit generosity are associated with increases in credit card and other unsecured debt. Using the Consumer Finance Monthly survey (CFM), we then show a seasonal pattern of debt accumulation for low-income households that reflects the once-a-year timing of benefits structure: low-income households are much more likely to pay down their debt in the months surrounding tax filing compared to their higher-income counterparts, while there is little or no difference in their debt accumulation and payoff compared to higher-income families throughout the rest of the year.

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Since the advent of welfare reform in 1996, spending on tax credits targeted towards low-income families has far surpassed spending on traditional welfare, (Temporary Assistance for Needy Families, or TANF). As of 2011, spending on TANF was around 30 billion dollars nationally, while the two largest tax credits for low-income families, the Earned Income Tax Credit (EITC) and the Child Tax Credit (CTC), were each worth nearly 60 billion dollars (Tax Policy Center 2012). The shift away from delivery of transfer income through the welfare system to delivery through the tax code means that instead of receiving a consistent, monthly welfare check, many families receive a lump-sum payment when they file their taxes each year.

While lump-sum delivery of benefits can be a helpful savings mechanism to allow families to purchase large items that would be otherwise unaffordable (Halpern-Meekin, Edin, Tach, and Sykes 2014; Tach and Halpern-Meekin 2014;), it may also induce families to take on costly debt throughout the year in anticipation of tax refunds come spring. Indeed, authors have argued that the lump-sum payment approach to distributing benefit income, which forces families to wait months for money that comprises up to 40 percent of annual income, can be extremely harmful (Holt 2009).

The Life Cycle/Permanent Income Hypothesis (LCPIH) suggests that for unconstrained individuals who have access to savings or credit, consumption should not change in response to anticipated income shocks such as tax benefits. Rather, families should smooth consumption over the course of the year, either by saving their tax benefit money and spending it slowly, or by accessing other sources of liquidity. Prior studies of how families respond to the receipt of tax refunds or rebates – not necessarily the EITC or CTC – indicate that while families smooth consumption to some extent, consumption of both durable and nondurable goods tends to increase after tax income payment (Souleles 1999; Shapiro and Slemrod 1995; 2003; 2009; Johnson, Parker and Souleles 2006; 2009; Parker et al. 2013). Among EITC recipients in particular, researchers have found evidence that some benefit money is spent on large, durable good purchases like cars, suggesting that the lump-sum approach to distributing benefits can be a useful savings mechanism. However, recipients also increase spending on nondurable goods like transportation, children's clothing, and fresh fruit and vegetables in EITC months (Barrow and McGranahan 2000; Goodman-Bacon and McGranahan 2008; McGranahan & Schanzenbach 2013). These findings raise an important question: how are families financing consumption of such everyday items during non-EITC months?

One possibility is that they consume less or none of such items in non-EITC months. However, the same set of papers has documented nondurable spending increases among EITC recipients at other times of the year, like the start of the school year or Christmas time. Another possibility is that families save a portion of their benefit income to be used throughout the year, or increase labor supply to accommodate for high-spending periods. For families who are unable to save or increase labor, though, high-cost credit card or payday loan borrowing may be the only means of smoothing consumption. In fact, prior work has shown that while benefit income is initially used to pay down credit card debt among liquidity constrained households, credit card spending quickly catches up and overtakes initial reductions (Agarwal, Liu, and Souleles 2007). Bertrand and Morse (2009) find limited use of tax rebates to pay down payday loan debt, especially among consumers who use payday loans more frequently and are likely to be constrained. Among the financially constrained, lump-sum payment of benefit income may have the perverse effect of inducing additional high-cost borrowing.

In this paper, we investigate the extent to which the once-a-year timing of benefit payments from the EITC and CTC induces families to take on additional unsecured debt. We approach this question from two angles, using data from two nationally representative surveys. We begin by investigating whether use and repayment of unsecured debt follows a seasonal pattern consistent with the disbursement schedule of tax refunds. Using self-reported, representative data from the Consumer Finance Monthly (CFM) survey, we estimate monthly patterns in debt accumulation and payoff for EITC-eligible households relative to higher-earning households, who typically receive much lower tax refunds or even negative tax refunds. This allows us to disentangle the seasonal patterns in debt accumulation and credit use of EITC-eligible households from the population as a whole. If the once-a-year disbursement of benefit payments leads families to use high-cost borrowing to smooth consumption over the course of the year, we should identify patterns of borrowing behavior among families eligible for the EITC that reflect the timing of benefit receipt—decreased borrowing in tax-filing season and accumulation of debt throughout the rest of the year.

Results from the CFM data suggest that credit card debt levels follow the predicted seasonal pattern if families borrow against their expected tax credits, with increasing debt holdings leading up to the payment months and decreases in the peak months of tax filing. We also find evidence that families are significantly less likely to use unsecured debt to pay bills during tax season. Finally, we show the same u-shaped pattern of behavior when we investigate the number of credit cards that families own. Our results suggest that high-cost debt may be an important means of consumption smoothing over the course of the year for families who are eligible for the EITC.

Next, we address the question of whether the federal and state expansions of the EITC and CTC over the last two decades have led to higher overall debt holdings among low and moderate-income households. Use of high-cost borrowing to smooth consumption in anticipation of benefit payments is especially worrisome if, over time, families are becoming increasingly leveraged. Using the Survey of Income and Program Participation (SIPP) wealth topical modules from 1990 to 2008, we estimate the impact of plausibly exogenous shocks to tax credit generosity on household credit card debt and unsecured debt more broadly. We exploit variation in state EITC policies and federal changes to the EITC and CTC over time in order to estimate the elasticity of debt relative to tax benefit income. We employ a simulated instruments method, whereby we create a treatment variable that captures policy variation in benefit generosity, net of income and demographic effects (Currie and Gruber 1996; Milligan and Stabile 2011; Jones, Milligan and Stabile 2015). The results of this analysis address the question of whether increasing tax credit generosity has induced higher debt holdings, not just seasonally throughout the year, but on a longer time horizon.

Results from the SIPP suggest that increases in tax credit generosity are associated with increases in credit card debt and other unsecured debt. This effect is concentrated among single mothers, 60% of whom are eligible for the EITC each year. We find that a 10% increase in average household tax credits leads to a 5% increase in the likelihood of holding credit card debt or unsecured debt more broadly, and a 17-20% increase in the total unsecured debt held. These results imply relatively elastic demands for debt with respect to tax credit income, with estimates ranging from 1.7 to 2.1. Further, we use the SIPP to confirm findings from the CFM that households pay down their debt when they receive their tax refunds and increase their debt holdings throughout the rest of the year. However, we show that on average, increasingly generous benefits are associated with increasing debt holdings among EITC-eligible families.

We make several important contributions with this paper. First, this is the first paper to our knowledge to analyze how the expansion of yearly tax credits for low and moderate-income households affects unsecured debt holdings. All previous studies on the effects of tax benefit income on consumer debt have investigated intra-year changes in debt behavior, tracking how behavior responds to the once-a-year disbursement schedule. Our two-pronged analysis extends the timing work, but additionally examines the effects of increasing benefit generosity *over* years.

Further, while previous work has looked at how household consumption is affected by tax refund receipt, many studies have relied on relatively small, one-time changes in the tax code such as the 2001 stimulus rebate, which was worth between $300-$600, or roughly 1.5 percent of median annual income (see Shapiro and Slemrod 1995; Shapiro and Slemrod 2003; Agarwal, Liu, and Souleles 2007; Bertrand and Morse 2009). The EITC and CTC, in contrast, are each 60 billion dollar federal programs that are worth up to 45% of annual household income. Examining how household debt changes in response to increases in generosity of the largest anti-poverty program in the United States is policy interest in its own right. Unlike TANF, there are no lifetime limits to claiming the EITC and CTC and households typically receive these benefits for several consecutive years (Ackerman, Holtzblatt, Masken 2009). Households might react very differently to small changes in tax rebates that occur at a single point in time compared to a tax credit that they typically receive every year.

Additionally, we build on prior work examining the seasonal consumption responses to tax refund receipt. Previous work has focused on how patterns of saving and spending change over the course of the year among the EITC-eligible; we expand this literature by investigating how debt behaviors change after tax refund season. This adds to the picture of how consumption, debt and savings behavior respond to large income shocks among low-income families. Finally, we add to the discussion of whether the permanent income hypothesis holds among populations that are likely to be liquidity constrained. We find that families increase debt in anticipation of tax benefit season, a finding that suggests that the EITC-eligible smooth consumption. Our results are important because they extend the literature on tax benefits, consumption and debt. Furthermore, if the timing of benefit payments induces families to take on high-cost credit, at least some government expenditures will be transferred to lenders through interest payments, and program effectiveness will be compromised.

We begin by providing background on the Earned Income Tax Credit and the Child Tax Credit policies. In the Data and Methods section, we first discuss the CFM data and related empirical strategy before detailing our analytical approach with the SIPP data. The Results section follows, where we present the results from the CFM followed by those from the SIPP.

Background

The Earned Income Tax Credit and Child Tax Credit

The EITC began as a small, temporary credit in 1975, worth up to $400 ($1,770 in 2013 dollars) or 10% of household earnings. Since then, the credit has been expanded several times at both the federal and state level, with the federal credit worth up to $6,000 in 2013, or up to 45% of household earnings. It is also fully refundable, so households with no tax liability receive the EITC as a part of their tax refund. In total, federal spending on the EITC was nearly 60 billion dollars as of 2013, while spending on TANF was less than 30 billion dollars. In addition to the federal benefit, 23 states and the District of Columbia have their own EITCs, which increase the total benefit by 3-45 percent of the federal benefit. States implemented their own EITCs beginning in the late 1980s, but the majority implemented credits following welfare reform in the late 1990s and early 2000s. A list of states that have ever implemented EITCs, as well as the year of implementation, can be found in Appendix Table 1.

While there is quite a bit of variation in the timing of implementation of state EITCs, several states also changed benefit generosity over time. For instance, New York implemented an EITC in 1994 worth just 7.5 percent of the federal EITC. As of the 2011 tax year, New York had increased the value of its EITC to 30 percent of the federal EITC. Other states have reduced or eliminated their EITCs entirely. Colorado, for instance, had an 8.5 percent EITC in 1999 but suspended it in 2003 due to lack of funding.

In addition to the EITC, which is targeted towards households that earned less than $52,000 in 2013, households can also claim the Child Tax Credit (CTC), which is worth up to $1,000 per child in 2013 for households earning less than $110,000. The CTC was established in 1998 and has been gradually expanded at the federal level since. In 1998, the credit was non-refundable and worth $400 per child. By 2013, the credit was worth up to $1,000 per child under the age of 17, and is partially refundable for households earning more than $3,000.[1]

With the formulation and expansion of these credits since the 1990s, the United States has largely shifted from a welfare system that provided monthly benefits for non-working households with children to a social safety net largely operated through the tax code, providing annual benefits to working households with children. This shift has had several implications for

[1] One-child households earning at least $10,000 in 2013 could claim the full $1,000 CTC per child.

low-income households. Individuals now have a strong incentive to work, as EITC and CTC benefits require at least some earnings and increase with every dollar earned up to a threshold. Second, benefits are now received through the tax code, simplifying the process of applying for benefits and reducing the stigma of applying for, and claiming, government benefits. EITC and CTC-eligible households file their taxes like all other households, and benefits are distributed via a tax refund, similar to higher-earning households. Finally, and importantly for our purposes, the shift towards provision of benefits through the tax code also means that benefits are distributed annually rather than monthly.

There has been considerable interest in analyzing how households allocate EITC benefits (Barrow and McGranahan 2000; Romich and Weisner 2000; Smeeding, Phillips, and O'Connor 2000; Tach and Halpern-Meekin 2014). Much of the initial work relied on surveys and in-depth interviews of small, non-nationally representative groups, finding that households use their refunds primarily to pay down debt or past-due bills (Romich and Weisner 2000; Smeeding et al. 2000). Several families also saved at least a portion of their refund, or made payments towards a car, school tuition, or other social mobility investments (Smeeding et al. 2000; Halpern-Meekin et al. 2014). All of these studies find that EITC-eligible households have trouble making ends meet each month and that tax refunds are used to catch up on past bills, or even pay rent and utilities several months in advance (Romich and Weisner 2000; Smeeding et al. 2000; Halpern-Meekin 2014).

Other work has utilized the Consumer Expenditure Survey to examine trends in consumption patterns of EITC-eligible households over the course of the year. Barrow and McGranahan (2000) find an increase in consumption around tax time, and later work by McGranahan and co-authors has also shown that households are more likely to purchase used cars, children's clothing, as well as fresh fruits and vegetables in the months following tax refund receipt (Goodman-Bacon and McGranahan 2008; McGranahan and Schanzenbach 2013). A recent paper by Shaefer, Song, and Shanks (2013) used the SIPP to show that the federal expansions of the EITC for two-child households in the early 1990s led to a decrease in the value of unsecured debt among single mothers with at least two children, suggesting that households use the EITC to pay down debt. The authors' identification strategy investigates how debt patterns changed among different subsets of EITC-eligible families after the expansion, an approach that differs substantially from the one used herein.

Current Study

This analysis builds on prior work, using two distinct approaches to investigate the question of whether increased tax benefit generosity has led consumers to increase their debt levels. We hypothesize that households use the EITC to pay down debt, but that there is a seasonal component to the pattern of debt accumulation and payoff. We additionally hypothesize that as the benefit policies have become more generous over time, families have taken on increased debt in anticipation of their lump-sum benefit payment. Because the EITC is typically received in February or March, we expect to find declines in household debt in those months, but increases in household debt throughout the rest of the year in anticipation of tax refunds. We disentangle these two effects by first examining the monthly pattern in debt accumulation and payoff for EITC-eligible households compared to non-eligible households, and then evaluating how the value of unsecured debt changes in response to increases in tax credit generosity over time.

We use plausibly-exogenous variation in tax benefits within states over time to make causal inference about the overall, long-run impact of tax credits on household debt accumulation. Finally, we calculate different elasticities of unsecured debt with respect to tax credit generosity based on the month of observation. We test for negative elasticities in March, when tax refunds are typically received, and positive elasticities throughout the rest of the year.

Data and Method

Seasonality of Debt Behavior: The CFM

Data

We employ two data sources in our analyses. First, we use data from the Consumer Finance Monthly (CFM) survey, a nationally representative cross-sectional survey which is administered to a monthly sample of 300-500 households. The data collected cover a wide array of demographic and financial characteristics. For the current study, we focus on the rich data available on credit card use and repayment, bill payment behavior and overall debt and asset holdings. We use data collected between June 2006 and June 2013, on households with children, producing a sample of 6,980 families.

The CFM asks a broad array of questions about financial behavior. We focus on questions that provide information on credit card borrowing and debt, and on unsecured debt behavior more broadly. To measure credit card behavior, we use questions that ask about the family's debt position at the time of the last statement. Specifically, we construct three variables: an indicator that equals 1 for families that report having any outstanding credit card debt after payments; the natural log of the total outstanding credit card debt; and a count of the total number of credit cards the family owns. For families who report owning no credit cards, we set values of all variables to 0.

In addition, we construct measures of unsecured debt use. We construct a measure of the natural log of total unsecured debt by summing the total outstanding credit card debt, payday loan, installment loan, bank loan and other loan variables; we choose to omit student loan debt from this total, since its value is unlikely to be sensitive to seasonality. We also create an indicator that equals 1 for families who have any unsecured debt. Finally, using questions from the survey module that asks about bill payment methods, we construct a measure of whether a family uses unsecured debt to pay bills. For a series of spending categories, respondents are asked whether they "use *payment method* to pay bills" in the given category; we construct an indicator that equals 1 if the respondent indicated that they pay any bills using either credit cards, store credit cards, gas cards or payday loans. The means of these variables, along with sample demographics, are displayed in Table 1.

Approximately 36% of sample households are eligible for the EITC according to reported family income. Thirty-six percent of all households (and 29% of EITC-eligible households) have credit card debt, while over 50% report having some outstanding unsecured debt. Among the full population with children, the average outstanding credit card debt equals just over $3,200, while EITC-eligible families owe about $2,100. EITC-ineligible families own just over 2.5 credit cards, and 45% use unsecured debt to pay bills. Among the EITC-eligible, families own 1.4 credit cards; 27% of families pay bills with unsecured debt. Compared to the general population with children, the EITC-eligible are more likely to be black and female, they are less likely to be married, and have lower household income, net worth, debt and savings.

Empirical Strategy

Following Barrow and McGranahan (2000) We use the CFM to examine whether there is a seasonal pattern to household debt accumulation and pay off for EITC-eligible households. We examine credit card and unsecured debt behavior using residual plots of the CFM data that compare trends in monthly debt behavior of EITC-eligible households to those of ineligible households. We implement models of the following form:

$$Y_i = \delta ELG_i + Month'\alpha + (ELG_i * Month)'\lambda + X_i'\beta + \gamma_y + \varepsilon_i \,, \tag{1}$$

where Y_i represents the outcome of interest. The vector γ_y is a set of year fixed effects and X_i contains covariates including the number of minors in the household, age, and indicators of gender, race, marital status, and educational attainment. ELG_i is an indicator for whether the household income of individual i falls within the EITC-eligible range, which we calculate for each household using the state-, year- and family size-specific eligibility rules. $Month$ is a set of calendar month indicators that denote the month in which respondent i was surveyed, and $(ELG_i * Month)$ is the interaction of the EITC-eligibility indicator with each calendar month indicator. In all cases, we use March as the base month, and we estimate linear models with robust standard errors clustered at the state level. We are primarily interested in this vector of coefficients, λ, which indicate the relative change in the outcome variable of interest for EITC-eligible households compared to March levels. If our hypothesis is true, we expect to find low debt levels among EITC-eligible households in February and March, with increases later in the year.

We explore the results of estimated equation (1) both graphically, and using statistical tests. We begin by plotting the monthly residuals by month for the EITC-eligible versus ineligible populations. These pictures allow us to compare the monthly trends in debt behavior between those who are likely to receive the EITC and those who are not, after controlling for observables. Second, we conduct t-tests for seasonality by testing whether the coefficients in vectors α and λ are jointly equal to zero. Specifically, we conduce three formal t-tests:

Test 1: seasonality among the EITC-ineligible

$$\alpha_j = \alpha_f = \alpha_a = \cdots = \alpha_d = 0$$

Test 2: seasonality among the EITC-eligible

$$\alpha_j + \lambda_j = \alpha_f + \lambda_f = \lambda_a = \cdots = \alpha_d + \lambda_d = 0$$

Test 3: difference in trends between EITC-eligible and –ineligible populations

$$\lambda_j = \lambda_f = \lambda_a = \cdots = \lambda_d = 0$$

In all cases, we test the null hypotheses that there is no seasonality (or that seasonality between the two groups is equal, in the case of test 3). Low p-values will allow us to reject the null hypotheses and conclude that, after controlling for observables, there is seasonality in debt behavior.

Overall Increases in Debt: The SIPP

Data

Our second data source is the Survey of Income and Program Participation (SIPP). The SIPP is a large, nationally-representative panel dataset surveying families for up to 60 months per panel. We utilize panels from 1990 to 2008, which span the years from 1990 through 2013. In addition to the main survey, which is conducted every four months, the SIPP also conducts a number of topical modules on specific areas such as fertility, education, and wealth. We utilize the wealth and assets topical modules, which are conducted once every twelve months and contain information on net worth, the value of secured and unsecured debt and credit card debt specifically. The SIPP employs a rotation group structure to its interviews. Households are assigned to one of four rotation groups and are interviewed over the course of four months. For the wealth topical modules, a household will always answer questions about wealth and debts in the same calendar month each year. Appendix Table 2 lists the months when households are surveyed about their wealth and debts for each panel. In the 2008 SIPP, for example, the wealth topical modules are assessed in September through December. We include calendar month fixed effects in all analyses to control for the seasonality of debt throughout the year. For example, credit card debt tends to peak around the end of the summer with back to school shopping, as well as the holiday season in November and December. These topical modules provide information on households up to four times per panel, although prior to the 1996 panel, household wealth and assets information was only collected once per panel. Some information from these topical modules is collected at the household level, so we restrict our analysis to household heads and their spouses, randomly selecting one person per household. Because the EITC and CTC (by definition) mostly benefit households with children, we further restrict our analysis to households that have at least one child under the age of 19 at the start of the survey. This results in a sample of 121,932 household-years. In some analyses we focus on single mothers, who are the primary recipients of the EITC, which yields a sample of 27,809 person-years.

Our primary outcomes of interest include whether the household had any credit card debt or unsecured debt, and the value of those debts at the time of the survey. Households are asked about the value of mortgages, car loans, store credit cards, bank loans, and other miscellaneous debt. These debts are then aggregated into secured and unsecured debt. Unsecured debt includes any debt not including mortgages, home equity loans, or car loans. We are able to separately analyze the presence of and value of credit card debt, but 'other' debt is assessed in the SIPP as the combined value of: medical bills not paid by insurance, education loans, money owed to private individuals, and "any other debt not covered, and excluding mortgages, home equity loans, and car loans." We therefore analyze unsecured debt as a whole, as well as credit card debt specifically.

Table 2 shows descriptive statistics from the SIPP for households with children under the age of 19. In the full sample, about two-thirds of households have at least some unsecured debt, and only 20 percent of households have any credit card debt. The average amount of unsecured debt held is about $13,000, or 20% of household income. The average household tax credit from the EITC and CTC is $1,600, or 2% of family income[2]. Single mothers are less likely to have unsecured debt, but are twice as likely to have credit card debt compared to the whole sample of households with children. Unsecured debt makes up a larger share of household income for single mothers, at nearly 30% of total household income. Single mothers also are more likely to be eligible for the EITC, with nearly 60% of single mothers eligible in the first year of each SIPP panel, compared to only a third of all households with children. Not surprisingly, single mothers are also eligible for larger tax credits than the broader sample of households with children, amounting to 6% of household income.

Empirical Strategy

[2] Not surprisingly, this varies by household income, with households in the bottom income quintile receiving tax credits worth about 32% of their annual income.

We use a simulated instruments approach to model the impact of an increase in tax credit generosity on household debt accumulation. This approach has several advantages over other identification strategies. Using own tax credit eligibility reflects variation in benefits that is driven by the policy changes, which is the variation of interest, but also variation due to other household processes that may be endogenous to the outcomes of interest, such as changes in income or family structure over the course of the year. Using the maximum potential credit value in a given state and year by household size eliminates concerns of endogeneity of own eligibility to the outcomes of interest, but not all families are eligible for the maximum credits. Instead, we calculate the average household EITC and CTC in a given state and year, using the National Bureau of Economic Research's (NBER) TAXSIM model. Because different states may have different concentrations of EITC-eligible households, rather than using the population of the state to generate the average household credit in a given state, we simulate an average household credit for each state in each year by calculating the value of the EITC and CTC for a nationally-representative sample of households, simulating what their tax credits would be in each state-year combination. We then average these values at the state-year cell level. Variation in this term reflects only policy changes across states in a given year and within states over time, eliminating variation due to endogenous decisions about geographic location, household size, or household income in relation to the outcomes of interest.

Figure 1 shows how the maximum and average EITC and CTC changed over time. The maximum EITC and CTC represents the maximum value of these combined credits, averaging across states in each year. The average EITC and CTC represented by the red line is calculated using the simulated instruments method described above. In 2011 dollars, the maximum value of the combined federal and state EITC and CTC grew from less than $2,000 in 1991, to over

$8,000 in 2011 for a household with 2 children. The average household tax credit nearly quadrupled over this time period as well, increasing from less than $500 in 1991 to more than $2,000 in 2011. Due to the variation in when states began implementing EITCs, there was also significant variation in the average household EITC and CTC across states over this time period. Figure 2 illustrates this variation, with each dot representing a different state. Once again, the variation illustrated here is due solely to differences in tax laws across states, eliminating the variation due to the endogenity of geographic location. Figure 2 illustrates that, in any given year, the variation in average household tax credit between the most generous state EITC and the least generous was about $500.

Using this variation across states in a given year as well as within states over time, we model the impact of tax credit generosity on debt using the following model:

$$Y_i = \beta_0 + \beta_1 \ln(C) + \beta_2 X_i + \delta_s + \gamma_t + \varepsilon_i \ , \tag{2}$$

where *i* indexes individuals, *s* indexes states, and *t* indexes years. Y_i is the outcome of interest: an indicator for whether a household has any credit card or other unsecured debt, or the natural log of total credit card and unsecured debt. Our primary coefficient of interest, β_1, is the coefficient on the natural log of the average household tax credit in a given state and year, represented by *C*. This term varies at the state-year level. We also include a vector of demographic characteristics at the individual level such as age, race, number of children living in the household, as well as state and year fixed effects. State fixed effects control for time-invariant differences across states, such as political ideology, that may affect debt levels in a given state. Year fixed effects control for national trends such as recessions or changes to credit card laws at the federal level. In all analyses, standard errors are clustered at the state level to allow for the correlation of errors within state. In some analyses, we restrict our sample to the SIPP panels 1990 through 1996 and calculate separate elasticities of debt with respect to tax credit generosity in March compared to all other months.

Results

CFM results: Is there seasonality in debt behavior?

We look for seasonality in debt behavior using residual plots and the CFM data on families with children. The results of this analysis are presented in figures 3 and 4. In all graphs, we plot two lines: the line marked *EITC eligible* (colored black) shows the coefficient estimates of the (*Month * EITC)* indicators, and shows the marginal monthly effect relative to March levels among EITC-eligible households. The line marked *EITC ineligible* indicates the coefficient estimates from the *Month* indicators and shows the behavior trends (relative to March values) among the ineligible population. This line is intended as a comparison to show how debt behavior among the general population changes over the year.

Figure 3 shows results for the three credit card debt behavior variables we investigate. The top two graphs show how the likelihood of having any credit card debt and the natural log of total credit card debt evolve over the course of the year. Among the EITC-eligible population, debt holdings appear low in February, March and April, and increase over the course of the year, with highs in September. The low levels in tax season correspond with the timing of the lump-sum payment of benefits. The trend is more striking when compared to the rest of the population: among the EITC-ineligible population, there is evidence of the opposite trend, with higher debt levels around tax season. This may reflect the tendency for families to keep cash on hand in anticipation taxes owed in April (Dunn et al. 2011). There is also a striking decrease in November in the amount and likelihood of owing money among the EITC population. Families may be paying off debt in anticipation of increased spending over the holiday season.

The third picture shows trends in the number of credit cards owned by a family. The behavior pattern among the EITC-eligible population is especially pronounced here: families own the fewest credit cards in March, and increase their ownership over the course of the year. This may reflect the tendency for families to pay off credit card debt with their benefit income, and subsequently close accounts. Again, the pattern among the EITC-eligible population is distinct from that among the general population.

Figure 4 show graphs that describe seasonality in unsecured debt behavior. The top two graphs show the likelihood of owing, and natural log of total amount owed, on unsecured loans, excluding student loans. Again, there is a pattern of low debt level in February and March, with gradual increases over the course of the year. Families exhibit high debt levels in December. The third graph shows the likelihood of paying bills with unsecured debt[3], and illustrates a pronounced pattern in debt behavior. Among the EITC-eligible population, families are unlikely to use unsecured debt to pay bills in February, March and April; the likelihood increases dramatically in the months following tax season. Again, the pattern is not evident among the general population, which appears to have fairly stable debt usage over the course of the year. Overall, the figures indicate a pattern of seasonality among the EITC-eligible population that confirms the hypothesis that families respond to the timing of tax benefit payment.

[3] Recall that the third measure of unsecured debt behavior includes a different set of debt products than the first two. The bill payment measure includes use of credit cards, payday loans, gas cards and store credit cards.

The results in Table 3 suggest the same conclusions with the use of t-tests. We show the estimated monthly residuals for the EITC-eligible and –ineligible populations.[4] The first thing to note is the lack of statistical significance among the monthly coefficient for the EITC-ineligible. This reflects what our graphs show: that there is little seasonality in the debt behavior of the EITC-ineligible. The results of *test 1* confirm this: for three of the four outcomes we consider, we are not able to reject the null hypothesis of there being no seasonality in debt behavior among the EITC-ineligible. *Test 2* shows the opposite: in all cases, we can reject the null that there is no seasonality among the EITC-eligible. Further, *test 3* shows that there are statistically distinct patterns in behavior among the eligible and ineligible populations. In sum, our analysis reveals statistically significant seasonality in debt behavior among the EITC-eligible that reflects the timing of the lump-sum payment of tax benefits.

SIPP results: Are families increasing debt over time?

We next examine whether the expansion of tax credits over the last two decades has affected household debt among low and moderate-income households using data from the SIPP. If families borrow against expected tax benefits – which our analysis from the CFM strongly suggests – increasingly generous benefits could generate increasingly leveraged families if families are unable to fully pay-back their outstanding debt at tax time. We begin by presenting results using the value of own tax credits, as calculated using TAXSIM, as the treatment variable. As mentioned above, this measure reflects the variation in EITC and CTC benefits geographically and over time, but also reflects potentially endogenous factors such as own family income. Households with larger tax credits are likely lower-earning households, and these

[4] In the interest of space, we exclude results for the propensity of having any credit card or unsecured debt, since these variables are constructed from the total debt variables and demonstrate similar results. Results available upon request.

households might be more likely to take on debt than higher-earning households regardless of their tax credit eligibility. On the other hand, lower-earning households may have less access to credit, and we might therefore expect to find a negative association between tax credits and household debt. Table 3 presents results from these OLS regressions, first for all households with children and then for only single mothers. All regressions include demographic controls, as well as state and year fixed effects. Each cell represents a different regression, with each row representing a separate outcome of interest. Results indicate small, positive associations between household tax credits and propensity to take on credit card debt and unsecured debt. A 10% increase in own tax benefits is associated with a 0.1 percentage point increase in the propensity for single mothers to have unsecured debt or credit card debt more specifically. Associations are even smaller for all households with children: a 10% increase in tax credits is associated with a 0.03 percentage point increase in the propensity to have credit card debt. Similarly, we find small, positive associations between household tax credits and the value of household debt as well: a 10% increase in household tax benefits is associated with about a 1% increase in the value of unsecured debt held among single mothers and a 0.2% increase in the value of unsecured debt held among all households with children.

We present results using our simulated instrument in Table 4, which reduces concerns of endogeneity of own tax credit eligibility to household debt. We present the reduced-form estimates here, where the coefficient indicates the change in the outcome variable of interest when the average household tax credit in a state and year increases. Again, variation in this treatment variable is generated solely due to policy differences across states and within states over time, and not due to demographic or economic differences in populations across states. Using our simulated instrument, we find much larger impacts of tax credit generosity on household debt, particularly among single mothers, who are the primary recipients of the EITC. We find that a 10% increase in tax credit generosity leads to an insignificant 1 percentage point increases in the likelihood of holding unsecured debt among all households with children, and a significant 2 percentage point increase among single mothers. We find a similar result for the likelihood of holding credit card debt. These effect sizes represent a 4-6% increase in unsecured debt holdings among single mothers. Turning to the results for the value of debt held, we find no significant results for the broader sample of households with children, but large, significant results for single mothers. We estimate elasticities of 1.7 to 2.0 for the value of unsecured debt with respect to tax credit generosity. This implies that a 10% increase in tax credit generosity leads to a 17-20% increase in the amount of unsecured debt held: a fairly elastic result.

Robustness Checks

An alternative theory for why households may increase their credit card debt in response to increases in tax credit generosity is that tax credit generosity improves access to credit among low-income households. It is well-known in the EITC literature that the EITC encourages work among single mothers (Ellwood 2000; Meyer and Rosenbaum 2001). Increasing the labor force participation may also lead to better access to credit among low-income households, and thus access to credit cards and other forms of unsecured debt that may have been previously unavailable. An increase in credit card debt may be a signal of an improved financial situation among these households.[5]

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[5] It should be noted that our measures in the SIPP capture debt holdings rather than credit card balances before payments. While increased credit card debt may be a signal of improved financial stability and access to credit markets, it also comes with a high cost.

We conduct a number of robustness checks in attempts to disentangle the effect of the distribution method of the tax credits from the income effect of the tax credits through increasing labor supply. First, we exploit the fact that the SIPP wealth topical modules are administered in different months to test whether the relationship we find between benefit generosity and debt holdings depends on whether the respondent is surveyed in an EITC or non-EITC month. If increased debt is a response to improved access to credit, we would expect to find no difference in the relationship between debt and tax credit generosity by the month of the survey. If increased debt is in response to the distribution method of the tax benefits, we would expect to find declines in debt in EITC months and increases in debt in non-EITC months. The results of this robustness check can also corroborate the seasonality results from the CFM.

Second, we evaluate the relationship between household debt and tax credit generosity on a sample of EITC-eligible households that do not tend to increase their labor supply in response to tax credit generosity: married women. Previous work has shown that married women with children actually decrease their labor supply as a function of EITC generosity, suggesting that the EITC subsidizes leisure among married women (Eissa and Hoynes 2004). If we find a similar relationship between household debt and tax credit generosity among married mothers as single mothers, we would conclude that the positive relationship between household debt and tax credit generosity is not due solely to improved access to credit markets gained from an increase in labor supply.

Robustness checks: variation by month of survey

If the estimates presented in Table 4 are due to the annual distribution method of the tax credits, we would expect to find differential responses to tax credit generosity in March compared to other months surveyed. Namely, we would expect to find a decline in debt in

March, but an increase in debt in all other months, as a function of tax credit generosity. If the results are due to an income effect associated with tax credit generosity—that household are more likely to work when tax credits are more generous—then we would expect to find no variation in the relationship between household debt and tax credit generosity based on the month of the survey. We conduct this exercise using data from the SIPP between 1990 and 1999, the years in which individuals are asked about household debt in December through May. We run the same regressions as in Table 4, but separately estimate models for observations in March and all other months.

We illustrate these results for single mothers in Table 5, which confirm our findings from the CFM. If we evaluate the relationship between tax credit generosity and debt in March, we indeed find a negative relationship: a 10% increase in tax credit generosity leads to a 5 percentage point decline in the likelihood of holding unsecured debt, or a 10% decline. This is in contrast to results when we focus on observations in all other months during this time period: December, January, February, April, and May. Those results are similar to those presented in Table 4: a 10% increase in tax credit generosity leads to a 2 percentage point increase in the likelihood of holding unsecured debt. We estimate elasticities that are slightly smaller than those presented in Table 4, but still relatively elastic at 1.7 and not statistically different from those presented in Table 4. These results imply that households are taking on more debt throughout the year to finance consumption, using their tax refunds in March to pay down the debt they accumulated throughout the rest of the year. This is consistent with our hypothesis that the distribution method of tax refunds is responsible for the fluctuations in unsecured debt holdings among low-income households, rather than the income effect generated through increased labor supply.

Robustness checks: results for married mothers

If the relationship between household debt and tax credit generosity is due solely to an increase in labor supply that also improves access to credit markets among low-income households, then we would expect to find no relationship between debt and tax credit generosity among married-couple households. Married men tend to have very inelastic labor supply, and married women tend to reduce their labor supply in response to tax credit generosity (Eissa and Hoynes 2004). We should therefore expect to find no changes in household debt with respect to tax credit generosity if the sole mechanism is through increased labor supply, and thus, access to credit among low-income households. Table 6 presents results of regressing the debt variables of interest on our simulated instrument for the sample of married women with children and family income below $50,000 in 2011$. Households with earnings above $50,000 are ineligible for the EITC, while approximately 70% of married-couple households with children and income below $50,000 are eligible for the EITC in our SIPP sample.

Results from this exercise provide further support for the annual distribution of tax benefits mechanism. We find a positive relationship between household debt and tax credit generosity among married mothers: a 10% increase in tax credit generosity is associated with a 7% increase in the likelihood of holding unsecured debt and a 36% increase in the amount of unsecured debt held. This implies that the relationship between debt and tax credits is not driven solely by increased labor supply and improved access to credit markets among low-income households, since married women typically do not increase their labor supply in response to tax credit generosity.

Conclusion

In this paper we investigate how lump-sum delivery of tax benefits impacts borrowing behavior among low-income families. Significant research has been undertaken on the seasonal patterns in consumption and savings among the EITC-eligible. We extend this work by investigating whether high-cost debt positions also follow the expected pattern if families are borrowing against their expected return. We find significant evidence to confirm our hypothesis: families do appear to pay down debt during tax season and increase debt over the course of the year. The results confirm the permanent income hypothesis – families appear to smooth consumption – and suggest that at least some of the benefit income might be better distributed on a periodic schedule.

The fact that families use credit cards and other unsecured debt to finance consumption over the course of the year is not necessarily welfare reducing. While it is certainly costly to carry credit card debt for months while waiting for lump sum payment of tax benefit income, the income shock afforded by lump-sum delivery of benefits may be valuable enough to warrant the use of credit cards to finance consumption throughout the course of the year. This argument becomes less persuasive if over time, families are increasing credit card debt without ever fully paying it off. We investigate this question using a simulated instruments approach that relates debt holding to exogenous changes in benefit generosity.

Results from this analysis indicate that households are significantly more likely to take on credit card and other unsecured debt as a function of tax credit generosity. A 10% increase in the average household tax credit from the EITC and CTC in a given state and year leads to a 4-6% increase in the likelihood of holding any credit card debt, and a 20% increase in the amount of unsecured debt held among single mothers. These results suggest that while households may prefer to receive benefits in large lump-sum distributions, the forced savings mechanism comes at a cost. While this form of credit may allow households to smooth consumption, these same households are likely paying steep interest rates in order to do so. The evidence from the SIPP analysis suggests that over time, this method of consumption smoothing may be causing families to sink into debt that they do not fully pay off at tax time.

With the expansion of the EITC and the CTC beginning in the 1990s, we have shifted from a welfare system that primarily targeted non-working single mothers, to a system where many benefits are contingent upon work and distributed through the tax code. This shift has had several implications for the low-income population in the United States. Distributing benefits through the tax code simplifies the process of determining eligibility and claiming benefits, leading to lower stigma and higher claiming rates—typically near 90% of the eligible population, compared to averages of less than 50% for welfare benefits. Distributing benefits through the tax code also means that eligibility and benefits are determined annually rather than monthly. Determining eligibility annually may be beneficial in reducing the time spent proving eligibility, but it also means that households only receive benefits once a year. While qualitative research suggests that families strongly prefer to receive these benefits in lump sums to allow for the purchase of large items, there is also evidence that these same households have trouble making ends meet throughout the rest of the year (Halpern-Meekin et al. 2014). Further, there has been recent evidence indicating spending on non-durable goods increases in the months following tax refund receipt as well (Barrow and McGranahan 2000, McGranahan and Schanzenbach 2013, Jones et al. 2015). This suggests that households may benefit from receiving at least a portion of their benefits at a more regular interval.

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Table 1. Descriptive Statistics from the CFM for households with children under the age of 19, by EITC-eligibility

	All households with children	EITC-eligible households
EITC eligible	0.36	1
Debt behavior outcomes		
Has credit card debt	0.36	0.29
Total credit card debt	3,229	2,123
Number of credit cards	2.66	1.43
Has unsecured debt	0.59	0.52
Total unsecured debt	10,430	6,039
Uses unsecured debt to pay bills	0.44	0.27
Value of assets and debts		
Houeshold networth	323,735	113,458
Total savings	36,672	20,209
Total debt	104,337	41,817
Total family income	81,824	23,276
Demographic characteristics		
Black	0.09	0.20
Female	0.62	0.72
Age	40.62	39.72
Married	0.81	0.65
Number of kids in the household	1.86	1.88
Number of Observations	6,980	1,958

Source: Consumer Finance Montly survey, 2006-2013. Respondents of households with at least one child under the age of 19 living in the household. All dollars in 2013$.

Table 2. Descriptive Statistics from the SIPP for households with children under the age of 19, by family structure

	All households with children	Single mothers
Indicator for presence of assets and debts		
Has unsecured debt	0.64	0.51
Has credit card debt	0.20	0.39
Value of assets and debts		
Total unsecured debt	12,587	6,996
Total credit card debt	1,233	2,384
Total family income in first year of SIPP	63,072	26,035
Average household credits by state-year	1,607	1,622
Total household credits in first year of SIPP	1,327	1,616
Total household credits as a percent of income	2.1%	6.2%
Eligible for the EITC in first year of SIPP	32.9%	58.7%
Demographic characteristics		
Black	0.14	0.31
Female	0.47	1.00
Age	39.22	37.12
Married	0.71	0.00
Number of kids in the household	1.90	1.80
Number of Observations	121,932	27,809

Source: Survey of Income and Program Participation 1990-2008. Respondents of households with at least one child under the age of 19 living in the household at the start of the survey. All numbers are weighted by monthly person weights. All dollars in 2011$.

Table 3. Regression results comparing monthly trends in debt behavior among EITC-eligible versus ineligible, families with children

Outcome	**ln(Total CC Debt)**		**Number of CCs**		**ln(Ttl Unsec Debt)**		**Used Unsec Debt**	
Monthly coefficient estimates	Inelig.	Eligible	Inelig.	Eligible	Inelig.	Eligible	Inelig.	Eligible
January	0.365	-0.879	-0.071	-1.357***	0.133	-1.888***	-0.056	-0.069
	(0.472)	(0.660)	(0.346)	(0.252)	(0.429)	(0.651)	(0.046)	(0.068)
February	0.126	-1.402***	0.101	-1.770***	-0.036	-2.305***	0.099**	-0.199**
	(0.440)	(0.494)	(0.419)	(0.320)	(0.433)	(0.652)	(0.043)	(0.084)
March		-1.212***		-1.870***		-1.857***		-0.267***
		(0.314)		(0.335)		(0.650)		(0.057)
April	0.150	-1.442**	-0.388	-1.368***	0.443	-1.019	0.002	-0.200***
	(0.436)	(0.548)	(0.320)	(0.295)	(0.360)	(0.673)	(0.046)	(0.073)
May	0.470	-1.187**	-0.050	-1.508**	0.211	-1.320**	0.064	-0.233***
	(0.455)	(0.561)	(0.541)	(0.569)	(0.384)	(0.539)	(0.049)	(0.059)
June	0.106	-0.081	-0.524	-0.852***	-0.324	-0.829	-0.015	-0.129**
	(0.368)	(0.583)	(0.332)	(0.261)	(0.453)	(0.578)	(0.042)	(0.052)
July	-0.003	-0.818*	-0.497	-0.914***	-0.088	-1.332**	-0.020	-0.110***
	(0.370)	(0.454)	(0.350)	(0.297)	(0.418)	(0.544)	(0.044)	(0.041)
August	0.200	-0.411	-0.291	-0.717**	0.130	-1.624***	0.011	0.014
	(0.526)	(0.555)	(0.334)	(0.316)	(0.465)	(0.524)	(0.041)	(0.051)
September	-0.089	0.480	-0.276	-0.745*	-0.334	-0.558	0.014	-0.058
	(0.388)	(0.570)	(0.305)	(0.392)	(0.390)	(0.680)	(0.049)	(0.049)
October	-0.039	-0.239	-0.386	-1.218***	-0.162	-0.785	0.034	-0.130***
	(0.332)	(0.407)	(0.315)	(0.205)	(0.441)	(0.603)	(0.038)	(0.049)
November	0.000	-1.137***	-0.364	-1.268***	-0.485	-0.625	-0.016	-0.133*
	(0.361)	(0.391)	(0.291)	(0.214)	(0.511)	(0.637)	(0.051)	(0.066)
December	0.398	-0.705	-0.069	-0.994**	-0.271	-0.071	0.016	-0.154**
	(0.347)	(0.607)	(0.369)	(0.391)	(0.428)	(0.765)	(0.042)	(0.058)
N	6132		6567		6600		6600	
F	51.85		184.29		88.53		369.79	
T-tests for seasonality								
Test 1: No seasonality ineligible	p=0.886		p=0.338		p=0.097		p=0.002	
Test 2: No seasonality eligible	p=0.001		p=0.008		p=0.000		p=0.000	
Test 3: Eligible= ineligible	p=0.000		p=0.000		p=0.000		p=0.000	

* p<0.10; ** p<0.05; *** p<0.001; Notes: Consumer Finance Monthly data 2006-2013 for families with kids. OLS regressions explaining debt behaviors. Additional controls include age, race, marital status, female head of household, education, number of children, and year fixed effects. Robust standard errors clusterd at the state level in parentheses.

Table 4. OLS Regressions of debt on own logged tax credits, by family structure

Outcome	All households with children	Single mothers
Has unsecured debt	0.002	0.010 ***
	(.001)	(.001)
Has own credit card debt	0.003 ***	0.009 ***
	(.001)	(.001)
ln(unsecured debt)	0.001	0.079 ***
	(.009)	(.008)
ln(credit card debt)	0.024 ***	0.062 ***
	(.004)	(.01)
1st stage	1.060 ***	2.110 ***
	(.33)	(.745)
State FE	Y	Y
Year FE	Y	Y
Number of Observations	121,932	27,809

Source: Survey of Income and Program Participation 1990-2008. Respondents of households with at least one child under the age of 19 living in the household at the start of the survey. All regressions include state, year and month fixed effects, as well as demographi controls (age, race, gender, number of children living in the household). All dollars in 2011$. *p<.10 ** p<.05 *** p<.001

Table 5. Reduced form regressions of debt on logged average tax credits using simulated instrument, by family structure

Outcome	All households with children	Single mothers only
Has unsecured debt	0.101	0.236 ***
	(.077)	(.085)
Has own credit card debt	0.079 *	0.231 ***
	(.041)	(.063)
ln(unsecured debt)	1.006	2.023 ***
	(.681)	(.718)
ln(credit card debt)	0.521	1.731 ***
	(.337)	(.479)
State FE	Y	Y
Year FE	Y	Y
Number of Observations	121,932	27,809

Source: Survey of Income and Program Participation 1990-2008. Respondents of households with at least one child under the age of 19 living in the household at the start of the survey. All regressions include state, year and month fixed effects, as well as demographi controls (age, race, gender, number of children living in the household). All dollars in 2011$. *p<.10 ** p<.05 *** p<.001

Table 6. Reduced-form regressions of debt on logged average tax credits using simulated instrument; separate estimates for March and all other months, 1990-1999, single mothers only

Outcome	Mean dep var	March	All other months
Has unsecured debt	0.50	-0.541 **	0.180 **
		(.205)	(.074)
Has own credit card debt	0.38	-0.333	0.247 ***
		(.208)	(.081)
ln(unsecured debt)	4.13	-4.369 ***	1.710 **
		(1.605)	(.64)
ln(credit card debt)	2.88	-2.168	1.653 **
		(1.962)	(.64)
Number of Observations		3057	9234

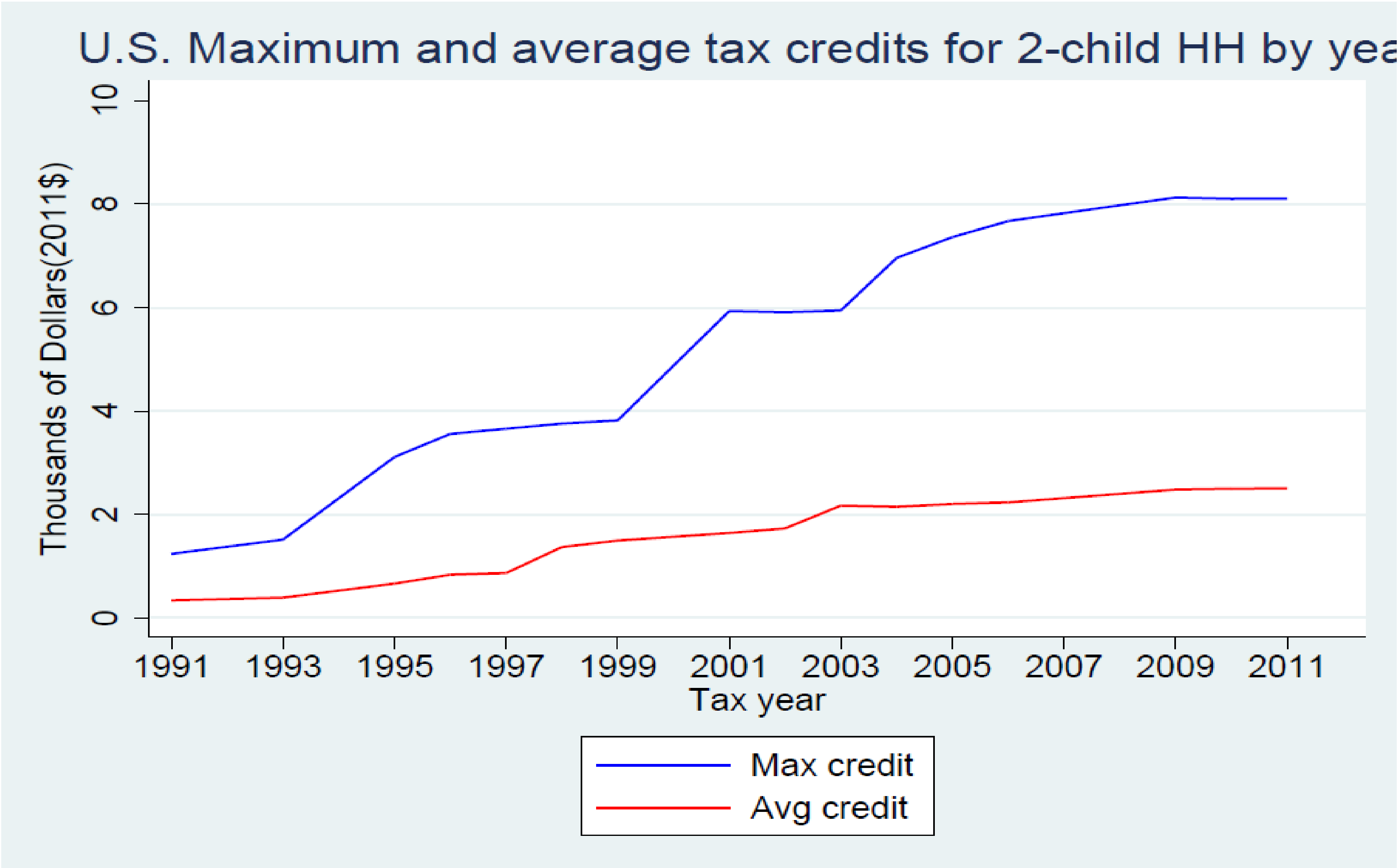
Note: Sample of respondents from 1990-1996 SIPP. Only households with children are included. All regressions include state, year and month fixed effects, as well as demographi controls (age, race, gender, number of children living in the household). *p<.10 ** p<.05 *** p<.001

Table 7.Reduced form regressions of debt on logged average tax credits using simulated instrument for married women with children

Outcome	Mean dep var	Married women with children, family income< $50,000
Has unsecured debt	0.60	0.432 *
		(.246)
Has own credit card debt	0.13	0.134
		(.161)
ln(unsecured debt)	5.10	3.624 *
		(1.962)
ln(credit card debt)	1.03	0.533
		(1.279)
State FE		Y
Year FE		Y
Number of Observations		12,472

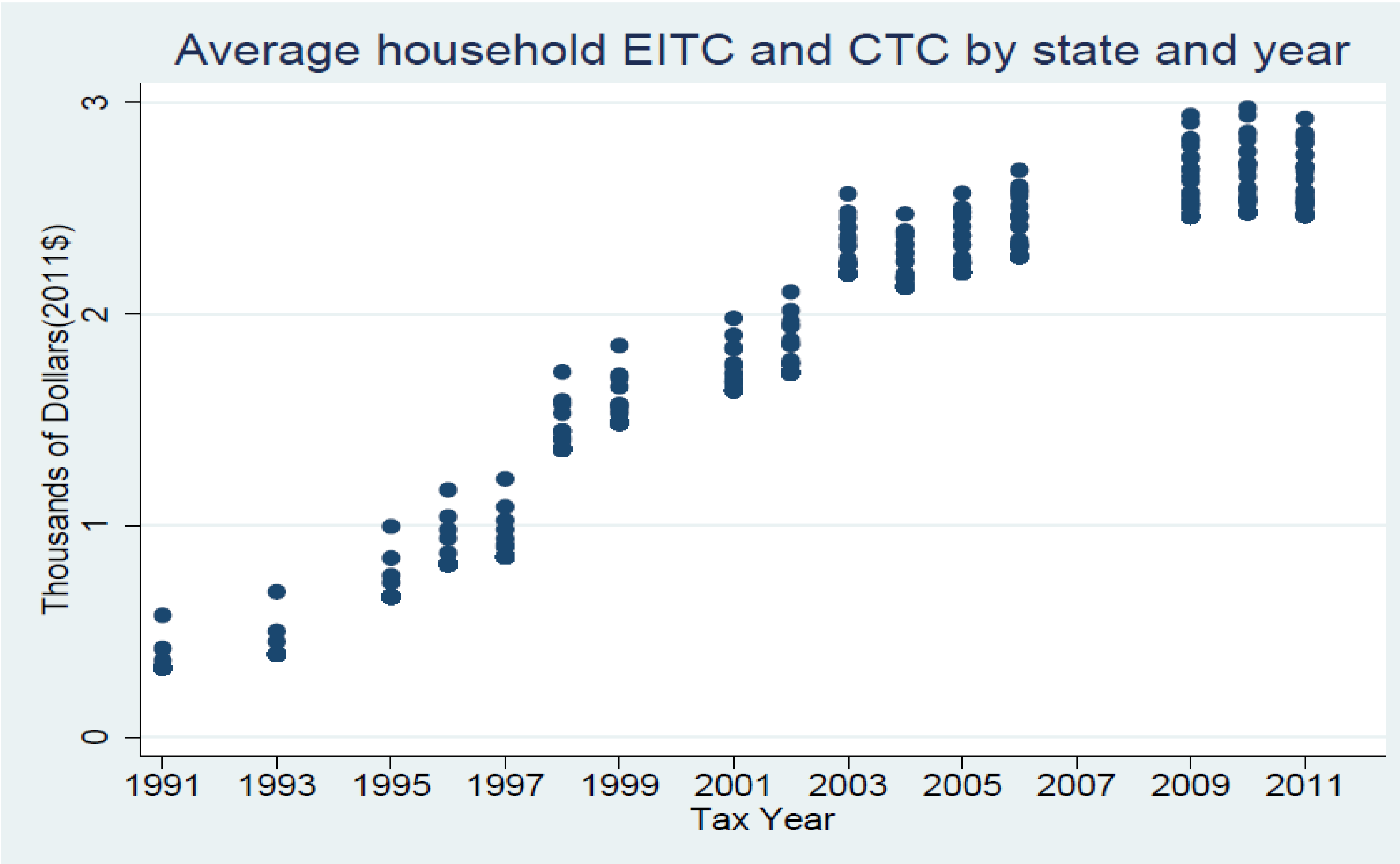
Source: Survey of Income and Program Participation 1990-2008. Respondents of households with at least one child under the age of 19 living in the household at the start of the survey. All regressions include state, year and month fixed effects, as well as demographi controls (age, race, gender, number of children living in the household). All dollars in 2011$. *p<.10 ** p<.05 *** p<.001

Figure 1. Maximum and average EITC and CTC for 2-child household by year



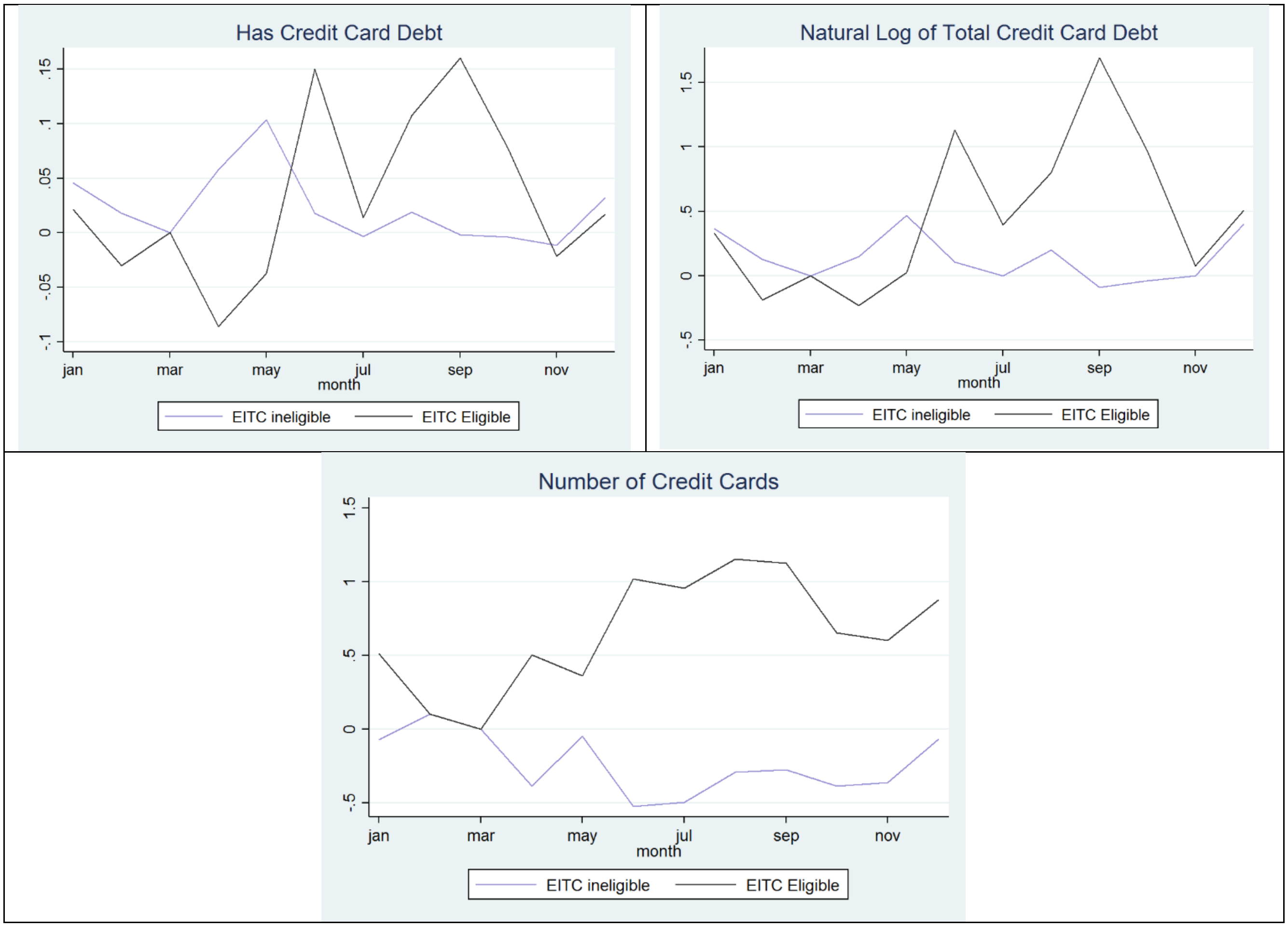
Source: Survey of Income and Program Participation 1990-2008. All numbers are weighted by monthly person weights. All dollars in 2011$.

Figure 2. Average household EITC and CTC by state and year



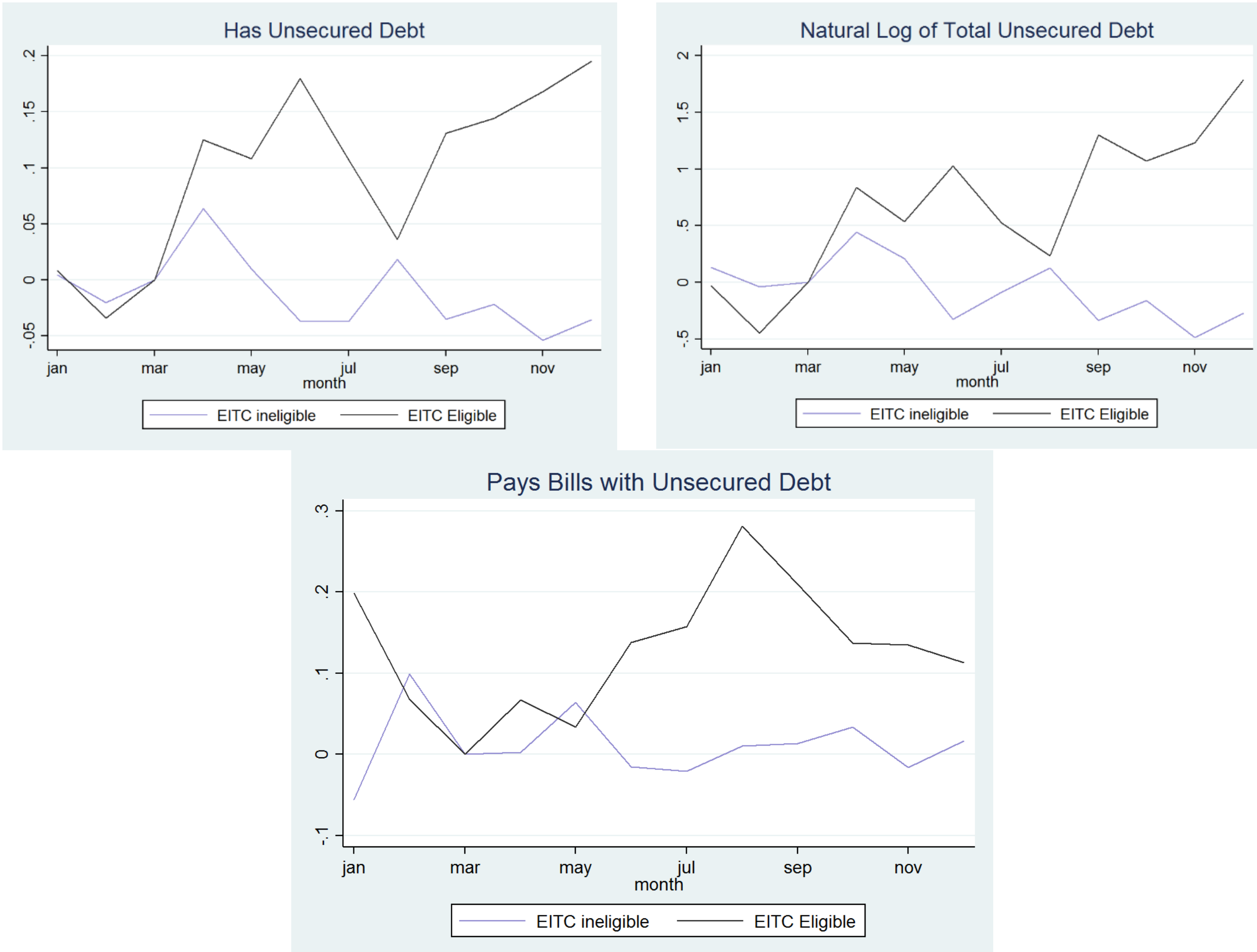
Source: Survey of Income and Program Participation 1990-2008. All numbers are weighted by monthly person weights. All dollars in 2011$.

Figure 3. Tests for seasonality in credit card behavior in the CFM



Notes: source: Consumer Finance Monthly Survey 2006-2013. Families with children. Residual plots of monthly deviations from group-specific March levels among EITC-eligible vs ineligible families.

Figure 4. Tests for seasonality in unsecured debt behavior in the CFM



Notes: source: Consumer Finance Monthly Survey 2006-2013. Families with children. Residual plots of monthly deviations from group-specific March levels among EITC-eligible vs ineligible families.

Appendix Table 1. States with Earned Income Tax Credits, year of implementation

	Year of Implementation
Rhode Island	1986
Vermont	1988
Wisconsin[1]	1989
Iowa	1990
Minnesota[2]	1991
New York	1994
Massachusetts	1997
Oregon	1997
Kansas	1998
Maryland	1998
Colorado	1999
DC	2000
Illinois	2000
Maine	2000
New Jersey	2000
Oklahoma	2002
Indiana	2003
Nebraska	2003
Delaware	2006
Virginia	2006
New Mexico	2007
North Carolina	2008
Michigan	2008
Louisiana	2008
Connecticut	2011
Washington	2008 (announced)
Ohio	2013

Source: Tax Policy Center
http://www.taxpolicycenter.org/taxfacts/displayafact.cfm?Docid=293

1: Wisconsin has a system based on the number of children in the household. Rate shown here is for households with 3 or more children.

2: Minnesota has a system based on whether there are any children living in the household, and after 1997, household earnings. Rate shown here is for households with children and the maximum possible rate given income.

Appendix Table 2. SIPP panel years and months of wealth topical modules

SIPP Panel	Months of wealth topical module	Years covered	Number of times sampled
1991	Febuary-May	1991	1
1992	Febuary-May	1992	1
1993	Febuary-May	1993	1
1996	December-March	1996-2000	4
2001	October-January	2001-2004	3
2004	October-January	2004-2007	2
2008	September-December	2008-2012	3

Appendix Table 3. Regressions of debt on logged average tax credits, single mothers only, by income quintile

	Mean income	Has unsecured debt	Has own credit card debt	ln(unsecured debt)	ln(credit card debt)
Main effect	26,556	0.115	0.114 *	1.045	0.880 *
		(.092)	(.065)	(.75)	(.464)
Bottom income quintile*ln(treatment)	14	0.090 ***	0.085 ***	0.638 ***	0.554 ***
		(.018)	(.014)	(.15)	(.108)
Second income quintile*ln(treatment)	6,916	0.066 ***	0.070 ***	0.521 ***	0.470 ***
		(.016)	(.015)	(.144)	(.121)
Third income quintile*ln(treatment)	18,424	0.018	0.012	0.172	0.092
		(.018)	(.019)	(.162)	(.151)
Fourth income quintile*ln(treatment)	31,804	0.026 *	0.009	0.200	0.011
		(.015)	(.013)	(.134)	(.109)
State FE		Y	Y	Y	Y
Year FE		Y	Y	Y	Y
Number of Observations		27,809	27,809	27,809	27,809

Source: Survey of Income and Program Participation 1990-2008. Respondents of households with at least one child under the age of 19 living in the household at the start of the survey. All regressions include state, year and month fixed effects, as well as demographi controls (age, race, gender, number of children living in the household). All dollars in 2011$. *p<.10 ** p<.05 *** p<.001