

High-frequency Spending Responses to the Earned Income Tax Credit

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Abstract

We estimate spending out of federal tax refunds to recipients of the Earned Income Tax Credit (EITC) in the weeks around refund issuance. To do so, we use a new dataset of anonymized daily, state-level spending and plausibly exogenous variation in the timing of refund issuance to this group. We find EITC recipients spend 15 cents out of each refund dollar at retail stores and restaurants within two weeks of issuance, with two thirds of the spending occurring in the week of receipt. We also document an effect on non-durable consumption, as spending at grocery stores and restaurants rises with receipt of the EITC refund. Given that these refunds are large, predictable payments, our results point to excess sensitivity among low-income working families in the U.S. and suggest that alternatives to the lump sum EITC refund payments might better support consumption throughout the year.

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1. Introduction

Does the spending of low-income working families in the U.S. respond immediately to receipt of a large, anticipated income flow? If so, what is the strength, timing, and composition of the response? Moreover, does a small surprise in the timing of income receipt affect the spending response? The answers to these questions are important for evaluating the efficacy of cash transfers in lump sum versus periodic payments, as well as improving our understanding of how these households' cope with the high-frequency income fluctuations that recent survey evidence has shown they are prone to facing (Murdoch and Schneider, 2017; Board of Governors, 2018).

To address these questions, we estimate high-frequency spending out of a large and predictable income flow to low-income workers – federal tax refunds claiming the Earned Income Tax Credit (EITC) or Additional Child Tax Credit (ACTC). Federal tax refunds to tax filers claiming the EITC or ACTC (hereafter, “EITC refunds” for brevity) are in many cases the largest income flow accruing to these households in a given year (Maag et al., 2016).¹ EITC refunds also tend to be highly anticipated, often well in advance of refund receipt. Recent research has shown that low-income filers have correct mean expectations about the magnitude of their refunds just prior to filing (Caldwell et al., 2018). Moreover, there is a high degree of persistence in EITC eligibility over the course of a decade (Stevens et al., 2018), so EITC recipients may expect to receive the refundable tax credit, and in turn sizeable federal tax refunds, well into the future.

To estimate the spending response to EITC refund receipt, we use a new dataset of daily, state-level spending at retail stores and restaurants in conjunction with administrative Internal Revenue Service (IRS) tax data on daily, state-level EITC refund issuance magnitudes. The data span the 2015-2018 tax filing seasons. We focus our analysis on spending in the weeks just prior to, concurrent with, and following EITC refund issuance by the IRS in order to investigate not only whether there are contemporaneous spending effects associated with EITC refund receipt, but also lead and lag effects. Furthermore, we decompose the spending response by retail category (e.g. grocery v. electronics store) to assess whether any observed spending response is concentrated in durable goods, which was the focus of previous survey-based analysis of EITC spending responses, or may also extend to non-durable necessities.

¹ The refund data used in this study includes refunds with an ACTC, but we abstract from the ACTC in the text. Many, but not all, filers who receive an ACTC also receive an EITC.

Our identification of high-frequency spending responses to EITC refund receipt relies primarily on plausibly exogenous high-frequency time-series variation in EITC refund issuance generated by the Protecting Americans from Tax Hikes Act (PATH). The PATH Act legislation took effect during the 2017 tax season and permanently delayed issuance of federal tax refunds to early EITC claimants by roughly two weeks.

Under our baseline specification, we estimate that about 15 cents of each EITC refund dollar is spent on retail goods and food services within two weeks of refund issuance. We interpret this effect as sizeable for a few reasons, and evidence that spending out of EITC refunds is not smoothed evenly throughout the year. First, retail goods and food services spending comprise only about 30 percent of total consumer spending, so our estimate likely serves as a lower bound on the overall spending response upon receipt. Moreover, spending 15 percent of the refund on retail goods and food services in four weeks is about five times the average monthly share of this category in overall consumer spending. Second, recent survey evidence of EITC recipients reveals that over two-thirds use some of their refund to pay down debt immediately (Maag et al., 2016), and if so the implied spending response out of the remaining refunds would be quite large. Spending a large fraction of the cash available on receipt would also reinforce the cycle of having bills to pay (with some accrued interest and fees) before the next refund. Finally, the aggregate retail spending effect is large, as total EITC refunds have exceeded \$110 billion in recent years.

About two-thirds of the estimated spending response occurs during the contemporaneous week of refund issuance, before petering out over the next two weeks. We also observe a small, but statistically significant spending response in the week prior to EITC refund issuance, which could reflect temporarily running down account balances, the use of short-term credit, or spending enabled by refund anticipation loans (RALs). Tools from the IRS, such as the ‘Where’s My Refund website,’ provide a projected deposit date for the refund and may allow for some very short-term smoothing of spending. RALs, which are offered by third-party tax preparers such as H&R Block, are no-interest loans that typically provide access to a portion of a household’s projected refund within hours of filing.

The spending response also is *not* limited to durable goods. Indeed, we observe that one fifth of the spending response to the EITC refunds occurs at grocery stores and restaurants. Previous research on spend-out of the EITC documented larger increases in durable goods, like

autos and transportation spending (e.g. Barrow and McGranahan, 2000; Goodman-Bacon and McGranahan, 2008), than nondurables. Unlike the previous findings based on household surveys, our study combines administrative IRS data with card transactions and this approach allows us to more precisely identify the spending response on receipt. With merchant-level, not item-level transactions, we cannot observe the exact mix of storable versus non-storable goods and thus cannot clearly identify the consumption flow around refund receipt. Nevertheless, a large portion of groceries and the full amount of restaurant meals are likely to be current consumption.

Finally, we show that regression estimates excluding 2017 or 2018 are little changed from the overall results. This evidence suggests that our spending estimates are *not* driven by any possible surprise associated with implementation of the PATH Act's EITC refund delay in 2017, but rather the delay itself. In other words, the observed spending responses are consistent with excess sensitivity to a predictable change in income rather than deviations in spending resulting from a transitory liquidity shock.

Using new daily transactions data and a novel identification strategy based on the PATH Act, our findings contribute to the literature on high-frequency spending responses to predictable changes in income. As with prior studies of daily and weekly data, we find a jump in spending on receipt, suggesting excess sensitivity of consumption. While the overall spend rates are often difficult to compare across studies since the types of spending covered, the size and regularity of the payment, and the populations receiving the income often differ, the basic patterns are similar. As one example, using daily spending diaries, Stephens (2003) finds that weekly spending rose 7 to 20 percent in the week of monthly Social Security benefit receipt. Of course, even some nondurable goods can be stored temporarily, which could drive a wedge between spending and consumption. Yet both Stephen's study and ours also find an increase in (non-storable) services spending.

A common explanation for this excess sensitivity to predictable income changes—that certainly could apply to EITC recipients—is a lack of liquidity. In their study of one-time, pre-announced stimulus payments, Broda and Parker (2014) find that during the four weeks from receipt spending on a narrow set of consumer goods rose by 3.5 to 5.5 percent of the payment. The spend rate was nearly triple for households in the bottom 40 percent of the liquid wealth distribution. Even so, our study cannot speak directly to the mechanism behind the spending

response and low liquidity is not the only possible explanation. Kueng (2018) studied the spending response to the Alaska Permanent Fund payments, which like the EITC is a large, annual payment, and finds that 11 percent of payment was spent in the month of receipt on nondurables and services (rising to 25 percent within the quarter). However, this spending response was driven by high-income households with high levels of liquidity. Our contribution is to show that spending—across a range of goods and services—also rises in the week of EITC receipt.

In addition to the implications for the EITC as a financial support to low-income working families, our results are consistent with a growing literature showing that fiscal stimulus in the form of lump sum payments can provide a rapid boost to spending on receipt. As two prominent examples, Johnson, Parker and Souleles (2006) and Parker, Souleles, Johnson, and McClelland (2013) find that a sizeable fraction of the 2001 and 2008 tax rebates, respectively, were spent within three months of receipt. The rapid spending response of EITC recipients here suggests that this group, if targeted with stimulus income, would quickly help boost aggregate demand.

2. EITC refunds and the PATH Act

The EITC is a refundable tax credit claimed by a large share of low-income working households. During 2017 (tax year 2016), 27 million households claimed the credit – 18 percent of all tax returns processed.² Of these households, receipt is concentrated among families whose incomes after other taxes and transfers would be between 75 percent and 150 percent of the poverty line in the absence of the credit (Hoynes and Patel, 2018).

Among households claiming the EITC, federal tax refunds are generally a large payout as a share of income. During the 2017 tax season, the average EITC refund was \$4,247. For early tax filers claiming the EITC – those most likely to be affected by the refund delays resulting from the PATH Act legislation – average refunds were somewhat larger (\$4,762).³ Maag et al. (2016) note that EITC refunds are equal to roughly two months of pay for a typical EITC

² Source: Internal Revenue Service (January 2018). Statistics for Tax Returns with EITC. Retrieved from: <https://www.eitc.irs.gov/eitc-central/statistics-for-tax-returns-with-eitc/statistics-for-tax-returns-with-eitc>.

³ Authors' calculations using administrative data on EITC refund issuance magnitudes during the 2017 tax season, which we define to be February to May. We consider early tax filers to be those who received their EITC refund before March 4, 2017. Source: Internal Revenue Service: Research, Applied Analytics, & Statistics.

claimant, and Jones (2012) finds that a typical EITC recipients' refund is equal to 12 percent of income.

In addition to being a large payout, EITC refund amounts are known prior to receipt. At the time a tax return is filed, EITC claimants learn the expected amount of their refund. But even prior to filing, Caldwell et al. (2018) document that low-income households have correct mean expectations about their refund on average.⁴ One potential explanation for low-income taxpayers' accurate refund expectations is that EITC eligibility is highly persistent over time. Stevens et al. (2018) find that for all households beginning a spell of EITC eligibility, over one half are eligible for more than five years in the next decade.

The financial situation of many EITC claimants is somewhat tenuous in general. Survey evidence in Maag et al. (2016) documents that nearly four in five claimants of the EITC or Child Tax Credit with children report having faced financial hardship, such as skipping a rent payment, at some point in the six months prior to being surveyed. In addition, 4 out of 10 of these families report use of an alternative financial service, such as a payday loan, in the six months prior to filing their return. At tax filing time, the median household reports liquid assets of only \$400 and credit card debt of \$2,000.

EITC claimants tend to file early in the tax season; prior to 2017, the earliest issued federal tax refunds accrued primarily to this group. Maag et al. (2016) document that during the 2015 and 2016 tax seasons, 56 percent of EITC claimants filed their taxes before February 15. As a substantial majority of EITC claimants use third-party tax preparers – who by and large are required to e-file – claimants could expect their refund to be issued by the IRS less than three weeks after the filing date.^{5,6} Indeed, we estimate that during the 2016 tax season, refunds were issued to over 60 percent of EITC claimants by early March. In contrast, only 40 percent of refunds were issued to non-claimants by that point.⁷ The left panel of figure 1, which displays

⁴ The authors also find that low-income working taxpayers face considerable self-reported uncertainty about the size of their tax refund, and that this self-reported uncertainty tracks “true” uncertainty, as measured by the difference between realized and mean expected tax refund amounts.

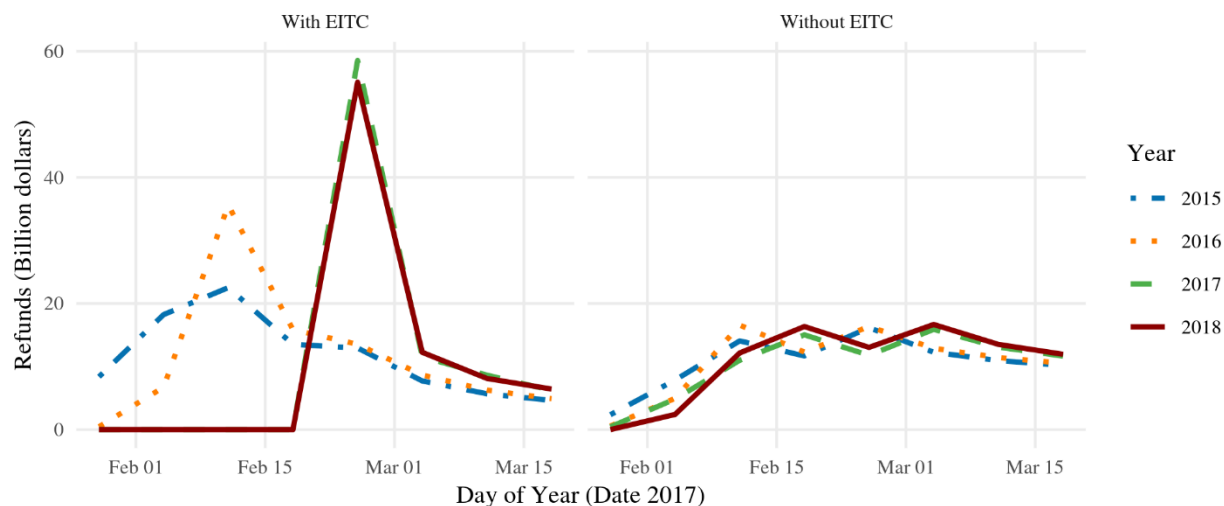
⁵ Nichols and Rothstein (2016) cite an IRS estimate that 15 million EITC recipients—roughly half—used paid tax preparers in 2013. Some receive assistance from nonprofit tax preparation services such as the Volunteer Income Tax Assistance program, but many use for-profit services such as H&R Block.

⁶ E-file requirements for paid tax preparers retrieved from <https://www.irs.gov/e-file-providers/frequently-asked-questions-e-file-requirements-for-specified-tax-return-preparers-sometimes-referred-to-as-the-e-file-mandate>.

⁷ Authors' calculations using administrative data on EITC and non-EITC refund issuance counts during the 2016 tax season, which we define to be late January through May. We consider early tax filers to be those who received their EITC refund before March 5, 2016. Source: Internal Revenue Service: Research, Applied Analytics, & Statistics.

weekly EITC refund issuance in billions of dollars during the 2015-2018 tax seasons, shows that issuance peaked in the second week of February during the 2015 and 2016 tax seasons and declined precipitously thereafter. Moreover, EITC refund issuance in early February during the 2015 and 2016 tax seasons dwarfed non-EITC refund issuance (right panel).

Figure 1. Weekly issuance of federal tax refunds with and without EITC (\$ billions)



Source: Internal Revenue Service: Research, Applied Analytics, & Statistics. Note: The first week of the year is the one which has both a Monday and Friday within January. Dates are the Fridays of each week, and we align the Fridays in 2015, 2016, and 2018 to the corresponding Friday in 2017. Peak refund issuance occurred in the week of Friday, February 24 (23) in 2017 (2018), two weeks later than the peak in earlier years.

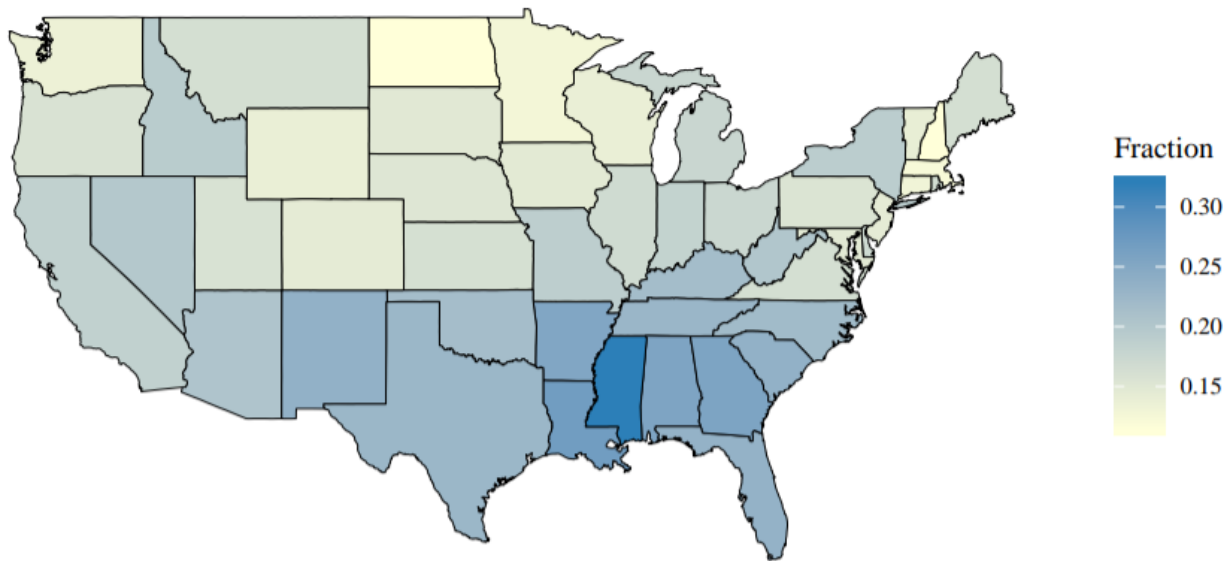
Beginning in 2017, EITC refund issuance timing changed in response to the PATH Act, providing us with plausibly exogenous time-series variation to identify high-frequency spending responses to the tax credit. Specifically, the PATH Act prohibited the IRS from issuing any federal tax refunds claiming the EITC before February 15.⁸ As a result, EITC claimants waited longer to receive their tax refunds than in prior years. The left panel of figure 1 demonstrates that whereas EITC refund issuance peaked in early February during the 2015 and 2016 tax seasons, it was nonexistent during this period in 2017 and 2018. Instead, the figure reveals that EITC refund issuance in 2017 and 2018 peaked two weeks later, while issuance over the remainder of the 2017 and 2018 tax seasons was similar to prior years. Consistent with the fact

⁸ The required waiting period before refund issuance was intended to provide the IRS with additional time to detect tax fraud. The legislation stipulated that the entire refund to the tax filer must be held for processing, even the portion of the refund that was unrelated to the EITC or ACTC. Source: Internal Revenue Service, Refund Timing for Earned Income Tax Credit and Additional Child Tax Credit Filers. Retrieved from <https://www.irs.gov/individuals/refund-timing>.

that the PATH Act legislation left refund issuance for non-EITC tax filers unaffected, we observe little time series variation in non-EITC refund issuance before and after implementation of the legislation (right panel). Thus, the PATH Act legislation served to shift issuance of more than \$40 billion of EITC refunds by about two weeks in 2017 and 2018.

Our analysis also takes into account cross-state variation in EITC refund receipt each year. Figure 2 shows the fraction of federal tax returns in each state that received the EITC in 2016, which ranges from over 30 percent of all returns in Mississippi to less than 15 percent in North Dakota.⁹

Figure 2. Fraction of federal tax returns receiving EITC by state in 2016



Source: Internal Revenue Service.

Utilizing this time-series and cross-sectional variation in EITC refund issuance, what sort of retail spending response might we expect to observe? The survey evidence from Maag et al. (2016) suggests that any response will be short lived and cover a broad swath of retail spending categories, but it will not necessarily be “large” (e.g. MPC > 0.5) despite the substantial liquidity constraints many EITC recipients face. Nearly 30 (85) percent of respondents reported using all (some) of their refund to pay down debt or for new spending within one month of refund receipt. 83 percent said they used some of their refund to pay rent, mortgage, bills, or groceries and 75 percent used it for necessities such as clothes. A smaller proportion (42 percent) reported using

⁹ There is a strong correlation between a states’ share of federal tax returns receiving the EITC and its per capita EITC refund dollar amounts. The latter is our regressor of interest in the empirical analysis presented in Section 4.

some of their refund to purchase big ticket items such as furniture, electronics, or a car. Interviews with tax preparers for the survey respondents reveal that their clients often need the money to avoid dire financial circumstances, and consequently we would not necessarily expect the majority of their tax refund to go towards new retail spending.

3. Data

3.1. Daily, state-level spending indexes

Central to our study of the high-frequency spending responses to EITC refunds during recent tax seasons are new daily, state-level indexes of spending at retail stores and restaurants, as developed by Aladangady et al. (2019). These indexes are available for 2010 forward and have been used to study the spending effects of several recent hurricanes (Aladangady et al, 2016 & 2019), as well as state sales tax holidays (Aladangady et al, 2017). The indexes were constructed using anonymized, filtered, and aggregated credit, debt, and other electronic transactions (including electronic benefit transfers, or EBT) from First Data (FD), a global payment technology company that processes \$2 trillion dollars in annual card transaction volumes and is the largest payment processor in the United States. In this section, we provide a high-level overview of construction and validation of the spending indexes. We direct readers interested in additional details to Aladangady et al. (2019).

Merchant-level card transactions processed by FD provide the raw data used to construct our spending indexes. The microdata include authorization and settlement amounts and dates from the swipe of a card, as well as the merchant address, name, and category code (MCC). The MCCs are then mapped to 3-digit NAICS codes in order to identify spending at retail stores and restaurants, as defined by the Census Bureau. This subset of consumer spending—which the authors refer to as the retail sales group—comprises about one quarter of GDP and is well-measured by card transactions.¹⁰ The retail sales group excludes sales at building materials stores (i.e. stores like Home Depot or Lowe’s), gasoline stations, and motor vehicle dealers. Thus, our analysis will miss any purchases of new and used vehicles enabled by EITC refunds. In addition, e-commerce sales are not well identified in FD transactions. Sales at non-store

¹⁰ According to the 2017 Diary of Consumer Payment Choice, consumers use credit and debit cards for 30 percent of their payments (in dollar value), while using cash for just 8½ percent of dollars paid. The share of card payments at retail stores and restaurants is even higher.

retailers are therefore excluded, though it is possible that some online spending is being captured and allocated to other retail categories.

On their own, the raw data are not suitable as statistics of overall consumer spending. For one, they are very noisy. Much of this noise results from FD's acquisition of other payment processing firms over time, clients utilizing multiple payment systems due to fee schedules, and choices by individual merchants to start or end their contract with First Data, a phenomenon Aladangady et al. (2019) refer to as "client merchant churn." In addition, the transactions data have no sample frame. Consequently, it is not possible to distinguish actual merchant births and deaths from client merchant churn.

To address these issues, Aladangady et al. (2019) adopt a "constant merchant approach" – filtering the data to include only "well-behaved" merchants that have a stable relationship with the FD platform over a specified time period. The principle of the approach is to base spending growth estimates between two time periods, say one month, on the subset of FD merchants that regularly transact between the two periods.¹¹ The authors focus on 12-month growth rates to filter constant merchants and define 14-month constant merchant samples. Each sample includes all merchants in a given reference month that also transacted in each of the preceding 13 months.¹² Thus, for any given calendar month, there exist 14 overlapping merchant samples, as shown in Appendix Figure A.1. The authors also apply several additional filtering criteria to further hone in on a set of merchants with stable attachment to FD for whom sales growth is well-measured in the data. The final, filtered sample accounts for just over one half of the dollar transaction volume in the raw data.

After filtering the data, Aladangady et al. (2019) combine the overlapping 14-month constant merchant samples to construct a daily index of spending by 3-digit NAICS code and state. Towards that end, they first level adjust spending in each 14-month sample, and then average together spending for each day in the overlapping samples. Finally, they benchmark the spending indexes for each 3-digit NAICS code/state cell in 2012 to the values in the 2012

¹¹ This filtering approach therefore excludes both client merchant churn and merchant births and deaths. Aladangady et al. (2019) show that so long as merchant births and deaths are small relative to the constant merchant growth rate or are roughly offsetting, the constant merchant spending growth rate should closely approximate the "true" spending growth rate.

¹² Each 14-month window includes the 12-month change ending in the reference month, which requires 13 months of transactions, plus an extra month at the start of the sample to ensure that merchants that become FD clients in the middle of the month do not affect the 12-month change while in the process of "ramping up" operations.

Economic Census to better represent the composition of spending across industries and states, and then seasonally adjust the indexes at the monthly level.¹³

The coverage statistics, validation exercises, and applications presented in Aladangady et al. (2019) provide us with confidence that the FD spending indexes measure consumer spending well, including the high-frequency, state-level spending data we rely on for our EITC analysis. Nationally, the FD coverage ratio – computed as total FD sales used in the creation of the index divided by total estimated sales – has increased from 5.5 percent in 2010 to 7.5 percent in 2018. Coverage is not uniform across states (Appendix Figure A.2), but always exceeds 3 percent. Reassuringly, spending growth in the FD series compares favorably to official statistics, and in particular the Census Monthly Retail Trade Survey (MRTS). As illustrated in Appendix Figure A.3, 12-month growth rates from the spending index (at a monthly frequency) closely track the MRTS since 2012, with a correlation of 0.9.

3.2. EITC refunds

The counterpart to our daily, state-level spending indexes in this analysis is daily, state-level EITC refund issuance dollars obtained from the IRS’s Research, Applied Analytics, and Statistics group. “Issuance” refers to the day in which the Treasury made a withdrawal from its operating cash balance in order to send out an EITC refund. It does not imply that the refund appeared in an EITC household’s bank account on that day.¹⁴

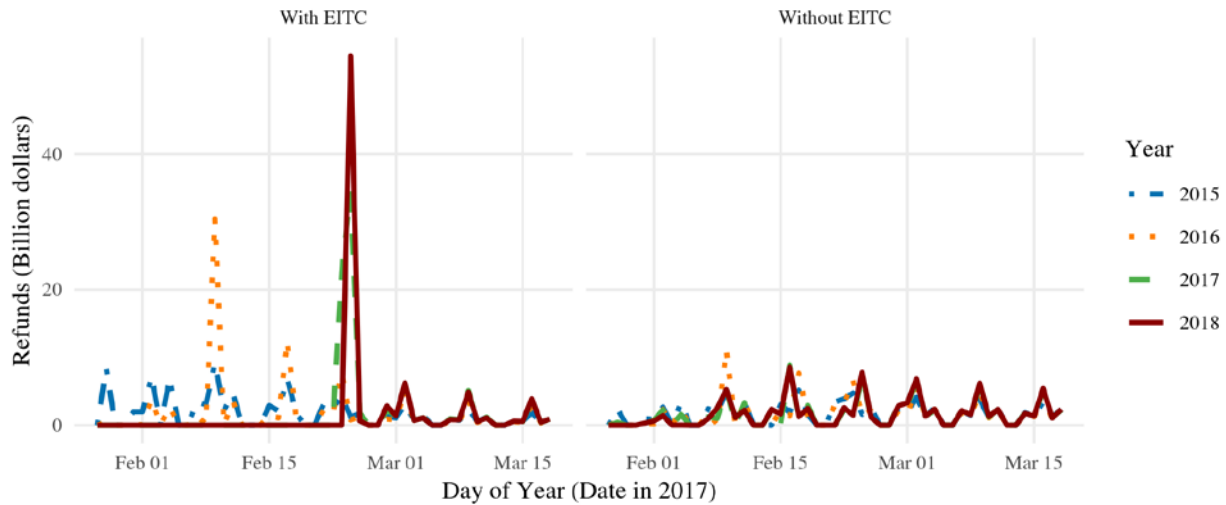
These data display considerable time-series and cross-state variation which will ultimately enable us to estimate spending out of the EITC. Figure 3 displays daily issuance of EITC refunds at the national level over the 2015-2018 tax seasons. Relative to figure 1’s weekly issuance patterns, some additional differences emerge. First, after implementation of the PATH Act, nearly all of the refunds filed by early EITC claimants were issued over the course of 1 to 2 consecutive days in late February. Second, early EITC refund issuance during the 2015 tax season was much less lumpy than in 2016, providing us with additional time-series variation in EITC refund issuance unrelated to the PATH Act. Figure 4 plots the share of EITC refunds

¹³ The most recent Economic Census was conducted in 2012; it is the only source of retail spending with comparable industry and geographic detail.

¹⁴ The vast majority of tax filers – 83 percent in 2017 – receive their refunds as a direct deposit, and these refunds generally appear in a tax filer’s bank account within a few days of refund issuance. The time between issuance and receipt is slightly longer for those who receive their refunds in other forms, such as a paper check. Direct deposit statistics retrieved from <https://www.efile.com/efile-tax-return-direct-deposit-statistics/>. E-file.com is an IRS authorized e-file provider.

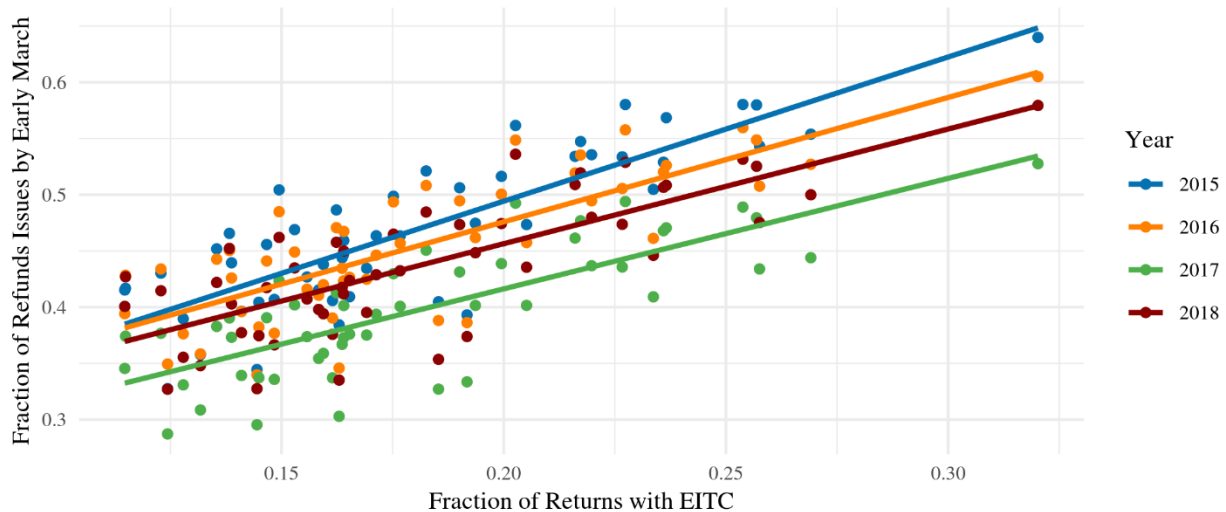
issued by the beginning of March for each state in each year of our analysis against the share of returns in each state receiving the EITC. The figure also includes a line of best fit for each year. We observe a clear positive relationship between the shares, with a 10 percentage point increase in the share of returns receiving the EITC being associated with roughly a 6 percentage point increase in the share of EITC refunds issued by the beginning of March.

Figure 3. Daily issuance of federal tax refunds with and without EITC (\$ billions)



Source: Internal Revenue Service: Research, Applied Analytics, & Statistics. Note: The first week of the year is the one which has both a Monday and Friday within January. We align the Fridays in 2015, 2016, and 2018 to the corresponding Friday in 2017.

Figure 4. States' shares of early-issued EITC refunds by share of filers receiving EITC



Source: Authors' calculations based on data obtained from Internal Revenue Service: Research, Applied Analytics, & Statistics

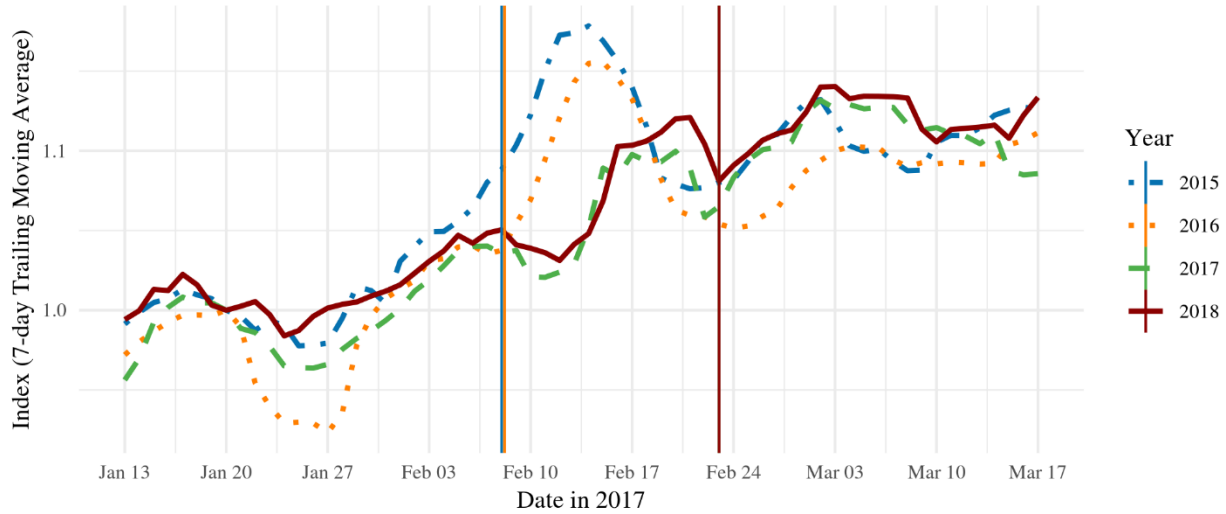
3.3. Plots of spending indexes during tax season

Before turning to a more formal analysis of the high-frequency spending responses to the EITC, in figure 5 we first simply plot a 7-day trailing moving average of our national retail sales group spending index during the early portion of the 2015-2018 tax seasons to search for graphical evidence that spending is significantly affected by the timing of EITC refund issuance. We use a 7-day moving average of spending to smooth through large and regular day-of-week effects, align weeks of the year in 2015-2016 and 2018 to match with their corresponding week in 2017, and index spending to the third week of January in each year. We otherwise do not control for any other factors that might affect spending during the time periods shown. Vertical lines correspond to the end of the week of peak EITC refund issuance during each tax season.

What is immediately apparent from figure 5 is that retail spending in early to mid-February of 2017 and 2018 – when EITC refunds were delayed due to the PATH Act – deviated considerably from previous years. Whereas spending in 2015-2016 picked up in the week of peak EITC refund issuance in those years and peaked the week after, spending in 2017 and 2018 remained relatively flat. In the week after peak refund issuance in 2015-2016, retail spending was about 10 to 15 percent greater than in 2017 and 2018. We also do not observe the prominent hump-shaped pattern in retail spending around the time of peak EITC refund issuance in 2017 and 2018 that was observed in 2015-2016. Instead, retail spending appears to have ramped up somewhat more gradually as peak refund issuance approached and then remained elevated through mid-March.

Of course, other factors beyond EITC refund issuance likely affected spending during the early tax season period displayed in figure 5. For example, severe winter weather often disrupts spending early in the year, muddling such summary statistics. Consequently, in Section 4 we present our regression methodology for isolating high-frequency spending responses to the EITC.

Figure 5. Index of daily spending at retail stores and restaurants



Source: First Data Merchant Services. Note: The first week of the year is the one which has both a Monday and Friday within January. We align the Fridays in 2015-2016 and 2018 to the corresponding Friday in 2017. Spending is indexed to the third week of January in each year. Vertical lines correspond to end of each week of peak refund issuance. The peak is the same from 2015 to 2016, and for 2017 and 2018.

4. Regression methodology and results

4.1 State-by-state estimates

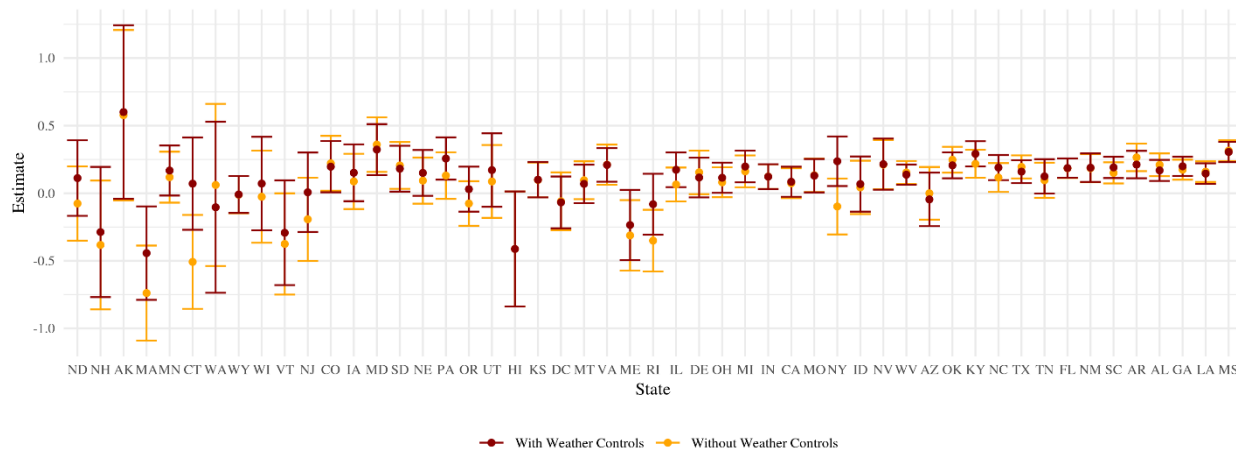
We start by using just the time-series variation to estimate state-by-state marginal propensities to spend at retail stores and restaurants out of the EITC. For the rest of this paper, we refer to this propensity with the standard acronym of an MPC (marginal propensity to consume), although we do not actually measure total consumption. To estimate the MPCs, for each state we regress daily per capita spending against day-of-week effects, week-of-year effects, dummies for Valentine’s Day and President’s Day, and a set of leads and lags of the weekly EITC refund issuance per capita.¹⁵ The sum of the coefficients on the leads and lags of the EITC refund issuance gives us the estimated MPCs on a state-by-state basis by taking advantage of the time-series variation in EITC refund issuance, particularly between the pre- and post-PATH act eras. The week-of-year effects soak up any weekly patterns in spending that are unrelated to EITC refund issuance over the months of interest.

The results of this exercise are shown in light orange in Figure 6. We arrange states on the x-axis by the fraction of their federal tax returns that received the EITC in 2016. The dots represent the estimated MPCs for each state, and the bars span the 95% confidence intervals.

¹⁵ Our weekly EITC refund issuance per capita regressor is a 7-day trailing average. Thus, on date t the regressor for the contemporaneous week of issuance is the average of EITC refund issuance over dates $t - 6$ to t .

There are a few striking findings. First, many states, and particularly those with the highest EITC concentrations, have positive and fairly tightly estimated MPCs out of the EITC refund issuance. For example, the MPC estimate for Mississippi is 31 cents out of every refund dollar, with a 95 percent confidence interval of 24 to 39 cents. Secondly, a number of states—many of which have larger standard errors—have very negative MPC estimates.

Figure 6. Estimated MPCs by State, Ordered by (Low to High) EITC Exposure



Note: The coefficients are estimated in a regression using 2 leads and lags.

The states with the implausibly negative MPC estimates appear to be concentrated in New England or at least in states that are subject to harsh winter weather. In 2017, there were two major snowstorms in New England during the time surrounding the EITC payouts: one at the beginning of February, and one at the beginning of March. The latter snowstorm, in particular, served to reduce spending at a time when the delayed 2017 EITC refunds may have otherwise been expected to boost spending. Without controlling for this snowstorm, we would expect the MPC in those states to be biased downward.

Generally, idiosyncratic winter storms have the potential to bias the results to the extent that their timing overlaps with the timing of the EITC spending responses. Thus, to account for winter weather, we add in dummies in each regression for 10 bins for daily snowfall, as well as 10 bins for the seven-day cumulated snowfall in the state.¹⁶ The results that include these controls are shown in the red bars of Figure 6. As expected, the estimated MPCs for the New

¹⁶ To calculate the 10 bin cutoffs, we estimate the decile cutoffs of snowfall amounts in that state, conditional on positive snowfall, over the period 2005 to 2017. Because the cutoffs are determined on a state-by-state basis, the importance of snowfall is allowed to affect spending in a different way in southern states—where small amounts may have a large effects—than northern states—where small amounts are likely to have only a very minimal effect.

England states affected by the storms shift upward, such that most of their confidence intervals now include zero, even though their standard errors remain large.

4.2 Combining time-series and cross-sectional information

To estimate an average MPC over all states, we combine the state-by-state regressions into one regression. We continue to allow day-of-week, week-of-year, year, holiday, and weather effects to vary by state by interacting each of these controls with state dummies. Doing so is particularly important because it is possible that these different effects would vary across states in ways that are correlated with the EITC. For instance, as Figure 2 shows, EITC concentration is correlated with latitude (i.e. the south tends to receive more EITC dollars per capita than the north). It is therefore particularly important to allow the week-of-year fixed effects to vary by state so that we do not falsely attribute to the EITC differences in the weekly pattern of spending that are actually attributable to climate. Since it is possible that the state-week-of-year effects may be soaking up too much variation, we also show results below where we no longer interact the week-of-year effects by state.

However, we now equate the coefficients on the lags and leads of per capita EITC refund issuance over states, with the goal of calculating the average treatment effect across states. The baseline specification is:

$$\begin{aligned} \frac{Spend_{i,t}}{Population_{i,t}} = & \omega_i(Week\ of\ Year)_t + \delta_i(Day\ of\ Week)_t + \Omega_{i,t}StateYear_{i,t} + \theta_i T_{i,t} \\ & + v_i(Valentine's\ Day)_t + \rho_i(President's\ Day)_t + \\ & + Weather_{i,t} + \sum_{j \in \{-14, -7, 0, 7, 14\}} \beta_j \frac{(EITC\ Refunds)_{i,t+j}}{Population_{i,t}} \quad (1) \end{aligned}$$

The estimates of β_j from this baseline regression are identified off of two sources of variation: the first is the time-series variation that was present in the state-by-state regressions. The second is the cross-sectional variation that comes from differential concentrations of EITC over states such that we would expect those states that received more EITC dollars per capita to experience larger movements in spending per capita. These estimates are shown in Figure 7. The largest impact of EITC refunds on spending is in the week of issuance, during which 9 cents

are spent out of every dollar. In addition, there is a small amount of spending the week before issuance (of roughly 2 cents), and an additional 4 cents of spending in the two weeks after receipt. While the total MPC over four weeks—achieved by summing all of the β_j —of 15 cents on the dollar may appear small, it is important to reiterate that the categories of spending that we observe comprise only one-third of total consumer spending. If a dollar of refunds were spent evenly throughout the year, we would expect an increase of only 3 cents per month in this subcategory. The estimated MPC is about five times that amount.¹⁷ Furthermore, we only capture spending responses that are used through cards rather than cash.¹⁸ For both of these reasons, our estimate of the MPC is likely to be a lower bound and the total MPC could be substantially higher. Moreover, it is worth emphasizing that the aggregate spending response is quite large given that EITC refund issuance has been greater than \$110 billion dollars over our sample period.

Figure 7. Baseline regression results: Fraction of EITC refund spent on retail sales group

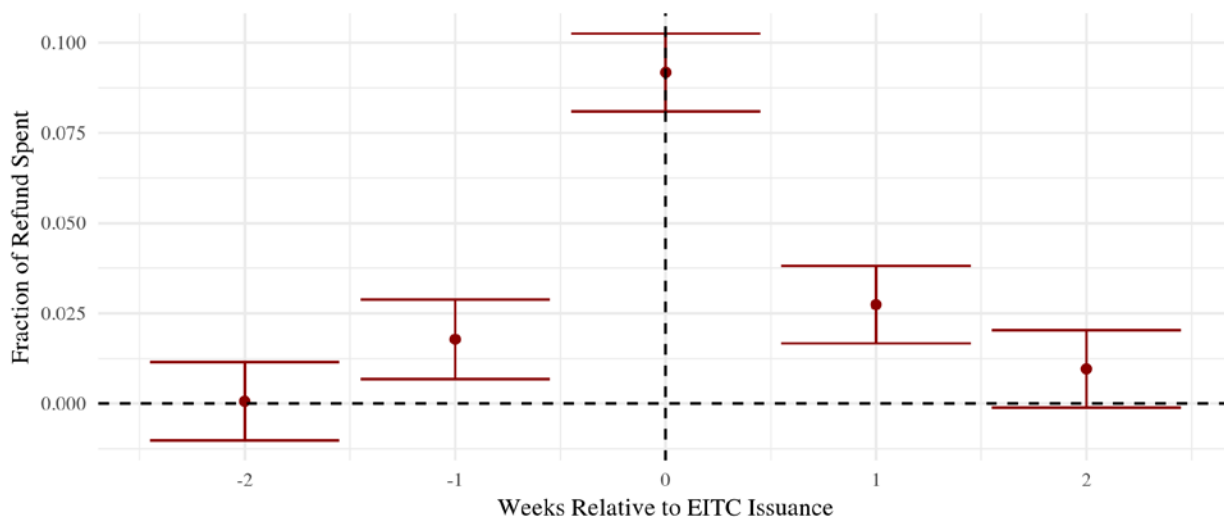


Figure 7 displays point estimates and 95 percent confidence intervals for the β_j coefficients in Equation (1) when the dependent variable is daily, state-level spending per capita in the retail sales group. We interpret the coefficients as yielding the fraction of each EITC refund dollar spent at retail stores and restaurants j weeks from refund issuance.

¹⁷ This calculation assumes that the spending shares of EITC recipients are roughly similar to non-EITC recipients. Using the Consumer Expenditure Survey, Goodman-Bacon and McGranahan (2008) find the *level* of spending among the EITC eligible is lower than non-EITC eligible, but the spending *shares* are similar (except for the share spent on groceries and children’s clothing being somewhat higher among the EITC eligible).

¹⁸ Related to this point, the 2018 Diary of Consumer Payment Choice shows that card use among low-income households is low relative to high-income households. For example, households with incomes below \$50,000 use cash or check for approximately 45 to 50 percent of their payment volume. For higher income groups, cash and check payments account for roughly only 30 to 35 percent of payment volume. Retrieved from: <https://www.frb services.org/news/fed360/issues/010219/010219-cash-diary.html>.

The initial spending response to EITC refunds is short lived, subsiding within two weeks of refund issuance. Given the merchant-centric nature of the spending indexes, we cannot determine what mechanisms drive this quick response on the part of EITC households (e.g. liquidity constraints or impatience). Nevertheless, the results suggest that the lump sum EITC refund is eliciting a sizeable spending response on receipt. Unlike fiscal stimulus payments that are designed to quickly boost spending, the purpose of the EITC is to support low-income working families throughout the year. The use of annual, lump sum payments, as opposed to smaller, periodic payments may be at odds with the EITC's goal.¹⁹

To our knowledge, the small anticipatory spending effect that we observe in the week prior to EITC refund issuance has not been documented in previous research on spending responses to predictable income changes. In the case of EITC refunds, it is possible that these households are willing to run down account balances or use short-term credit once their projected refund magnitude and issuance date are known, facilitated in recent years by tools such as the IRS' 'Where's my refund' website. Another potential explanation is that EITC households make use of no-interest RALs offered by third-party tax preparers like H&R Block. RALs, which are available as a portion of a tax filer's projected refund, are often accessible via prepaid card within hours of filing.²⁰ Consequently, we would expect to observe any immediate spend out of RALs in the weeks prior to refund issuance.

Using the same baseline specification, we can also decompose the spending effect by category of spending within retail stores and restaurants. Table 1 shows the regression coefficients for the following four categories: grocery spending (12.5% of retail sales group), restaurants (12.1%), electronics stores (1.6%), and general merchandise stores (11.9%). All four categories show significant responses in the week of EITC refund issuance, and often in the weeks immediately surrounding issuance as well.

¹⁹ Until 2011, EITC recipients could choose to receive a portion of their credit with each paycheck rather than as a lump sum at tax filing time. But take up of this option was very low, leading to its cancellation. See Nichols and Rothstein (2016) for further discussion.

²⁰ For example, during January and February 2019 H&R Block offered refund advances in four loan amounts: \$500, \$750, \$1,250, and \$3,000. These loan amounts retrieved from <https://www.hrblock.com/offers/refund-advance>.

Table 1: Spending Categories MPC estimates

	Sales / Population			
	Grocery	Restaurants	Electronics	General Merchandise
	(1)	(2)	(3)	(4)
EITC Shock Lead 2 Weeks	0.003** (0.001)	0.003*** (0.001)	-0.001* (0.001)	0.0001 (0.003)
EITC Shock Lead 1 Week	0.001 (0.001)	0.008*** (0.001)	0.002*** (0.001)	0.007** (0.003)
EITC Shock	0.005*** (0.001)	0.007*** (0.001)	0.008*** (0.001)	0.035*** (0.003)
EITC Shock Lag 1 Week	0.006*** (0.001)	0.0002 (0.001)	0.001* (0.001)	0.015*** (0.003)
EITC Shock Lag 2 Weeks	-0.001 (0.001)	-0.00002 (0.001)	0.001** (0.001)	0.010*** (0.003)
Total MPC	0.013*** (0.003)	0.018*** (0.002)	0.010*** (0.001)	0.067*** (0.008)

Note:

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 1 displays point estimates and standard errors for the β_j coefficients in Equation (1) when the dependent variable is daily, state-level spending per capita for establishment-type subsets of the retail sales group category. We interpret the coefficients as yielding the fraction of each EITC refund dollar spent at a particular establishment type j weeks from refund issuance.

The total MPC for each retail sales category is shown at the bottom of the table, as well as in Figure 8. Although the MPCs are small (ranging from 1 cent to 7 cents on the dollar for each category), they are highly significant. Furthermore, the spending responses in establishments that sell nondurable goods and services such as grocery stores and restaurants comprise one fifth of the overall response at the refund receipt. Thus consumption—not just expenditures—jump on receipt. This spending is not exclusively on durable goods, and is perhaps a signal of liquidity constraints.

Figure 8. Total MPCs by Establishment Type

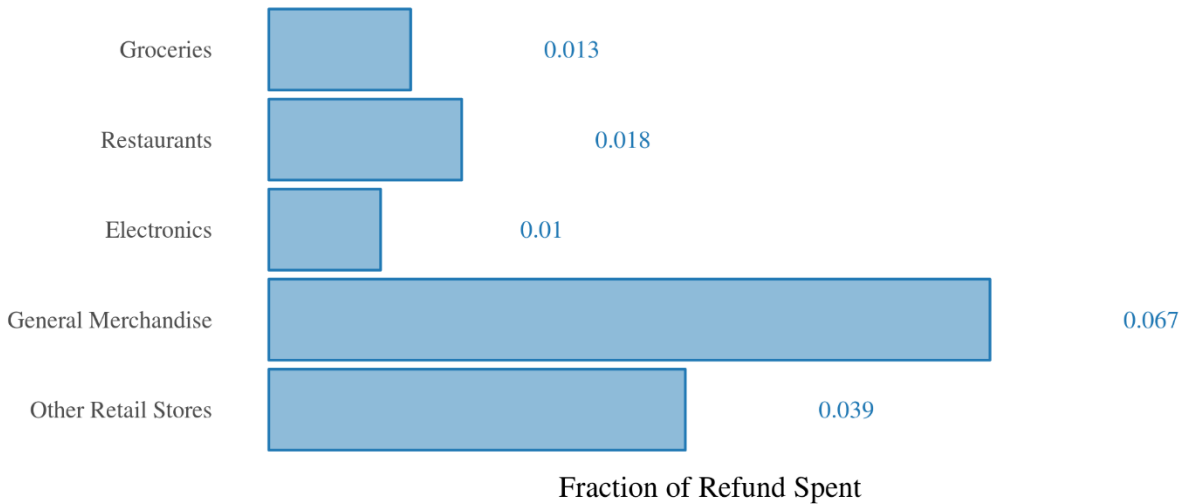


Figure 8 displays point estimates for the β_j coefficients in Equation (1) when the dependent variable is daily, state-level spending per capita for establishment-type subsets of the retail sales group category. We interpret the coefficients as yielding the fraction of each EITC refund dollar spent at a particular establishment type j weeks from refund issuance.

4.3 Are the results the effect of a surprise?

The results in the baseline specification are highly dependent on the time-series variation between the pre- and the post-PATH act eras. Consequently, we are able to identify the categorical spending out of EITC refunds precisely because issuance was delayed by roughly two weeks in 2017 and 2018 relative to the pre-PATH act. Because the results are identified from this delay, one might ask whether they are due to the *surprise*, or simply to the delay itself. In other words, do EITC recipients spend 15 cents on the dollar out of EITC refunds, in general, or do they only spend 15 cents out of their refund when the refund is delayed *unexpectedly*, thus disrupting their pre-planned spending paths? Since the 2018 disbursements were also delayed relative to the pre-PATH act—but *not* surprisingly so since they matched the 2017 disbursement pattern—we test to see whether the results excluding 2017 (and thus the potential surprise) match those excluding 2018.²¹ Figure 9 shows that the results excluding 2017 or 2018 are very little changed from the overall results, suggesting that the spending response to a “surprise” delay is not driving our results.

²¹ Maag et al. (2016) document that, in 2016, over 90 percent of EITC households were unaware that EITC refund issuance would be delayed starting in the 2017 tax season. However, it is not clear what fraction of EITC households were aware of the refund delay closer to the 2017 filing season or at the time of filing.

Figure 9. Fraction of EITC refund spent on retail sales group excluding 2017 or 2018

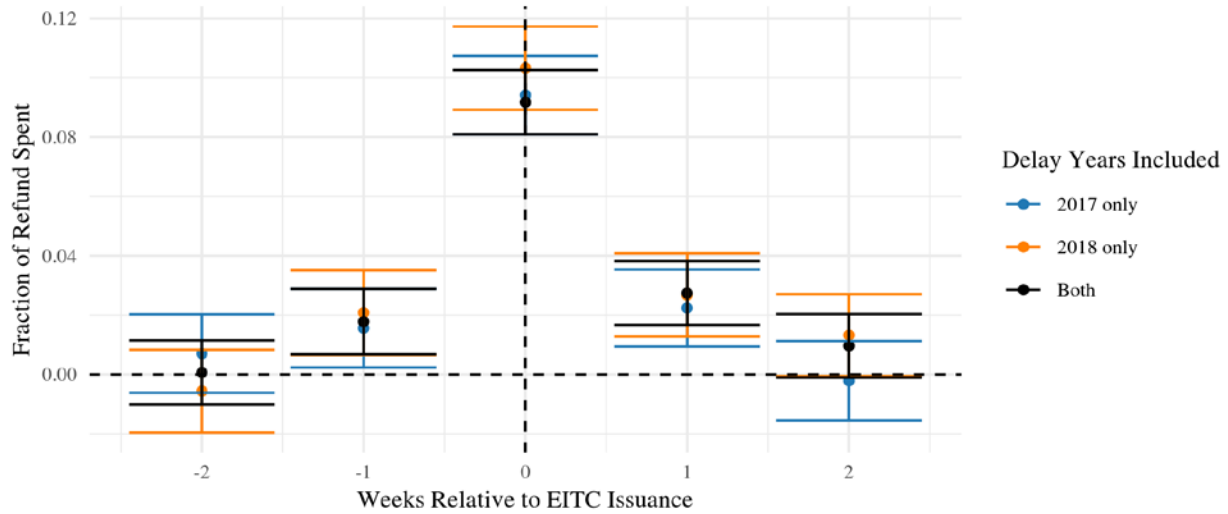


Figure 9 displays point estimates and 95 percent confidence intervals for the β_j coefficients in Equation (1) when the dependent variable is daily, state-level spending per capita in the retail sales group and we exclude particular years from the regression analysis. The estimates excluding 2017 and 2018 are represented by the orange and blue plots, respectively. The baseline estimates including both 2017 and 2018 are represented by the black plot. We interpret the coefficients as yielding the fraction of each EITC refund dollar spent at retail stores and restaurants j weeks from refund issuance.

4.4 Robustness tests

In Table 2, we explore a few alternate specifications. First, in column one, rather than using the weather controls described above, we drop all snow storm states.²² The MPC is almost identical, demonstrating the results are not dependent on the exact nature of the weather controls. In the second and third columns, we add leads and lags. When we add four leads and lags, the total MPC drops a little due to negative coefficients in the outer leads and lags. However, those coefficients are barely significant and quite small, and the coefficients on the interior leads and lags continue to be highly significant and little changed in magnitude. Finally, in the fourth column, we replace the state-week-of-year fixed effects with week-of-year fixed effects that do not vary by state. The results are little changed, with the total MPC just a touch higher.

²² Specifically, we exclude North Dakota, Alaska, New Hampshire, Maine, Massachusetts, New Jersey, Rhode Island, Connecticut, Vermont, New York, and Delaware.

Table 2: Robustness

	Sales / Population			
	RSG	RSG	RSG	RSG
	(1)	(2)	(3)	(4)
EITC Shock Lead 4 Weeks			-0.005 (0.006)	
EITC Shock Lead 3 Week		-0.008 (0.006)	-0.011* (0.006)	
EITC Shock Lead 2 Weeks	0.006 (0.005)	-0.0005 (0.006)	-0.004 (0.006)	0.002 (0.006)
EITC Shock Lead 1 Week	0.028*** (0.005)	0.017*** (0.006)	0.013** (0.006)	0.021*** (0.006)
EITC Shock	0.095*** (0.005)	0.091*** (0.006)	0.087*** (0.006)	0.099*** (0.005)
EITC Shock Lag 1 Week	0.032*** (0.005)	0.028*** (0.006)	0.023*** (0.006)	0.036*** (0.005)
EITC Shock Lag 2 Weeks	0.000 (0.005)	0.011* (0.006)	0.006 (0.006)	0.020*** (0.005)
EITC Shock Lag 3 Week		0.006 (0.005)	0.002 (0.006)	
EITC Shock Lag 4 Weeks			-0.012** (0.005)	
Total MPC	0.161*** (0.011)	0.145*** (0.015)	0.099*** (0.018)	0.179*** (0.012)
Weather Controls	No	Yes	Yes	Yes
Storm States Excluded	Yes	No	No	No
Lags/Leads	2	3	4	2
State-Week-Year Effects	Yes	Yes	Yes	No

Note:

*p<0.1; **p<0.05; *** p<0.01

5. Next steps

Going forward, we are planning several additional steps to better exploit variation in EITC refund issuance and access to credit/liquidity, better understand the financial situation of EITC recipients around tax filing season, and better grasp what EITC recipients knew about the PATH Act's implementation and when.

First and foremost, we plan to shift our analysis from the state level to the MSA level. Doing so will allow us to take advantage of a substantial increase in cross-sectional EITC refund issuance variation. Beyond increasing the precision of our current estimates, with additional cross-sectional variation we will be better able to ascertain whether spending out of EITC refunds differed pre- and post-PATH Act.

Second, we will incorporate cross-state variation in RAL usage and the timing and generosity of state EITC refunds to better understand the role that short-term credit/liquidity play in the observed spending responses. Particularly after implementation of the PATH Act, RALs and state EITC refunds (at least those received quickly after filing) provided short-term liquidity while households waited an extra couple weeks for their refund to arrive.

Finally, we will examine zip code level credit outcomes (e.g. delinquent accounts) from the Equifax Consumer Credit Panel by share of tax filers with EITC refunds. This exercise should help us assess financial situations of households in highly-concentrated EITC areas around tax time. Moreover, we can investigate whether the refund delay associated with the PATH Act impacted credit outcomes.

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Figure A.1. Illustration of overlapping of 14-month constant merchant samples

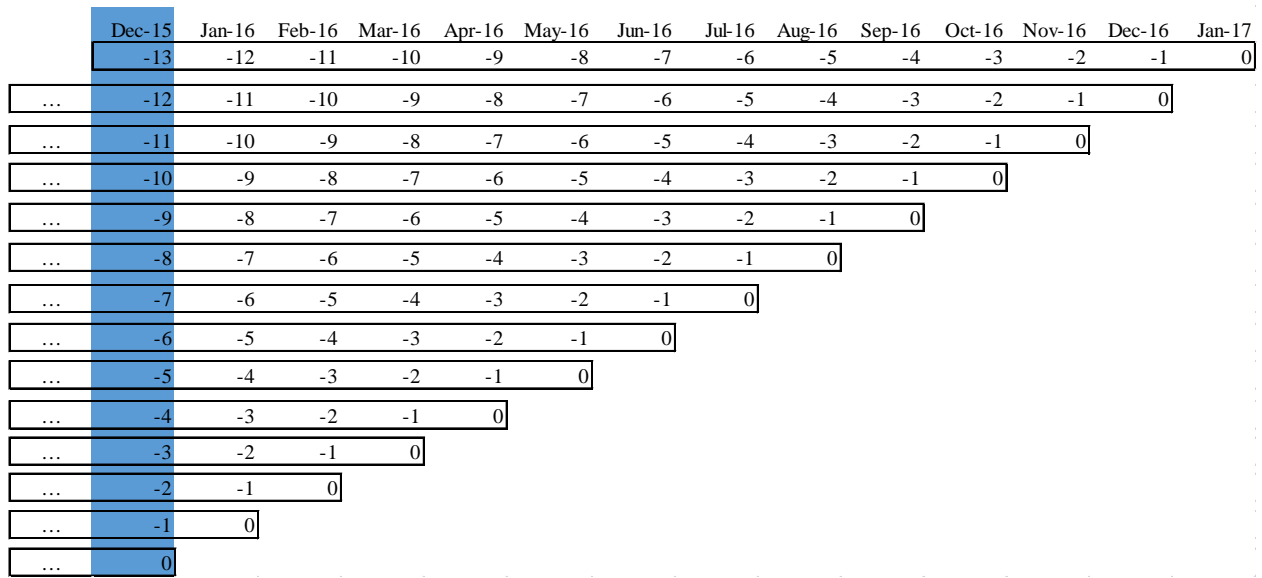


Figure A.2. First Data coverage of Economic Census Retail Sales Group by state, 2018

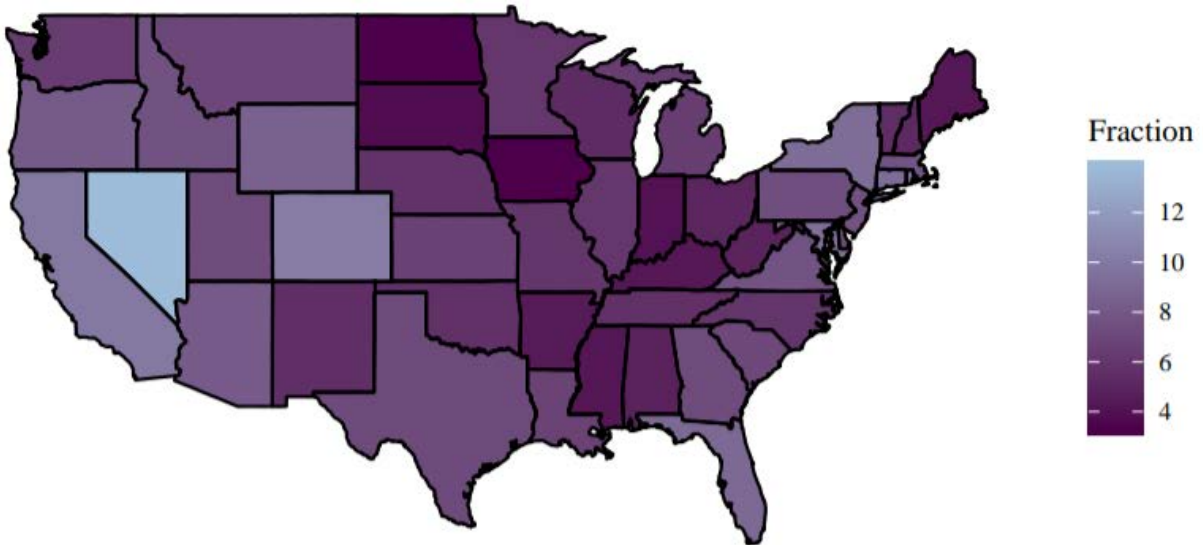
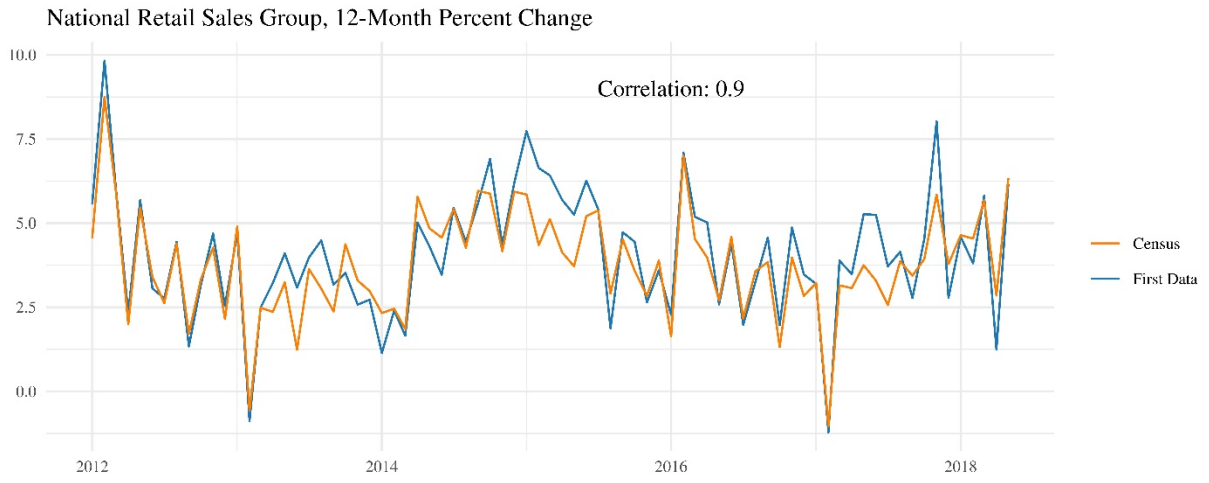


Figure A.3. National Retail Sales Group, 12-month percent change



Source: Census and First Data, not seasonally adjusted.