Macroeconomic Implications of the Earned Income Tax Credit

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September 29, 2003

Abstract

Changes in the monthly pattern of Earned Income Tax Credit disbursements over the past decade identify a large macroeconomic consumption response from EITC checks. This paper recovers a large and significant MPC out of EITC disbursements based on a comprehensive array of macroeconomic data and econometric specifications. Point estimates of the contemporaneous consumption response average 0.7 and do not attribute a disproportionate share of consumption to durable goods. Results are consistent with other empirical findings that consumption is excessively sensitive to income, and they suggest that the EITC is a much more effective fiscal stimulus tool than broad-based tax refunds. (*JEL*: D12, E21, H31; *Keywords*: Fiscal Policy, Consumption, Heterogeneity.)

The permanent income hypothesis of Modigliani and Brumberg (1954) and Friedman (1957) remains an influential framework for thinking about dynamic economic behavior. Its empirical relevance has been repeatedly

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questioned, however. Numerous studies such as Wilcox (1989, 1990), Souleles (1999), and Parker (1999) have documented large departures from the permanent income hypothesis in U.S. macro and microdata. Browning and Crossley (2001) describe the life-cycle framework as being in "disrepute" among economists for precisely this reason, although they argue that its theoretical insights remain valid. Carroll (2001) describes how a more nuanced reading of the permanent income hypothesis that accounts for uncertainty and liquidity constraints is a key element of modern consumption theory. Still, macroeconomists broadly accept that heterogeneity is an important element in aggregate fluctuations (Carroll, 2000; Mankiw, 2000). Models with representative agents behaving according to the permanent income hypothesis do not describe aggregate consumption behavior well. Rather, understanding the sources and implications of consumer heterogeneity is crucial.

An influential model that has grown out of the literature on this topic is the savers-spenders theory (Campbell and Mankiw, 1990). Since aggregate consumption is excessively sensitive to income, the model posits that only a constant share of individuals in the economy follows the permanent income hypothesis. The other share follows a simple rule of thumb and consumes current income. The aggregate marginal propensity to consume out of current income is therefore interpreted as the share of spenders in the economy. If this view is correct, fiscal policy has nonneutral effects to the extent that it impacts spenders. For a given fiscal tool, knowing the correct share of spenders in the target subpopulation is therefore critical to gauging the efficacy of the fiscal tool.

This paper investigates the excess sensitivity of aggregate consumption to a particular fiscal tool: the Earned Income Tax Credit (EITC). The EITC targets low-income working families with children, and most eligibles receive a single annual payment of around \$1,000. Previously, Barrow and McGranahan (2000) examined the consumption effects of the EITC using the Consumer Expenditure Survey (CEX), a well-known microeconomic dataset. They reported a same-month MPC of around 0.2, which is low but reasonably consistent with the economy-wide spender share found by Campbell and Mankiw (1990) in aggregate data: a range of 0.3 to 0.7 in a quarter. Still, the results are somewhat surprising given the fact that EITC recipients as a group are by design low-income. In fact, Barrow and McGranahan suspect that their estimates must be biased downward due to measurement error in the EITC variable, which is not reported well in the CEX. Although the cross-sectional richness of the CEX is advantageous, its relatively imprecise measurement of the EITC thus seems to be a liability.

The key insight of this paper is that macroeconomic data can be used to measure and characterize the consumption effects of the EITC more precisely. Macroeconomic data measure both the stimulus and the consumption effect along the timing and quantity dimensions, at the expense of the rich cross-sectional variation offered by microeconomic data. In the case of the EITC, a distinct pattern of shifting seasonality appears to provide the requisite identification. Estimates of the relevant spender share, around 0.7, are much higher than have been found among other groups, and they suggest that the EITC is a very effective fiscal tool for stimulating consumption.

This paper proceeds in four parts. The first section describes the structure of the EITC and explains recent trends that help identify the macroeconomic effect. The theoretical model is introduced and discussed in the second section. The third section discusses the data used to test the model, and the fourth section reports results from several different model specifications. The final section summarizes and offers concluding remarks.

1 The mechanics of the EITC

The EITC is a unique fiscal program for several reasons. As has been widely noted, the EITC is special among low-income support programs due to its incentivized, work-rewarding structure. Only taxpayers who earn labor income qualify for the transfer, which acts as a wage subsidy up to a phaseout. A second and less frequently cited characteristic of the EITC is its unusual timing pattern. While TANF/AFDC, food stamps, and SSI are distributed on a monthly basis, the EITC is usually released in an annual lump sum to individuals filing tax returns in the same way that regular tax refunds are. These annual EITC checks tend to be fairly large.[1] They are also fully expected; individuals must first fill out or pay preparers to fill out their tax returns and send them in before receiving their checks.

An interesting feature of the program is that recipients can arrange to receive advance EITC payments through their employers.[2] That is, instead of

[1]Based on the administrative data used in this paper, and on the number of recipient families reported by the Committee on Ways and Means (2000), the average refundable credit per family — the amount that the average family would receive in a check sent to them — was roughly $1,200 in 1998.

[2]This is called the Advance Earned Income Credit. A worker's total advance payments

getting a lump sum at tax time, people could receive much of it in increments throughout the previous year. Only a very small amount of annual EITC spending is paid out in advance, as evidenced by a highly seasonal character of disbursements. From a life-cycle perspective, it makes no sense why anyone would choose to receive the lump sum, since it is worth less in present value. In order to explain why people elect not to receive advance payments, we must resort to the usual suspects: transactions costs, capital market imperfections, or myopia. This line of reasoning suggests that it should come as no surprise that EITC recipients may immediately spend their checks, since they are already violating the permanent income hypothesis by not receiving advance credits.

1.1 Levels of the macrodata

The Earned Income Tax Credit underwent several expansions during the 1990s that significantly increased annual payouts as well as the number of participants. Currently, annual EITC program payments are around $30 billion, having grown from only around $3 billion at the end of the Reagan presidency. Since that time, the number of recipients has roughly doubled, reaching the current level of 20 million families.

Figure 1 shows both the EITC and personal income tax refund (PITR) series deflated by the chain-type price index for personal consumption expenditures (PCE).[3] Real EITC payments have been growing rapidly since the early 1990s, at roughly a 15 percent annual rate since 1993. Since the real level of EITC spending is now more than six times what it was in 1988, the

may not exceed 60% of the maximum credit for workers with one dependent child, and payments are calibrated to earnings on the job. The presence of another dependent child or of other labor earnings in the family can either raise or lower the total family credit, however. The maximum advance credit ends up roughly equal to the average total credit per family. This was roughly $1,400 in 2000.

[3]The data represent aggregate check disbursement rather than receipt, and they measure earned income credits net of income tax liability. That is, if a qualifying family at tax time were liable for $200 in personal income taxes but were also eligible for $1,000 in earned income credit, the administrative data would register an EITC disbursement in the amount of $800. A more complicated situation would arise if the family were also owed an income tax refund. Suppose in the previous example that the family had overpaid income taxes by $200. Since the EITC and tax refunds are different budget items — the EITC is scored as an outlay while refunds are offsets against revenue — the administrative data would show a $1,000 EITC payment alongside a $200 personal income tax refund, even though both payments were mailed to the same family.

real per-family credit has increased by a factor of over three. By comparison, real PITR levels have exhibited little growth.

As to whether the rapid growth in the EITC is big enough to show up in macrodata at the monthly frequency, the prospects appear good. In February 2000, the more than $13 billion in EITC disbursements represented about 5 percent of the level of total retail trade in that month, which includes purchases of durable and nondurable consumption goods but not services. The change in EITC disbursements between January and February of that year was over $12 billion.

1.2 The seasonality of the EITC

Not only has the level of EITC payments been macroeconomically large and growing, its monthly fluctuations have been significant, and more importantly, nonstationary. Like personal income tax refunds, the EITC is handled by the Treasury Department and is mostly administered during tax season: early February through May. As a result, both follow highly seasonal patterns of disbursements. The month with the largest concentration of EITC refunds in 1999 was February, with almost $12 billion, or about half the annual total. By contrast, PITR checks are frequently highest in either April or May. Since EITC recipients cannot have significant forms of income other than wage earnings (Committee on Ways and Means, 2000), their tax returns ought to be easier to complete than those of the average taxpayer. This may explain why most EITC checks are mailed out before most tax refund checks.

Ease of filing may also help explain why the highly seasonal pattern of EITC disbursement has changed over time. Figure 2 shows three consecutive multi-year averages of monthly disbursement rates: 1983–1988, 1989-1993, and 1994-1999.[4] Leftward motion in the hump shown in Figure 2 represents earlier and earlier receipt of earned income credits during the calendar year. In contrast, personal income tax refunds have generally maintained their monthly pattern over the last decade and a half, as shown in Figure 3.

The EITC's changing seasonal pattern appears to play a critical role in identifying the macroeconomic response of consumption to the EITC. An issue that arises in modeling is the exogeneity of these identifying seasonal trends, however. The timing of payments probably reflects the outcome of endogenous decisions made by EITC recipients rather than a truly exogenous

[4]Disbursement rates are the percentage of annual payments made in that month.

shock. For example, EITC recipients may have accelerated their tax filing in order to receive their checks more quickly. This type of endogeneity will not confound estimation of a consumption function specified in the usual way:

$$C = f(X) + \epsilon, \tag{1}$$

since innovations in consumption decisions do not drive right-hand-side variables like EITC checks. Formally, $\mathrm{Cov}(X, \epsilon)$ is still zero. If people were receiving EITC disbursements earlier and earlier because they wished to consume earlier and earlier, then innovations in C could be driving right-hand-side variables: $\mathrm{Cov}(X, \epsilon) \neq 0$.

This does not seem to be the case, however. Barrow and McGranahan (2000) compared seasonal consumption preferences among EITC recipients with those of low-income families and families with dependent children in the CEX — essentially two control groups. They reported that the two other groups had markedly different seasonal consumption patterns than those of EITC recipients. This suggests that to the degree that all three groups ought to be similar, preferences are not responsible for EITC recipients' patterns of consumption. Rather, the timing of EITC disbursements must be driving consumption. That is, $\mathrm{Cov}(X, \epsilon) = 0$.

2 A model of savers and spenders

This model is closely patterned after the savers-spenders framework of Campbell and Mankiw (1990), but it is modified to account for different sources of income and for seasonality at the monthly level. The economy is composed of two broad groups: rule-of-thumb consumers who spend all of their current incomes, and life-cycle consumers whose consumption follows Hall's (1978) random walk. There are fractions λ^i of rule-of-thumb consumers for each type of income i considered: the Earned Income Tax Credit, personal income tax refunds, and other income.[5] Let C, Y, EITC, and PITR represent consumption, income, the Earned Income Tax Credit, and refunds. Then consumption in t by rule-of-thumbers is

$$C_t^R \quad = \quad (\lambda^{EITC}) \cdot \mathrm{EITC}_t + (\lambda^{PITR}) \cdot \mathrm{PITR}_t + (\lambda^{Y}) \cdot Y_t, \tag{2}$$

[5]Ideally, a measure of disposable income excluding EITC and PITR payments ought to be used. As described in Section 3, it is difficult to obtain seasonally unadjusted measures of disposable income at the desired frequency. As a result, various measures of other income will be used to accommodate the data limitations.

where, for example, λ^{EITC} is the share of EITC recipients who are rule-of-thumbers. It is also the aggregate marginal propensity to consume out of EITC checks.

In terms of timing considerations, (2) is overly restrictive when t indexes months. Wilcox (1990) emphasizes the critical importance of correctly modeling the delay between the receipt of checks from the government and the act of consumption or saving. There will be some individuals receiving their checks late in month t who by waiting just a week or more to spend their income will end up pushing their consumption back to month $t+1$. What is modeled as a contemporaneous action in (2) might in fact show up in the data as being delayed. This argument holds for each of the income variables under consideration. Adding one lag of each of the right-hand-side variables in (2) yields

$$\begin{aligned} C_t^R &= (\lambda_0^{EITC}) \cdot \mathrm{EITC}_t + (\lambda_{-1}^{EITC}) \cdot \mathrm{EITC}_{t-1} \\ &\quad + (\lambda_0^{PITR}) \cdot \mathrm{PITR}_t + (\lambda_{-1}^{PITR}) \cdot \mathrm{PITR}_{t-1} \\ &\quad + (\lambda_0^{Y}) \cdot Y_t + (\lambda_{-1}^{Y}) \cdot Y_{t-1}, \end{aligned} \tag{3}$$

where the lag coefficients are allowed to be different from the contemporaneous λ's. The share of a particular type of income going to rule-of-thumbers is now measured by the sum of current and lag coefficients.

Seasonality requires explicit treatment in the regression equation. When t indexes months, C_t is affected by the particular month it is, by the days of the week that are most numerous in the month, and by the presence of holidays that can switch months. The first type of seasonality is easily captured with simple monthly dummy variables. The second type, frequently called "trading-day" variation, can be addressed with the use of 7 indicator variables for excess days of a particular type in a month.[6] The last type of seasonality is really only important here in the case of Easter, a lunar holiday that falls either in March or April.

Macroeconomic data display multiplicative or log-additive trends rather than additive trends; per-capita consumption and income grow exponentially rather than linearly. Seasonality is also log-additive, as shown in Figure 4, which plots monthly changes in real retail sales. Differences become wider and wider over time, indicating that seasonal fluctuations are better described

[6]These are constructed for each of the 7 days of the week as 0/1 indicators for whether there are 4 or 5 of them in the month in question. The trading-day variables are not collinear with the monthly dummies since there are several leap years in the sample.

as proportional rather than fixed. In an equation like (3), seasonality must therefore be parameterized with functions either of time or of other level variables.

To deal with log-additivity in the data, Campbell and Mankiw explore both taking logs of all variables and also scaling by the lagged level of income.[7] The first option is difficult to implement here, because EITC_t and PITR_t are frequently zero or very close to it. Extending the scaling technique to (3) requires introducing seasonal factors that are multiplied by $\lambda^Y Y_{t-1}$:

$$\begin{aligned} C_t^R \;=\; & \sum_{m=1}^{11} \beta_m M_{m,t} \cdot \lambda^Y Y_{t-1} + \sum_{d=1}^{7} \gamma_d D_{d,t} \cdot \lambda^Y Y_{t-1} + \theta Easter_t \cdot \lambda^Y Y_{t-1} \\ & + (\lambda_0^{EITC}) \cdot \mathrm{EITC}_t + (\lambda_{-1}^{EITC}) \cdot \mathrm{EITC}_{t-1} \\ & + (\lambda_0^{PITR}) \cdot \mathrm{PITR}_t + (\lambda_{-1}^{PITR}) \cdot \mathrm{PITR}_{t-1} \\ & + (\lambda_0^{Y}) \cdot Y_t + (\lambda_{-1}^{Y}) \cdot Y_{t-1}, \end{aligned} \tag{4}$$

where the $M_{m,t}$ are dummy variables for months, the $D_{d,t}$ are dummy variables for the number of trading days, and $Easter_t$ is a dummy variable equaling 1 in the months during which Easter occurs.[8] Differencing (4) yields

$$\begin{aligned} \Delta C_t^R \;=\; & \sum_{m=1}^{11} \beta_m (M_{m,t} \cdot \lambda^Y Y_{t-1} - M_{m,t-1} \cdot \lambda^Y Y_{t-2}) \\ & + \sum_{d=1}^{7} \gamma_d (D_{d,t} \cdot \lambda^Y Y_{t-1} - D_{d,t-1} \cdot \lambda^Y Y_{t-2}) \\ & + \theta Easter_t \cdot \lambda^Y Y_{t-1} - \theta Easter_{t-1} \cdot \lambda^Y Y_{t-2} \\ & + \lambda_0^{EITC} \Delta \mathrm{EITC}_t + \lambda_{-1}^{EITC} \Delta \mathrm{EITC}_{t-1} \\ & + \lambda_0^{PITR} \Delta \mathrm{PITR}_t + \lambda_{-1}^{PITR} \Delta \mathrm{PITR}_{t-1} \\ & + \lambda_0^{Y} \Delta Y_t + \lambda_{-1}^{Y} \Delta Y_{t-1}. \end{aligned} \tag{5}$$

It is convenient to assume that the difference between Y_{t-1} and Y_{t-2} is small, which allows the seasonal terms in (5) to be simplified. This step

[7]Scaling by lagged income accomplishes several things. First, seasonality can be appropriately parameterized and the error term behaves normally. Secondly, adjusting measures to a per-capita basis becomes unnecessary since population cancels out. Similarly, inflation also cancels out.

[8]This form of seasonality assumes that seasonal variation in tastes is identical across consumers.

implies

$$\Delta C^R_t = \sum_{m=1}^{11} \beta_m \Delta M_{m,t} \cdot \lambda^Y Y_{t-1} + \sum_{d=1}^{7} \gamma_d \Delta D_{d,t} \cdot \lambda^Y Y_{t-1} + \theta \Delta Easter_t \cdot \lambda^Y Y_{t-1}$$
$$+ \lambda^{EITC}_0 \Delta \mathrm{EITC}_t + \lambda^{EITC}_{-1} \Delta \mathrm{EITC}_{t-1}$$
$$+ \lambda^{PITR}_0 \Delta \mathrm{PITR}_t + \lambda^{PITR}_{-1} \Delta \mathrm{PITR}_{t-1}$$
$$+ \lambda^Y_0 \Delta Y_t + \lambda^Y_{-1} \Delta Y_{t-1}. \quad (6)$$

If $\Delta M_{i,t} = 1$, then $\Delta M_{i-1,t} = -1$, and the rest of the $\Delta M_{j,t}$'s are zero by construction. So for simplicity, $\sum_{m=1}^{11} \beta_m \Delta M_{m,t}$ can be rewritten as

$$\sum_{m=1}^{11} \beta_m \Delta M_{m,t} = 0 + 0 + ... - \beta_{m-1} + \beta_m + 0 + ... + 0$$
$$= 0 + 0 + ... + 0 + (\beta_m - \beta_{m-1}) + 0 + ... + 0$$
$$\equiv \sum_{m=1}^{11} \beta'_m M_{m,t}.$$

That is, by redefining the β coefficients, (6) can be recast in terms of M's rather than ΔM's. The same is not true, however, for $\Delta Easter$ and the trading-day dummies. With that in mind, (6) becomes

$$\Delta C^R_t = \sum_{m=1}^{11} \beta'_m M_{m,t} \cdot \lambda^Y Y_{t-1} + \sum_{d=1}^{7} \gamma_d \Delta D_{d,t} \cdot \lambda^Y Y_{t-1} + \theta \Delta Easter_t \cdot \lambda^Y Y_{t-1}$$
$$+ \lambda^{EITC}_0 \Delta \mathrm{EITC}_t + \lambda^{EITC}_{-1} \Delta \mathrm{EITC}_{t-1}$$
$$+ \lambda^{PITR}_0 \Delta \mathrm{PITR}_t + \lambda^{PITR}_{-1} \Delta \mathrm{PITR}_{t-1}$$
$$+ \lambda^Y_0 \Delta Y_t + \lambda^Y_{-1} \Delta Y_{t-1}. \quad (7)$$

The life-cycle consumers in the economy consume C^L and earn $Y^L = (1 - \lambda^Y)Y$. Following Campbell and Deaton (1989), a log-linear analogue of Hall's classic "random walk" consumption equation is adopted:

$$\Delta C^L_t / Y^L_{t-1} = a + u_t, \quad (8)$$

where the u_t innovations are *i.i.d.* and normally distributed. Adding seasonal dynamics and multiplying through by the appropriate income variable yields a difference equation similar to (7):

$$\Delta C^L_t = a(1 - \lambda^Y)Y_{t-1} + \sum_{m=1}^{11} \beta'_m M_{m,t}(1 - \lambda^Y)Y_{t-1} + \sum_{d=1}^{7} \gamma_d \Delta D_{d,t}(1 - \lambda^Y)Y_{t-1}$$
$$+ \theta \Delta Easter_t (1 - \lambda^Y)Y_{t-1} + (1 - \lambda^Y)Y_{t-1} \cdot u_t. \quad (9)$$

The change in total consumption is then just the sum of ΔC^R and ΔC^L as given by (7) and (9), which can be written as

$$\begin{aligned}
\Delta C_t &= \Delta C_t^R + \Delta C_t^L \\
&= a(1-\lambda^Y)Y_{t-1} + \sum_{m=1}^{11} \beta'_m M_{m,t} Y_{t-1} + \sum_{d=1}^{7} \gamma_d \Delta D_{d,t} Y_{t-1} \\
&\quad + \theta \Delta Easter_t Y_{t-1} + \lambda_0^{EITC} \Delta \mathrm{EITC}_t + \lambda_{-1}^{EITC} \Delta \mathrm{EITC}_{t-1} \\
&\quad + \lambda_0^{PITR} \Delta \mathrm{PITR}_t + \lambda_{-1}^{PITR} \Delta \mathrm{PITR}_{t-1} \\
&\quad + \lambda_0^Y \Delta Y_t + \lambda_{-1}^Y \Delta Y_{t-1} + (1-\lambda^Y) Y_{t-1} \cdot u_t. \qquad (10)
\end{aligned}$$

Finally, dividing both sides of (10) by Y_{t-1} and letting $\epsilon_t = (1-\lambda^Y)u_t$ and $\alpha = a(1-\lambda^Y)$ produces the central equation in the model:

$$\begin{aligned}
\frac{\Delta C_t}{Y_{t-1}} &= \alpha + \sum_{m=1}^{11} \beta'_m M_{m,t} + \sum_{d=1}^{7} \gamma_d \Delta D_{d,t} + \theta \Delta Easter_t \\
&\quad + \lambda_0^{EITC} \frac{\Delta \mathrm{EITC}_t}{Y_{t-1}} + \lambda_{-1}^{EITC} \frac{\Delta \mathrm{EITC}_{t-1}}{Y_{t-1}} \\
&\quad + \lambda_0^{PITR} \frac{\Delta \mathrm{PITR}_t}{Y_{t-1}} + \lambda_{-1}^{PITR} \frac{\Delta \mathrm{PITR}_{t-1}}{Y_{t-1}} \\
&\quad + \lambda_0^Y \frac{\Delta Y_t}{Y_{t-1}} + \lambda_{-1}^Y \frac{\Delta Y_{t-1}}{Y_{t-1}} + \epsilon_t + \rho \epsilon_{t-1}, \qquad (11)
\end{aligned}$$

where the autocorrelation term, $\rho\epsilon_{t-1}$, is included in order to model goods' durability. Caballero (1993) provides a discussion of why negative serial correlation, or $\rho < 0$, may be expected in the consumption of durables.

When a complete set of seasonally adjusted data is available, (11) reduces to its seasonally adjusted analogue:

$$\begin{aligned}
\frac{\Delta C_t}{Y_{t-1}} &= \alpha + \lambda_0^{EITC} \frac{\Delta \mathrm{EITC}_t}{Y_{t-1}} + \lambda_{-1}^{EITC} \frac{\Delta \mathrm{EITC}_{t-1}}{Y_{t-1}} \\
&\quad + \lambda_0^{PITR} \frac{\Delta \mathrm{PITR}_t}{Y_{t-1}} + \lambda_{-1}^{PITR} \frac{\Delta \mathrm{PITR}_{t-1}}{Y_{t-1}} \\
&\quad + \lambda_0^Y \frac{\Delta Y_t}{Y_{t-1}} + \lambda_{-1}^Y \frac{\Delta Y_{t-1}}{Y_{t-1}} + \epsilon_t + \rho \epsilon_{t-1}. \qquad (12)
\end{aligned}$$

For quarterly data, (11) and (12) maintain their general forms. In (11), the number of M_t's reduces to 3 from 11, to represent the 4 quarters, and the trading-day dummies are redefined for quarter t. In both equations, the lag structure is reduced to within-quarter comparisons only, in order to maintain consistency with earlier research.

3 The dataset and parameter estimates

The ideal macroeconomic dataset consists of high-frequency measures of consumption, EITC and PITR refund checks, and all other forms of disposable income, all measured consistently. Complete series of consumption and disposable income are not available seasonally adjusted at the monthly frequency. Moving up to quarterly aggregation can help with data availability, however. With two choices of seasonality and two choices of aggregation, four datasets in total are available.

At the monthly level, the Census Bureau publishes seasonally adjusted (SA) and not seasonally adjusted (NSA) retail trade data that roughly cover the goods side of aggregate PCE and which are further split into durable goods and nondurable goods spending.[9] Goods labeled durable accounted for between 30 and 45 percent of total retail trade during the time period in question, late 1982 to early 2001. A measure of NSA monthly labor income can be constructed using establishment data from the Bureau of Labor Statistics. It equals the product of monthly average weekly earnings of production workers, the number of workweeks in each historical month, and monthly total production workers.[10] Monthly NSA data on EITC and PITR disbursements are reported by the Treasury as described in Section 1. Seasonally adjusted monthly data on the national income aggregates are available from the Bureau of Economic Analysis (BEA). These include disposable personal income as well as all of PCE, whose major components are services, durables, and nondurables. The Census Bureau makes its seasonal adjustment software, X-12-ARIMA, available online, and it can be programmed to seasonally adjust the EITC and PITR series from the Treasury.[11]

[9] In 2001, the Census Bureau redefined its retail sample to be consistent with its new industrial classification scheme, NAICS. The traditional durables/nondurables classification was abandoned. To date, Census has not backcast its retail trade data into the 1980s, and its new monthly data are not compatible with its old SIC-based series. As a result, the current dataset ends in April 2001.

[10] Net workdays in each month were recovered using an array of the 10 big federal holidays, and dividing by 5 produced a measure of the number of workweeks per month.

[11] The quality of results is unclear, however. Specifying additive seasonality appeared to be the only way to obtain reasonable output from X-12-ARIMA. Corrections for trading-day variation and other advanced techniques could apparently not be used with additive seasonality. Trading-day seasonality ought to be important for both the EITC and for PITR's, since the Treasury sends out most checks on Fridays. This can be inferred from the Daily Treasury Statements, which are also available from the Treasury.

At the quarterly level, the BEA provides seasonally unadjusted figures in Table 9.1 of its National Income and Product Accounts (NIPA). A shortcoming is that the only measure of income reported is all of GDP, which is greater than disposable income. Quarterly NIPA series are widely available seasonally adjusted and include the more appropriate measure of disposable personal income. X-12-ARIMA can produce quarterly SA series for EITC and PITR flows once they have been aggregated.

In order to investigate robustness and to provide comparability with other studies, the next sections perform multivariate regression analysis on both SA and NSA data at monthly and quarterly frequencies. Section 3.1 examines these datasets using standard linear techniques that correct for autocorrelation, while Section 3.2 adds instrumental variables in order to correct for any bias or inconsistency. The key result, a large MPC out of EITC checks, turns out to be quite robust to specification.

3.1 FGLS

The first pass is feasible generalized least squares (FGLS) estimation using monthly data.[12] Table 1 reports the results of estimating (11) using NSA retail trade aggregates. The primary coefficient of interest is λ_0^{EITC}, the marginal propensity to consume out of EITC checks in the current month. It has the anticipated sign in all three regressions and is highly significant. The total MPC out of EITC checks, shown in the third row of the table, is roughly the same as λ_0^{EITC}; lagged behavior is not very important. Goods labeled durable account for about 40 percent of the retail trade stimulus. Since durables' share of total retail oscillated between about 30 and 50 percent during this time period, the relative size of these coefficients in relation to each other reveals no disproportionate impact of the EITC on durables.

There appears to be no consumption effect associated with personal income tax refunds. The current-month coefficients even have unexpected sign. The marginal propensity to consume out of labor income, λ^Y, is roughly 0.2, with most of the stimulus apparently coming from durables. This figure is outside the range of λ's found in quarterly data on nondurables and services by Campbell and Mankiw, suggesting that spending during adjacent months or on services may be important for the average consumer.

[12] The statistical software used throughout is TSP 4.5. Its advantages include the ability to model autocorrelation within an instrumental variables framework.

Accounting for spending on services requires shifting to seasonally adjusted data. Table 2 reports the estimation of (12) using monthly data on retail sales and disposable personal income that has been seasonally adjusted with X-12-ARIMA. Results are quite poor, with only one coefficient in all three regressions registering significance at the 5 percent level. The overall fit of the regressions, as shown by the R^2 statistics, is much worse than that of the NSA regressions of Table 1. A lone bright spot is that the sum of EITC coefficients in the total retail trade regression is more than 0.4 and almost significant at the 10 percent level.

In Table 3, retail trade data is replaced with NIPA consumption data, which measures purchases of services as well as durables and nondurables. Although standard errors are high and R^2's are low, the results are notably better than in Table 2. The total EITC coefficient is almost 0.6 for all of PCE, of which more than half represents activity in the current month. Within-month spending of personal income tax refunds is significant and positive, although the total effect is imprecisely measured. Other disposable personal income is also found to significantly stimulate PCE, with almost half of the stimulus centered in services. But λ^Y estimates are smaller than in Table 1, and the durables impulse is no longer significant. Across the table, point estimates are generally larger in the nondurables and services regressions, although the EITC does appear to stimulate durables spending.

Table 4 shows quarterly analogues of the seasonally unadjusted regressions in Table 1, while Table 5 displays the results of testing the model with seasonally unadjusted quarterly NIPA aggregates. In both cases, consumption stimuli are constrained to the current quarter only. Estimated EITC coefficients in Table 4 are large, significant, and quite similar to those reported in the monthly NSA regressions. Again there appears to be no consumption stimulus deriving from personal income tax refunds, and the coefficient on labor income is large and significant. Table 5 recovers a PCE stimulus that is one-for-one with EITC checks and estimated to be equally split between nondurables and durables. The latter result is consistent with earlier evidence from NSA data in Table 1, but it conflicts with seasonally adjusted estimates in Table 3. The impact of other income, almost 0.4 in aggregate, is split fairly equally among durables, nondurables, and services.

Table 6 shows the results of testing the model with seasonally adjusted retail sales data, while Table 7 uses seasonally adjusted NIPA data. As before with monthly data, seasonal adjustment appears to raise standard errors and worsen the fit of the model. EITC coefficients remain large but are insignificantly different from zero. Other income retains a somewhat more robust association with consumption, however.

This set of FGLS results suggests that the canonical Campbell and Mankiw result is sensitive both to the frequency of the data and to the definition of consumption. Shifting from monthly to quarterly frequencies generally raises the estimate of consumption out of income, regardless of the specific income measure used. Similarly, and not surprisingly, including services in the consumption measure also raises λ^Y. In contrast, estimates of consumption out of EITC checks are quite robust across specification and are large, near unity. There is little evidence of any consumption response to income tax refunds.

3.2 IV-FGLS

Parameter estimates in consumption functions are frequently subject to inconsistency due to correlation between the current income variable and the consumption error term, ϵ. That is, the arrival of new information about current income usually conveys information about permanent income, and therefore about consumption, as well.[13] The usual remedy is the method of instrumental variables (IV), or in this case, IV-FGLS, because autocorrelation is still present. The standard choice of instruments in time-series econometrics are lagged variables, which ought to be uncorrelated with ϵ_t since they are known at t. Other good instruments for income are asset returns, as noted by Campbell and Mankiw and others. Two measures are chosen: the change in the real interest rate on 3-month Treasury bills, and the change in the percentage increase in the S&P 500 stock index.

The choice of instrument sets is explored in Table 8, where IV-FGLS is used to estimate (11) using NSA retail sales as the measure of consumption. In each of the six columns, one of six different sets of instrumental variables is used in an IV-FGLS regression describing total retail sales. The instrument sets vary widely in terms of lag length and type of variables included, and they are described in the notes to the table. At the bottom of the table are three rows of F-statistics testing all coefficients equal to zero in the first-stage regressions of current-period EITC, PITR, and other income on the instrument sets. EITC coefficients are quite stable across instrument sets, as are their standard errors in all cases but the third column, where

[13] Innovations in EITC_t and PITR_t are obviously not correlated with ϵ_t since they are known in advance. Unfortunately, there is serial correlation in (11), which raises the possibility that EITC and PITR could be correlated with the error term after all.

the instrument set is truncated to lags 1–6. The sum of EITC coefficients remains significant in that equation, however, and across all columns its range of values is fairly tight at 0.67–0.79. As in the FGLS results, personal income tax refunds are found not to significantly impact consumption. Labor income frequently appears to be insignificant, but in most specifications λ^Y is estimated to be fairly large, in the range of 0.2–0.6. First-stage fit varies somewhat across instrument sets, but all F-statistics indicate rejection of the hypothesis that the first-stage coefficients are equal to zero. The fourth and fifth column use relatively small instrument sets in order to check for the finite sample bias that may plague instrumental variables estimates (Davidson and MacKinnon, 1993). The similarity of results in these two columns to those in the rest of the table suggests no such bias is present. The sixth column uses only lagged income variables as instruments, which also seems not to affect the results. Since the results are quite robust to the choice of instrument set, further IV-FGLS estimations will simply use the first set that appears in Table 8.

Table 9 is the instrumental-variables analogue of Table 1, showing the breakdown by type of spending within the retail trade group. The first column is identical to the first column in Table 8. Although point estimates of the EITC stimulus have fallen slightly in size relative to earlier FGLS results, standard errors have not risen. The share of durables in the stimulus has dipped slightly but remains around one-third. Table 10 shows the result of using instrumental variables in seasonally adjusted monthly regressions. Since the fit of monthly seasonally adjusted FGLS regressions was poor, it comes as no surprise that Table 10 also features imprecise estimates. Still, the total EITC coefficient in the PCE regression is significant and nearly 0.5, and λ^Y is significant but small.

The results of IV-FGLS applied to quarterly data are shown in Table 11.[14] The first column, using NSA data on retail trade, registers significant EITC and labor income coefficients even larger than their FGLS counterparts in Table 4. Results in the second column are likewise quite similar to earlier findings, with an EITC coefficient close to unity and λ^Y near 0.4. High standard errors once again plague estimates that use seasonally adjusted quarterly data, as shown in the third and fourth column. Point estimates of

[14]Efforts were undertaken to explore the sensitivity of quarterly results to the choice of instrument sets, and a year of data, or lags 1-4 in a quarterly framework, was again found to be an appropriate baseline.

the EITC effect are large but imprecise in seasonally adjusted data. Table 12 is the IV analogue of Table 5, and there is very little difference in results between the two tables. The EITC stimulus raises PCE one-for-one, with an almost equal split between durables and nondurables and apparently no spending on services. Personal income tax refunds are found to have an effect of 0.4–0.5, and the coefficient on other income is 0.4–0.45.

The array of results in this section have demonstrated that instrumental variables techniques confirm the key FGLS findings: a large and significant MPC out of EITC checks, in the range of 0.4 to 1.0 with an average of around 0.7; no robust effect of refunds on consumption; and excess sensitivity of consumption to other income that depends on the frequency of the data and the type of consumption. FGLS estimates appear to be neither biased nor inconsistent; IV-FGLS parameter estimates can be larger or smaller than their non-IV counterparts, and standard errors are not much different.

4 Conclusions and policy implications

This paper accomplishes two goals. First, it extends the literature on the excess sensitivity of consumption to current income by replicating earlier results and identifying a key channel, the Earned Income Tax Credit. Excess sensitivity of consumption to income other than tax refunds or EITC checks is largely confirmed, but the estimated size of λ^Y, the marginal propensity to consume or equivalently the spender share, appears to depend on the definition of consumption and the frequency of the data. The consumption of services is, not surprisingly, a key element of excess sensitivity for the average consumer. Whether due to measurement error or because consumption out of other income is temporally dispersed, monthly data do not indicate as large a response as quarterly data.

Second, this paper quantifies the consumption behavior of EITC recipients in terms of levels and timing. The growth and shifting seasonality of EITC disbursements identify a large and robust macroeconomic consumption response, with point estimates of the total MPC ranging between 0.4 and 1 and averaging 0.7. These results suggest that the Earned Income Tax Credit is a powerful fiscal tool because EITC recipients are disproportionately spenders rather than savers. Why they immediately spend about 70 percent of their EITC checks remains an open question. Macroeconomic data offer little support for the hypothesis that recipients plan to receive large lump sums in order to finance the purchase of durable goods. EITC checks appear to stimulate durables and nondurables spending fairly equally, while there is mixed evidence regarding spending on services. Exploring other rationales for the excess sensitivity of consumption to EITC checks, such as liquidity constraints, myopia, or psychology, is beyond the scope of this paper and remains a topic for future research.

This paper uncovers little evidence of any significant macroeconomic consumption stimulus due to personal income tax refunds. Given the stationary seasonality, the limited growth of refund disbursements over time, and the limitations of the current econometric framework, this result is not at all surprising. It is at odds with the high MPC's out of refunds found in microdata by Souleles (1999). But it is more in line with the less definitive results of Wilcox (1990), who uses macrodata on refunds and consumption, and also with the findings of Shapiro and Slemrod (2003), who estimate an MPC of just over 20 percent based on survey responses to questions regarding the federal income tax rebate of 2001. The present study suggests that the EITC would be a far more effective tool for stimulating the economy than federal income tax refunds. Had the roughly \$40 billion in broad-based tax refunds paid out in the summer of 2001 been directed instead toward EITC recipients, the total stimulus might have reached \$28 billion, or almost 0.3 percent of GDP, compared with the \$8–9 billion of actual stimulus implied by Shapiro and Slemrod's results.[15]

[15] An additional \$40 billion represents a 150 percent increase over the \$26 billion EITC program, however. It is conceivable that $\lambda^{EITC} = 0.7$ may only remain stable over changes closer to the 15 percent real annual rate of increase in EITC checks since 1993.

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Table 1: FGLS Estimation of (11) using monthly NSA retail trade

	Component of Retail Trade		
parameter	Total Retail	Nondurables	Durables
λ_0^{EITC}	0.7544*	0.4695*	0.2749*
	(0.1503)	(0.0736)	(0.1156)
λ_{-1}^{EITC}	0.0506	−0.0286	0.0740
	(0.1587)	(0.0767)	(0.1224)
$\sum \lambda^{EITC}$	0.8050*	0.4410*	0.3489*
	(0.2036)	(0.1002)	(0.1516)
λ_0^{PITR}	−0.0605	−0.0221	−0.0358
	(0.0587)	(0.0284)	(0.0454)
λ_{-1}^{PITR}	0.0396	0.0240	0.0150
	(0.0562)	(0.0273)	(0.0433)
$\sum \lambda^{PITR}$	−0.0210	0.0019	−0.0208
	(0.0823)	(0.0403)	(0.0612)
λ_0^{Y}	0.2011*	0.0559	0.1381*
	(0.0707)	(0.0343)	(0.0561)
λ_{-1}^{Y}	0.0534	0.0377	0.0189
	(0.0415)	(0.0199)	(0.0324)
$\sum \lambda^{Y}$	0.2545*	0.0936	0.1570*
	(0.0865)	(0.0422)	(0.0669)
R^2	0.99	0.99	0.94
obs	219	219	219
ρ	−0.2822	−0.2539	−0.3683

Notes: Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term and seasonal dummies as described in the text. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are monthly EITC and PITR payments, and Y is a measure of pre-tax monthly labor income. All variables are differenced and divided by lagged Y for estimation purposes.

Table 2: FGLS Estimation of (12) using monthly SA retail trade

	Component of Retail Trade		
parameter	Total Retail	Nondurables	Durables
λ_0^{EITC}	0.2295	0.0639	0.1660
	(0.1634)	(0.0534)	(0.1428)
λ_{-1}^{EITC}	0.1855	0.0795	0.1031
	(0.1760)	(0.0576)	(0.1538)
$\sum \lambda^{EITC}$	0.4150	0.1434	0.2691
	(0.2650)	(0.0883)	(0.2305)
λ_0^{PITR}	0.0855	0.0571*	0.0260
	(0.0733)	(0.0241)	(0.0640)
λ_{-1}^{PITR}	0.0041	0.0120	-0.0065
	(0.0737)	(0.0242)	(0.0643)
$\sum \lambda^{PITR}$	0.0895	0.0691	0.0195
	(0.1149)	(0.0384)	(0.1000)
λ_0^{Y}	0.0771	0.0255	0.0490
	(0.0478)	(0.0159)	(0.0418)
λ_{-1}^{Y}	0.0278	-0.0001	0.0283
	(0.0478)	(0.0157)	(0.0418)
$\sum \lambda^{Y}$	0.1049	0.0254	0.0773
	(0.0699)	(0.0236)	(0.0607)
R^2	0.12	0.09	0.13
obs	219	219	219
ρ	-0.3323	-0.2682	-0.3461

Notes: Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are monthly EITC and PITR payments, and Y is disposable personal income less EITC and PITR payments. All variables are differenced and divided by lagged disposable personal income for estimation purposes.

Table 3: FGLS Estimation of (12) using monthly SA NIPA data

	Component of PCE			
parameter	Total PCE	Nondurables	Durables	Services
λ_0^{EITC}	0.3459*	0.0802	0.1610	0.1050
	(0.1432)	(0.0561)	(0.1070)	(0.0584)
λ_{-1}^{EITC}	0.2334	0.0364	0.0701	0.1230*
	(0.1455)	(0.0568)	(0.1083)	(0.0594)
$\sum \lambda^{EITC}$	0.5793*	0.1165	0.2312	0.2280*
	(0.2252)	(0.0898)	(0.1690)	(0.0909)
λ_0^{PITR}	0.1781*	0.0639*	0.0604	0.0501
	(0.0663)	(0.0261)	(0.0495)	(0.0271)
λ_{-1}^{PITR}	−0.0106	−0.0013	−0.0152	0.0104
	(0.0665)	(0.0261)	(0.0498)	(0.0274)
$\sum \lambda^{PITR}$	0.1675	0.0626	0.0452	0.0605
	(0.1026)	(0.0410)	(0.0772)	(0.0414)
λ_0^{Y}	0.1394*	0.0455*	0.0339	0.0584*
	(0.0434)	(0.0171)	(0.0324)	(0.0177)
λ_{-1}^{Y}	0.0191	−0.0071	0.0170	0.0101
	(0.0434)	(0.0170)	(0.0324)	(0.0178)
$\sum \lambda^{Y}$	0.1585*	0.0384	0.0508	0.0685*
	(0.0625)	(0.0252)	(0.0470)	(0.0252)
R^2	0.18	0.12	0.14	0.20
obs	221	221	221	221
ρ	−0.3713	−0.3080	−0.3518	−0.4046

Notes: Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are monthly EITC and PITR payments, and Y is disposable personal income less EITC and PITR payments. All variables are differenced and divided by lagged disposable personal income for estimation purposes.

Table 4: FGLS Estimation of (11) using quarterly NSA retail trade

	Component of Retail Trade		
parameter	Total Retail	Nondurables	Durables
λ_0^{EITC}	0.7479*	0.4344*	0.3273*
	(0.2026)	(0.1035)	(0.1603)
λ_0^{PITR}	0.0542	0.0280	0.0176
	(0.0872)	(0.0425)	(0.0676)
λ_0^{Y}	0.6627*	0.2536*	0.3757*
	(0.1469)	(0.0804)	(0.1175)
R^2	0.99	0.99	0.94
obs	72	72	72
ρ	-0.2496	-0.0286	-0.1706

Notes: Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term and seasonal dummies as described in the text. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are quarterly EITC and PITR payments, and Y is a measure of pre-tax quarterly labor income. All variables are differenced and divided by lagged Y for estimation purposes.

Table 5: FGLS Estimation of (11) using quarterly NSA NIPA data

	Component of PCE			
parameter	Total PCE	Nondurables	Durables	Services
λ_0^{EITC}	1.0568*	0.5506*	0.5010*	0.0518
	(0.1883)	(0.0923)	(0.1175)	(0.1107)
λ_0^{PITR}	0.4184*	0.1849*	0.2289*	-0.0136
	(0.0833)	(0.0436)	(0.0528)	(0.0513)
λ_0^{Y}	0.3940*	0.1321*	0.1324*	0.1147*
	(0.0476)	(0.0278)	(0.0310)	(0.0323)
R^2	0.99	0.99	0.97	0.72
obs	72	72	72	72
ρ	-0.2182	0.0754	-0.1275	-0.0302

Notes: Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term and seasonal dummies as described in the text. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are quarterly EITC and PITR payments, and Y is GDP less EITC and PITR payments. All variables are differenced and divided by lagged GDP for estimation purposes.

Table 6: FGLS Estimation of (12) using quarterly SA retail trade

	Component of Retail Trade		
parameter	Total Retail	Nondurables	Durables
λ_0^{EITC}	0.9710	0.2357	0.7915
	(0.8323)	(0.2692)	(0.6882)
λ_0^{PITR}	0.1829	0.1035	0.0575
	(0.2047)	(0.0670)	(0.1682)
λ_0^{Y}	0.1302	0.0650*	0.0483
	(0.0715)	(0.0285)	(0.0585)
R^2	0.07	0.14	0.04
obs	72	72	72
ρ	−0.1323	0.2111	−0.1283

Notes: Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are quarterly EITC and PITR payments, and Y is disposable personal income less EITC and PITR payments. All variables are differenced and divided by lagged disposable personal income for estimation purposes.

Table 7: FGLS Estimation of (12) using quarterly SA NIPA data

	Component of PCE			
parameter	Total PCE	Nondurables	Durables	Services
λ_0^{EITC}	0.9620	0.2874	0.3081	0.4384
	(0.6771)	(0.2592)	(0.5235)	(0.2492)
λ_0^{PITR}	0.0671	0.1050	0.0034	−0.0451
	(0.1689)	(0.0638)	(0.1267)	(0.0624)
λ_0^{Y}	0.2412*	0.0876*	0.0432	0.1008*
	(0.0702)	(0.0273)	(0.0455)	(0.0276)
R^2	0.18	0.19	0.02	0.25
obs	73	73	73	73
ρ	0.0285	0.2020	−0.1200	0.2010

Notes: Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are quarterly EITC and PITR payments, and Y is disposable personal income less EITC and PITR payments. All variables are differenced and divided by lagged disposable personal income for estimation purposes.

Table 8: Choosing instrument sets with IV-FGLS estimation of (11) using monthly NSA total retail trade

parameter	Total Retail					
λ_0^{EITC}	0.6540*	0.6352*	0.5455	0.7737*	0.6086*	0.5997*
	(0.1672)	(0.1704)	(0.3243)	(0.2113)	(0.2106)	(0.1798)
λ_{-1}^{EITC}	0.1025	0.1261	0.1522	0.0121	0.1328	0.0748
	(0.1631)	(0.1861)	(0.1772)	(0.1875)	(0.1921)	(0.1711)
$\sum \lambda^{EITC}$	0.7565*	0.7613*	0.6977*	0.7859*	0.7414*	0.6745*
	(0.2115)	(0.2280)	(0.3304)	(0.2559)	(0.2478)	(0.2220)
λ_0^{PITR}	0.0464	0.0512	−0.0035	−0.1300	0.0503	0.0594
	(0.0702)	(0.0721)	(0.0844)	(0.1176)	(0.1289)	(0.0844)
λ_{-1}^{PITR}	0.0456	0.0223	0.0434	0.0666	0.0668	0.0507
	(0.0593)	(0.0701)	(0.0626)	(0.0649)	(0.0637)	(0.0668)
$\sum \lambda^{PITR}$	0.0920	0.0735	0.0399	−0.0634	0.1170	0.1101
	(0.0911)	(0.0976)	(0.1098)	(0.1404)	(0.1377)	(0.1010)
λ_0^{Y}	0.2099	0.2196	−0.0993	0.6165	0.3428	0.4890*
	(0.1391)	(0.1400)	(0.2223)	(0.3190)	(0.4101)	(0.2249)
λ_{-1}^{Y}	0.0693	0.0210	0.0414	0.0713	0.0744	0.0847
	(0.0434)	(0.0508)	(0.0498)	(0.0476)	(0.0476)	(0.0450)
$\sum \lambda^{Y}$	0.2793	0.2406	−0.0579	0.6878*	0.4173	0.5737*
	(0.1504)	(0.1529)	(0.2405)	(0.3357)	(0.4254)	(0.2371)
Inst. set	1	2	3	4	5	6
F-stat, $EITC$	31.36	24.75	5.89	58.94	70.43	57.46
F-stat, $PITR$	56.61	38.79	60.02	67.55	76.77	70.31
F-stat, Y	96.85	98.34	159.17	229.30	272.70	158.54
obs	207	207	213	207	207	207
parameters	27	27	27	27	27	27
instruments	92	86	56	38	32	56
ρ	−0.3498	−0.2895	−0.3063	−0.2722	−0.3224	−0.3533

Notes: Dependent variable is total retail trade, NSA. Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term and seasonal dummies as described in the text. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are monthly EITC and PITR payments, and Y is a measure of pre-tax monthly labor income. All variables are differenced and divided by lagged Y for estimation purposes. All right-hand side variables except the seasonal dummies are instrumented. Selected F-statistics test all coefficients equal to zero in the first stages.

Instrument sets:

1: seasonals, lags 1–12 of consumption, all income, real interest rates and stock returns.

2: seasonals, lags 2–12 of consumption, all income, real interest rates and stock returns.

3: seasonals, lags 1–6 of consumption, all income, real interest rates and stock returns.

4: seasonals, lags 1, 6, 12 of consumption, all income, real interest rates and stock returns.

5: seasonals, lags 1, 6, 12 of consumption and all income.

6: seasonals, lags 1–12 of all income variables.

Table 9: IV-FGLS Estimation of (11) using monthly NSA total retail trade

parameter	Total Retail	Nondurables	Durables
λ_0^{EITC}	0.6540*	0.4512*	0.1888
	(0.1672)	(0.0836)	(0.1265)
λ_{-1}^{EITC}	0.1025	−0.0245	0.1175
	(0.1631)	(0.0808)	(0.1241)
$\sum \lambda^{EITC}$	0.7565*	0.4268*	0.3063
	(0.2115)	(0.1058)	(0.1567)
λ_0^{PITR}	0.0464	0.0032	0.0492
	(0.0702)	(0.0352)	(0.0530)
λ_{-1}^{PITR}	0.0456	0.0277	0.0132
	(0.0593)	(0.0292)	(0.0447)
$\sum \lambda^{PITR}$	0.0920	0.0309	0.0624
	(0.0911)	(0.0456)	(0.0674)
λ_0^{Y}	0.2099	0.1753*	0.1089
	(0.1391)	(0.0716)	(0.1055)
λ_{-1}^{Y}	0.0693	0.0454*	0.0324
	(0.0434)	(0.0213)	(0.0335)
$\sum \lambda^{Y}$	0.2793	0.2207*	0.1413
	(0.1504)	(0.0767)	(0.1127)
Inst. set	1	1	1
obs	207	207	207
ρ	−0.3498	−0.3358	−0.4070

Notes: Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term and seasonal dummies as described in the text. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are monthly EITC and PITR payments, and Y is a measure of pre-tax monthly labor income. All variables are differenced and divided by lagged Y for estimation purposes. All right-hand side variables except the seasonal dummies are instrumented. Selected F-statistics test all coefficients equal to zero in the first stages.
Instrument set:
1: seasonals, lags 1–12 of consumption, all income, real interest rates and stock returns.

Table 10: IV-FGLS Estimation of (12) using monthly SA data

parameter	Total Retail	PCE
λ_0^{EITC}	0.1830	0.2871
	(0.1869)	(0.1644)
λ_{-1}^{EITC}	0.1799	0.2124
	(0.1753)	(0.1467)
$\sum \lambda^{EITC}$	0.3628	0.4995*
	(0.2835)	(0.2420)
λ_0^{PITR}	0.1381	0.1970*
	(0.1058)	(0.0957)
λ_{-1}^{PITR}	0.0238	0.0029
	(0.0768)	(0.0699)
$\sum \lambda^{PITR}$	0.1619	0.1999
	(0.1443)	(0.1293)
λ_0^{Y}	0.1046	0.1364*
	(0.0779)	(0.0682)
λ_{-1}^{Y}	0.0286	0.0095
	(0.0482)	(0.0440)
$\sum \lambda^{Y}$	0.1332	0.1459
	(0.0952)	(0.0823)
Inst. set	7	7
obs	207	209
ρ	-0.3558	-0.3978

Notes: Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are monthly EITC and PITR payments, and Y is disposable personal income less EITC and PITR payments. All variables are differenced and divided by lagged disposable personal income for estimation purposes. All right-hand side variables are instrumented.

Instrument set:

7: lags 1–12 of consumption, all income variables, real interest rates, and real stock returns.

Table 11: IV-FGLS Estimation of (11) and (12) using quarterly data

	NSA		SA	
parameter	Total Retail	PCE	Total Retail	PCE
λ_0^{EITC}	0.8750*	1.0229*	0.9364	1.0202
	(0.2312)	(0.1990)	(1.0133)	(0.8051)
λ_0^{PITR}	0.0424	0.4921*	−0.0936	−0.1067
	(0.1043)	(0.1266)	(0.2751)	(0.2123)
λ_0^{Y}	0.6930*	0.4543*	0.0252	0.2264
	(0.2325)	(0.0891)	(0.1458)	(0.1441)
Y	a	b	c	c
Inst. set	8	8	9	9
obs	67	67	67	68
ρ	−0.2276	−0.1298	−0.1777	−0.0452

Notes: Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are monthly EITC and PITR payments. All variables are differenced and divided by lagged income for estimation purposes. All right-hand side variables, excluding seasonal dummies when applicable, are instrumented.
Income variable: Y is either (a) labor income, (b) GDP less EITC and PITR, or (c) disposable personal income less EITC and PITR.
Instrument sets:
8: seasonals, lags 1–4 of consumption, all income, real interest rates and stock returns.
9: lags 1–4 of consumption, all income variables, real interest rates, and real stock returns.

Table 12: IV-FGLS Estimation of (11) using quarterly NSA NIPA data

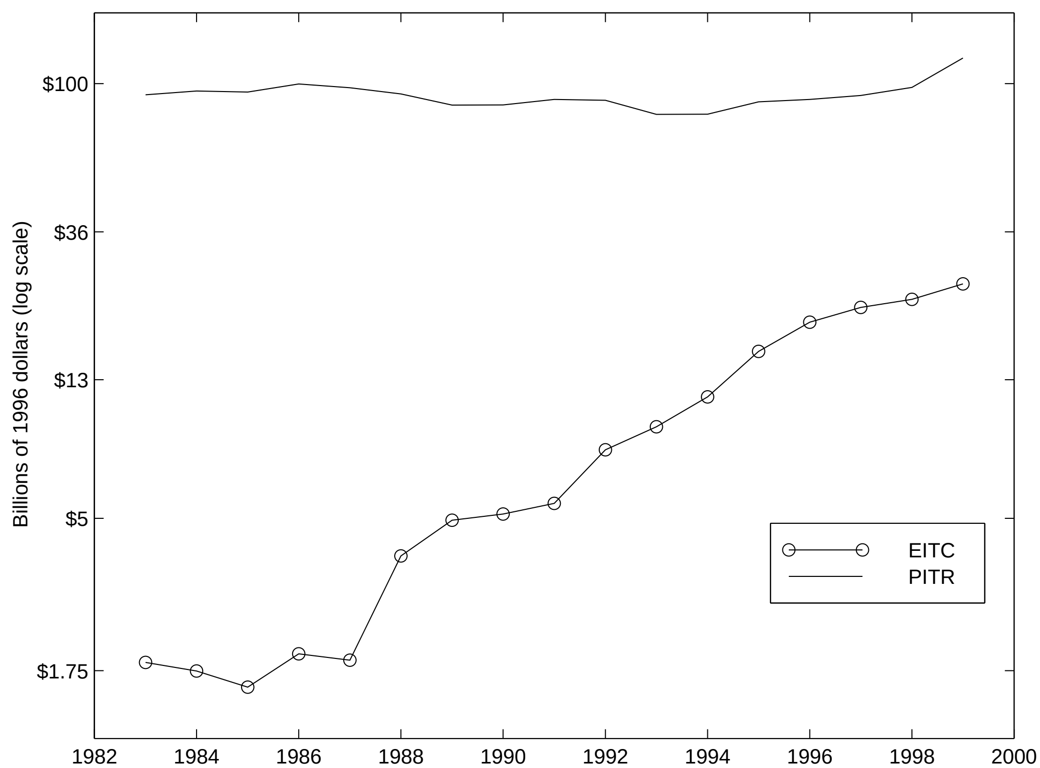
parameter	Total PCE	Nondurables	Durables	Services
λ_0^{EITC}	1.0229*	0.5166*	0.5063*	0.0664
	(0.1990)	(0.1037)	(0.1308)	(0.1181)
λ_0^{PITR}	0.4921*	0.3435*	0.1593	0.0053
	(0.1266)	(0.0706)	(0.0902)	(0.0799)
λ_0^{Y}	0.4543*	0.2563*	0.0783	0.1358*
	(0.0891)	(0.0512)	(0.0631)	(0.0584)
Inst. set	8	8	8	8
obs	67	67	67	67
ρ	-0.1298	0.0192	-0.0887	0.0512

Notes: Standard errors are in parentheses. Asterisks denote significance at the 5% level. All regressions include a constant term and seasonal dummies as described in the text. The coefficients (λ's) are marginal propensities to consume; $EITC$ and $PITR$ are monthly EITC and PITR payments, and Y is GDP less EITC and PITR payments. All variables are differenced and divided by lagged income for estimation purposes. All right-hand side variables are instrumented.

Instrument set:

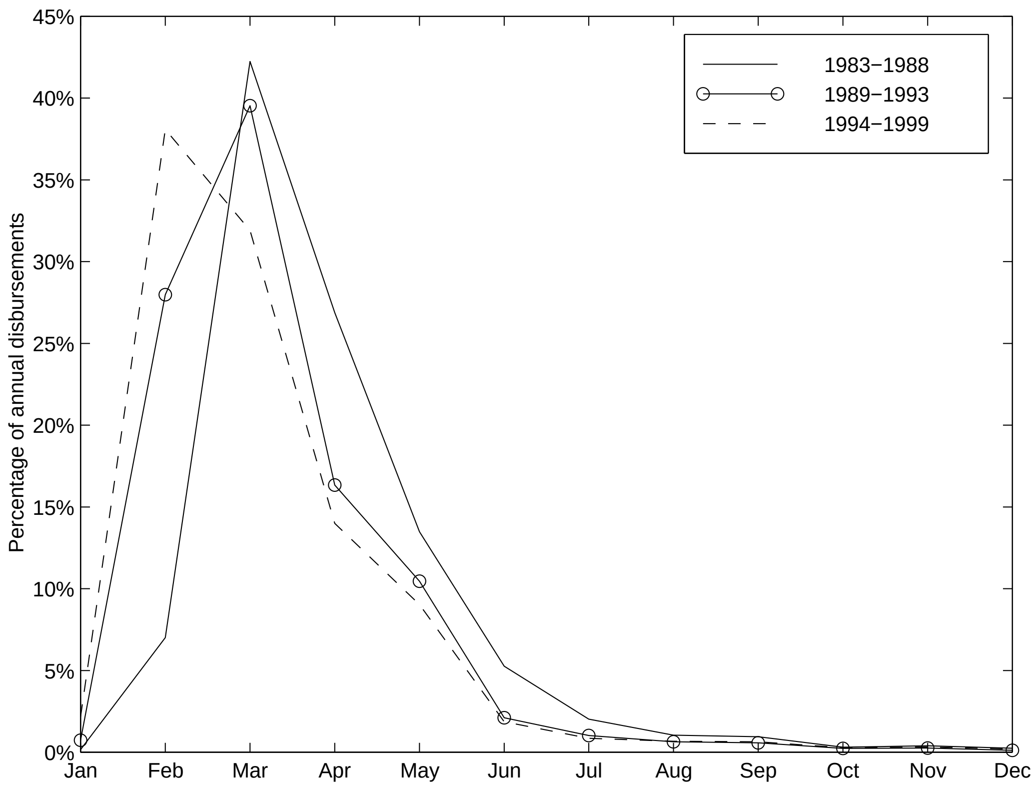
8: seasonals, lags 1–4 of consumption, all income, real interest rates and stock returns.

Figure 1: Real annual levels of the EITC and PITR's



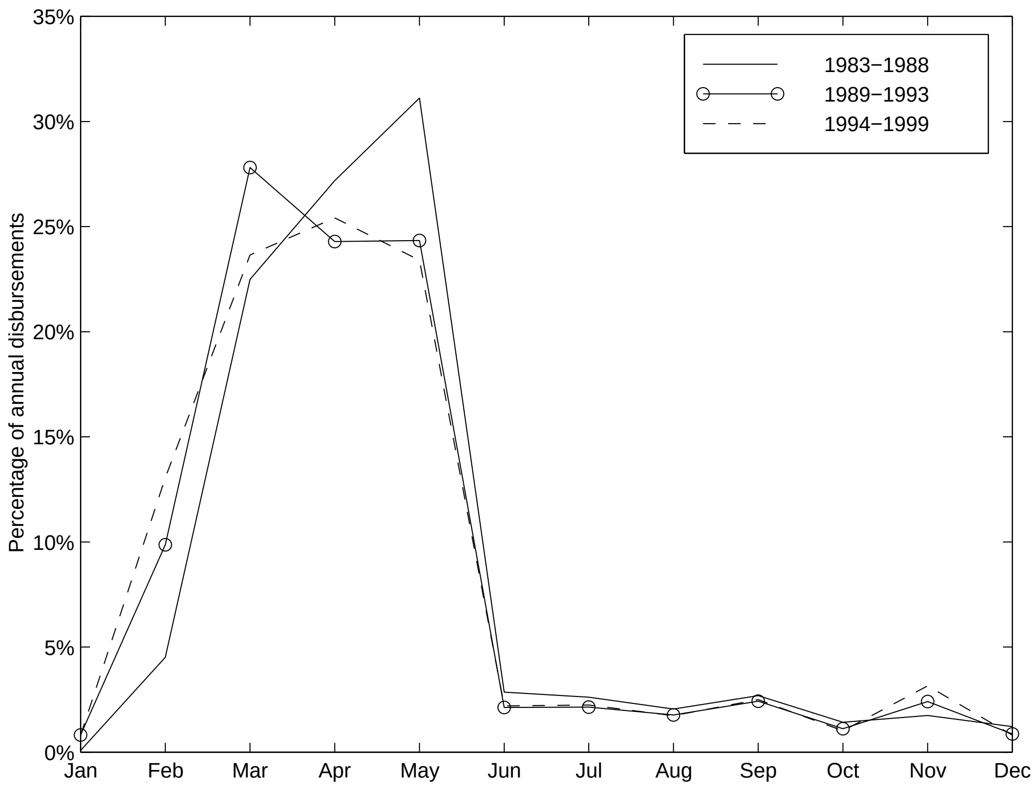
Notes: Data are annual totals of Earned Income Tax Credit disbursements and personal income tax refunds, both deflated to 1996 levels using the chain-type price index for personal consumption expenditures. Sources: Monthly Treasury Statement, Bureau of Economic Analysis.

Figure 2: The monthly pattern of EITC payouts over time



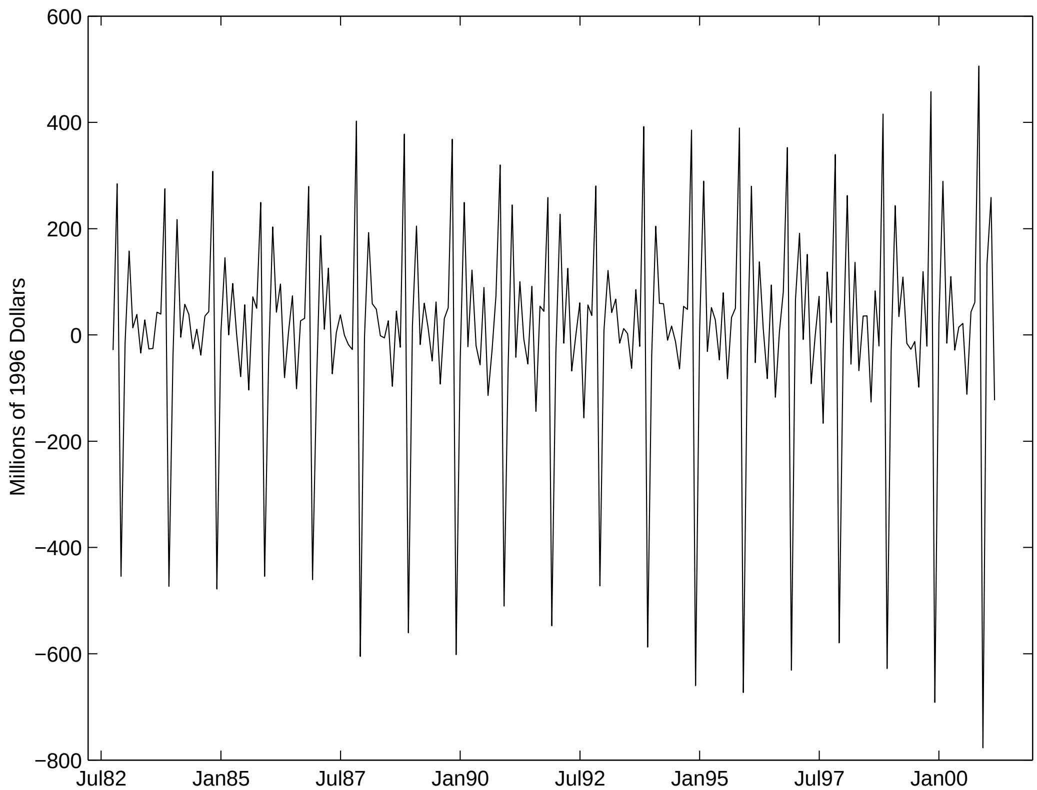
Notes: Data are monthly rates of Earned Income Tax Credit payouts, defined as the monthly total divided by the annual total. Multiple years of data are averaged to create each line as described in the legend. Source: Monthly Treasury Statement.

Figure 3: The monthly pattern of PITR payouts over time



Notes: Data are monthly rates of personal income tax refund payouts, defined as the monthly total divided by the annual total. Multiple years of data are averaged to create each line as described in the legend. Source: Monthly Treasury Statement.

Figure 4: First differences in real total retail trade



Notes: Data are monthly total retail trade, NSA, from the Census Bureau, divided by the monthly chain-type price index for PCE from the Bureau of Economic Analysis.