

# Tax Refund Expectations and Financial Behavior

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## Abstract

Many economic models predict that consumption decisions today depend on beliefs about risky future income. We quantify one contributor to income uncertainty and study its effects: uncertainty about annual tax refunds. In a low-income sample for whom tax refunds can be a substantial portion of income, we collect novel survey evidence on tax filers' expectations of and uncertainty about their tax refunds; we then link these data with administrative tax data, a panel of credit reports, and survey-based consumption measures. We find that while many tax filers have correct mean expectations about their refunds, there is substantial, and accurately reported, subjective uncertainty. Tax filers borrow moderate amounts out of expected tax refunds: for each dollar of expected refund, roughly 15 cents in revolving debt is repaid after refund receipt. This borrowing and repayment is less pronounced for more uncertain filers, consistent with precautionary behavior. The unexpected component of tax refunds is not used to pay down debt, but rather induces higher debt levels. Credit report and survey evidence both suggest that these higher debt levels are driven by newly financed durable purchases such as vehicles, illustrating how unexpected income can induce propensities to consume above 1 by relaxing down-payment collateral constraints.

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# 1 Introduction

Income uncertainty is thought to play a central role in household finances. While pre-tax income volatility is often emphasized as a source of this uncertainty, households may also have substantial uncertainty about their income tax. Tax-linked transfer payments, including payments from the Earned Income Tax Credit (EITC), comprise a substantial portion of annual income for many low income individuals.<sup>1</sup> Quantifying and understanding uncertainty about income taxes is therefore critical for understanding the role of transfer payments through the tax system in household finances, the potential consequences of changes to the tax system, and the effects of income uncertainty on consumption and financial decisions more broadly.

In this paper, we study what low- and moderate-income individuals do and do not know about their income tax refunds before they file taxes. We then examine how financial behavior responds to expectations of future tax refunds, refund uncertainty, and surprises in realized tax refund amounts. We do so using a unique combination of (1) administrative tax records, (2) a linked panel of consumer credit reports, and surveys to measure both (3) expectations of tax refunds before tax filing and (4) consumption behavior after tax refund receipt. One key innovation in our setting is our direct measurement of taxpayers’ beliefs about the probability distribution over their own future tax refund amounts. These expectations data allow us to study the amount of, and the effects of, income tax uncertainty on consumption without making strong assumptions about the sources of taxpayers’ uncertainty or how informed individuals are about the income tax schedule.

We start by showing that taxpayers have correct mean expectations about their refund on average, but that taxpayers also face substantial uncertainty about their tax refund. This self-reported uncertainty accurately tracks “true” uncertainty, as measured by the difference (“surprise”) between realized and mean expected tax refund amounts. We examine sources of refund uncertainty. Surprises are driven by changes in income and family structure in ways that are consistent with individuals misunderstanding how marginal tax rates change at different parts of the earned-income tax credit schedule. Nevertheless, we also find that much of this uncertainty is not explained by observables or by changes in household circumstances.

We then show that consumption and borrowing behavior depends on expectations about tax refund amounts, refund uncertainty, and refund surprises. Individuals borrow a moderate amount out of their expected tax refunds: for each dollar of expected refund, individuals

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<sup>1</sup>For instance, in our sample the mean refund is nearly seven percent of annual income (roughly one month of earnings), and nationally, a typical EITC recipient sees an average refund equal to 12% of income (Jones (2012)). Total individual refunds on federal income taxes now total around \$125 billion annually (<https://www.irs.gov/newsroom/tax-refunds-reach-almost-125-billion-mark-irsgov-available-for-tax-help>).

repay roughly 15 cents in debt shortly after tax refund receipt. Individuals also exhibit precautionary behavior in borrowing out of future tax refunds, as these borrowing and repayment patterns out of expected tax refunds are less pronounced for individuals that report being more uncertain about their refunds *ex-ante*. To our knowledge, this is some of the first evidence of precautionary behavior (prudence) among a low-income population in the US – that is, consumption out of future income is restrained when the future income is more uncertain. This finding contrasts with prior work which has interpreted the combination of high income volatility and low savings rates as evidence against the existence of precautionary behavior among low-income individuals (Carroll et al., 2003).

Finally, we examine the link between tax refund surprises and consumption behavior. We find that positive refund surprises are not used to repay debt, consistent with high marginal propensities to consume (MPCs) out of windfall income. In fact, we find that larger refund surprises lead to increases in overall debt, and that this debt increase is entirely driven by higher balances on installment loans such as auto loans. This pattern implies a medium-run marginal propensity to consume (MPC) out of windfall income above one, suggesting that positive refund surprises may be used to relax collateral constraints for newly financed durable purchases. We find suggestive evidence from a follow-up survey on durable consumption choices to corroborate this interpretation.

There are two primary advantages to our empirical approach. First, we obtain rich data on household balance sheets before and after the resolution of tax-related income uncertainty: administrative data on all reported income and nearly all financial liabilities, as well as survey-based measures of real and financial assets. Such data are particularly difficult to assemble for lower-income populations. Second, we directly elicit individuals’ uncertainty about the component of future income risk driven by tax refund uncertainty. This stands in contrast to much of the existing literature that looks for evidence of precautionary behavior in response to uncertainty; we know of one notable exception (Jappelli and Pistaferri, 2000).

One caveat to our approach is that we, like many researchers who use U.S.-based data, have relatively poor data on individuals’ real and financial assets. All of our asset measures are survey-based, whereas we have administrative data on income and debt liabilities. This limitation may be less consequential in our setting, however, as the low-income population in the United States has elsewhere been shown to hold low levels of financial and real assets (Campbell (2006)), a finding that we corroborate in our survey measures. A second important caveat is that, while we analyze differences in financial behavior within groups that are at similar stages in the life-cycle (age, income, and family structure), there nevertheless may be important unobservable differences across individuals within these groups – for example, in unobservable labor income risk – that we cannot control for and that are correlated with

tax-relevant uncertainty.

**Related Literature** This paper contributes to at least three distinct literatures. First, we contribute to a large empirical literature in macroeconomics on consumption, savings, and borrowing decisions. This work studies how individuals respond to income uncertainty ex-ante, and how individuals react to income surprises ex-post. A robust theoretical literature predicts that individuals will save precautionarily – maintaining a “buffer stock” – in the presence of future income uncertainty (Kimball, 1990; Deaton, 1991; Carroll, 1996, 1997), and calibration exercises suggest that the role of precautionary motives in saving over the life-cycle is substantial (Carroll and Samwick, 1998; Gourinchas and Parker, 2001; Parker and Preston, 2005). However, other empirical work has found limited evidence for precautionary behavior (Dynan, 1993; Aguiar and Hurst, 2013), especially among low-income individuals (Carroll et al., 2003); this latter result emerges from the facts that low-income individuals have low observed savings rates despite facing substantial labor income uncertainty. Much of the empirical work testing for precautionary motives uses labor income uncertainty implied by income processes imputed using observables such as age and occupation (Skinner, 1988; Dynan, 1993; Carroll and Samwick, 1998). One notable exception uses self-reported uncertainty measured through a survey, as we do (Jappelli and Pistaferri, 2000). We believe we are the first paper to link such survey-based measures of uncertainty to administrative data on income and borrowing, and one of the first to find evidence of precautionary behavior (prudence) among a low-income population in the US.<sup>2</sup>

Another vein of empirical macroeconomics research studies how consumers respond to windfall income surprises. Most closely related to our study of tax refund surprises is a set of papers analyzing responses to tax rebates (Johnson et al., 2006; Agarwal et al., 2007; Parker et al., 2013; Broda and Parker, 2014; Baugh et al., 2018). These papers find, as we do, high marginal propensities to consume (MPCs) out of such windfall income. Of particular note is Parker et al. (2013), which finds that up to 60 percent of tax rebate payments are used to purchase durables, and especially vehicles, within 3 months of rebate receipt.<sup>3</sup> These findings are consistent with our result that positive refund surprises are used to finance durable purchases, especially new car purchases and home repairs. We differ from most of

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<sup>2</sup>While it is beyond the scope of our paper to explore this further, one explanation for how low-income individuals can have low savings rates despite having precautionary motives and high labor income uncertainty is the implicit tax on savings imposed by means-testing in some social insurance programs (Hubbard et al. (1995)). Another intriguing explanation is that access to unsecured credit has replaced savings as a preferred buffer to draw down after future shocks (Fulford (2015)).

<sup>3</sup>Aaronson et al. (2012) also find that auto purchases rise after a positive income shock. Consistent with such durable purchases being in part debt-financed, Cookson et al. (2018) find that positive income shocks lead to an increase in debt for some constrained consumers.

this literature by focusing on windfall income associated with annual tax refunds, rather than tax rebates. Our approach is similar to that in Souleles (1999), who also examined the MPC out of annual tax refunds, but did not distinguish between anticipated and unanticipated income.

Second, we contribute to a growing literature on the limits of taxpayers’ understanding of the tax code and on the consequences of tax complexity for individuals and firms. Several recent papers have shown that individuals and firms fail to take full advantage of the credits and refunds for which they are eligible. Part of this is likely due to hassle costs: individuals may rationally choose not to invest the time or money required to optimize their tax benefits (Benzarti, 2017). Among low-income EITC filers, like those in our sample, part of this failure to optimize may be due to lack of information about the tax system (Aghion et al., 2017; Chetty et al., 2013; Zwick, 2018). Prior research has shown that many individuals are unaware of EITC program rules and that lack of information has real consequences for earnings behavior (Chetty and Saez, 2013; Chetty et al., 2013; Romich and Weisner, 2000; Smeeding et al., 2000). More broadly, taxpayers may misunderstand the difference between marginal and average tax rates (Rees-Jones and Taubinsky (2018); Ballard et al. (2017); Fujii and Hawley (1988)), and may be inattentive to how much tax has been withheld from their pay over the year (Jones (2012)). We contribute to this literature by directly quantifying the amount of uncertainty faced by our population of low-income taxpayers, and by linking this uncertainty to actual consumption decisions.

Third, we contribute to a diverse literature on the measurement and reliability of subjective expectations data (Manski, 2004; Dominitz and Manski, 2011). Following the pioneering work of Engelberg et al. (2009), we elicit not just point forecasts or mean expectations, but individuals’ subjective probability distributions over future events. These methods have previously shown success in measuring inflation expectations (Armantier et al., 2016), income expectations among college students (Zafar, 2011), and income expectations in a developing country (Delavande et al., 2011). Elicited expectations have been shown to affect financial behavior in lab settings (Wiswall and Zafar, 2014). Our results are also related to work by Delavande and Rohwedder (2011), who used data from the Health and Retirement Survey to show that uncertainty about Social Security benefits predicted portfolio choice. Our contribution is to link probabilistic income expectations with a panel of administrative data to study how financial behavior responds to such expectations in a “real world” (non-lab) setting, and to demonstrate success of these survey questions even in a low-income, relatively low-education U.S. population.

The rest of the paper proceeds as follows. The next section describes the empirical setting and data. Section 3 describes how we translate our survey measures of beliefs into proba-

bilistic distributions and compares these distributions to actual refund amounts. Section 4 shows how refund expectations, uncertainty, and surprises translate into consumption and borrowing decisions. Section 5 concludes.

## 2 Data and Empirical Setting

In this section we describe our data and empirical setting. We first provide institutional background on the setting, a clinic that provides free income tax preparation services in Boston. We then describe our administrative (tax and credit) and survey (expectations, assets, and consumption) data sources. We conclude by describing the characteristics of our sample.

### 2.1 Boston Tax Sites

Our data come from a Volunteer Income Tax Assistance (VITA) tax preparation center overseen by the Boston Tax Help Coalition (BTHC) and the Boston Office for Financial Empowerment (OFE). The BTHC and OFE support over thirty free tax preparation centers, which annually serve more than 13,000 clients. Our data come from one of the largest of these centers, Dorchester House.

Boston residents are eligible to receive these free tax preparation services if they worked in the prior year, earned less than \$54,000, and do not own their own business. Eligible individuals who come to the tax site (“clients”) typically go through three separate stations. First, they complete an intake survey, which includes questions on demographics, use of city services, savings behavior, and credit usage. Next, clients are offered a free “financial check-up” from a trained volunteer referred to as a “financial guide.” The financial guides offer the client a free credit report and provide information on other city services for which the individual may be eligible. Finally, the client is sent to a tax preparer who electronically prepares and submits the individual’s tax return.

We partnered with the Boston OFE to field a survey of clients’ expectations about their tax refund (detailed in Section 2.3) at the second of these three stations, together with the financial guide. This survey was completed before clients filed taxes, so it measures clients’ pre-filing uncertainty about their tax refund. At this stage, clients also provided consent for their tax, credit, and survey information to be used for research purposes. Figure 1 describes the sequence of data collection steps at Dorchester House.

Two operational features of the financial check-up stage deserve mention. First, because of financial guide shortages and constrained tax site operating hours, many taxpayers skipped

the financial check-up during busy periods. As a result, we obtained consent from only sixty percent of taxpayers. However, among clients who completed the financial counseling session our consent rate was ninety-six percent. Therefore, we do not believe that taxpayer consent was a major source of selection into our research sample.

Second, the OFE implemented a separate randomized controlled trial as part of the financial check-up wherein clients were randomly assigned to a more or less detailed check-up. Those assigned the more detailed check-up were given an in-depth explanation of their credit report, as well as financial advice and referrals to a variety of services provided by the City of Boston and state and federal agencies. Those assigned to the less detailed check-up also received their credit report, but no detailed financial advice or referrals. In our analysis of consumption responses in Section 4, we control for treatment status at the financial check-up stage.<sup>4</sup>

## 2.2 Administrative Tax and Credit Data

We use administrative tax return data for consenting clients who filed their taxes at Dorchester House.<sup>5</sup> These data include information on income, family structure (filing status and number of dependents), and refund amount. For individuals who previously used the BTHC's and OFE's tax preparation services, we are able to link these returns to those from earlier years. We have two years of returns for 59 percent of the taxpayers in our core sample.

We merge these administrative tax records with a short panel of consumer credit reports for clients who provided consent during the financial check-up. We have four reports for each individual in our sample: one that was pulled when they visited the tax site, and three that were pulled one, two, and six months later. The one and two month credit reports measure changes in debt levels soon after tax filing. For clients who receive their refund by direct deposit, both the first and second-month follow-up credit reports show loan balances after tax refund receipt; for clients who receive their tax refund by paper check, the first of these two credit reports likely show balances from prior to refund receipt. The six month report allows us to observe longer-run delevering and new loan originations (e.g. auto loans) that may not have been reported in time for the one and two month follow-ups.

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<sup>4</sup>An OFE analysis of the randomized controlled trial finds balance across treatment assignment on a range of taxpayer characteristics. The report can be accessed at [https://owd.boston.gov/wp-content/uploads/2017/07/DES-89-Financial-Check-up-Evaluation-2017-Web.pdf?utm\\_source=Office+of+Workforce+Development&utm\\_campaign=699487e955-EMAIL\\_CAMPAIGN\\_2017\\_07\\_24&utm\\_medium=email&utm\\_term=0\\_f071f9ca69-699487e955-226050949](https://owd.boston.gov/wp-content/uploads/2017/07/DES-89-Financial-Check-up-Evaluation-2017-Web.pdf?utm_source=Office+of+Workforce+Development&utm_campaign=699487e955-EMAIL_CAMPAIGN_2017_07_24&utm_medium=email&utm_term=0_f071f9ca69-699487e955-226050949)

<sup>5</sup>Given data access constraints, all data are accessed on-site with the OFE. In particular, no data points or statistics representing fewer than 10 tax returns are provided to researchers outside the OFE.

## 2.3 Expectations and Consumption Surveys

We supplement these administrative data sets with three distinct surveys. These surveys provide information on taxpayer demographics and assets, refund expectations, and consumption before and after refund receipt. Our first source of survey data is the demographics and assets survey that individuals completed when they arrived at Dorchester House. From this survey we obtain information on a client’s gender and level of education (high school degree or some college), and on a client’s savings behavior.<sup>6</sup> The response rate for this survey was high: of the 1,186 individuals who filed taxes at Dorchester House during the spring 2016 season, 995 completed the survey. A copy of the survey is available upon request from the authors.

We obtain information on taxpayers’ expectations and uncertainty about their refunds from a short four-question survey. Taxpayers completed this survey after they had been paired with a financial guide, but before they filed their taxes and learned their actual refund amount. We elicited beliefs in two ways. First, we directly asked each taxpayer how much they expected their refund to be, and their qualitative certainty that the refund would fall within \$500 of this amount. Second, we provided individuals with a set of six bins, and asked them the probability that their refund would fall within each bin. A copy of the survey is provided in Appendix B.1. We discuss how we translate the answers to these questions into probabilistic beliefs in Section 3.

Finally, we merge these expectations with data from a follow-up survey designed to measure saving and consumption behavior before and after refund receipt. While we obtain substantial information on consumption from the panel of credit reports – for example, the presence of new auto loans or pay-down of debt – these reports do not contain information on durable purchases or on the timing of purchases relative to refund receipt. They also contain no information on savings. The follow-up survey is designed to help provide data on these questions. The response rate to our follow-up survey was forty-six percent (286 out of 623 taxpayers in our sample), which is arguably high compared to some similar phone-based surveys.<sup>7</sup> The consent language and questions are provided in Appendix B.2.

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<sup>6</sup>Savings data are elicited using the question, “If you have bank account(s), how much money do you regularly keep in it (them) all together?” Respondents chose either \$0, \$1 - \$100, \$101 - \$500, \$501 - \$1,000, or More than \$1,000. Responses were encoded by mapping intervals to their midpoints, while More than \$1,000 was mapped to \$1,500. Thirty-nine percent of respondents reported either \$0 or \$1 - \$100, while 23% reported more than \$1,000.

<sup>7</sup>For example, Allcott and Kessler (2018) obtain an 18 percent response rate to a phone survey of energy usage.



## 2.4 Descriptive Statistics

Tables 1 and A1 present descriptive statistics from our sample of low-income Boston taxpayers. Table 1 presents statistics for our main analysis samples, which exclude a number of outlier observations who reported extreme levels of tax refund uncertainty or income realizations;<sup>8</sup> Table A1 repeats these analyses while including the outlier observations. Turning first to Table 1, Column 1 shows the 530 consenting taxpayers who completed the tax refund expectations survey and filed their taxes at Dorchester House during the spring 2016 tax season. Most taxpayers are unmarried, while 25 percent file as a single head of household and 30 percent have dependents (including married taxpayers). Eighty-three percent of taxpayers have at least a high school degree, but only 17 percent have attended college. The average age is forty-one years old. The average adjusted gross income (AGI) in this sample is \$21,038, and the mean refund size is \$1,428. Thirty-five percent of taxpayers receive the Earned Income Tax Credit (EITC). The taxpayers for whom we obtained credit and savings information have low savings rates and high debt levels. Average savings is less than one third of the average refund amount, and less than 5 percent of average non-mortgage debt. The mean FICO score for those with credit reports is 666, below the 2016 U.S. average of 700 (Dornhelm, 2017).

Column 2 of Table 1 presents the sample we refer to as our “core sample”; this sample further restricts the column (1) sample to include only individuals with available credit report data. Statistics for the core sample and the previous column are highly similar: the only statistically significant differences are the share with at least a high school degree (83% vs. 84%), average adjusted gross income (\$21,038 vs. \$21,822), and average age (39.9 years vs. 40.2 years). These similarities are consistent with the attrition from column (1) to (2) being largely idiosyncratic, with the vast majority of missing credit report data being the result of financial guide staff shortages rather than the result of active selection out of the sample.<sup>9</sup>

The remaining columns of Table 1 restrict the core sample to the subsets for which we additionally have asset and consumption survey responses, consumption proxies measured in credit report data, consumption measures elicited the follow-up survey two months after tax filing, and tax return data from the prior year (2015).

The economic and demographic statistics in the table remain largely stable across these

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<sup>8</sup>Specifically, these observations are individuals with subjective uncertainty (as measured by standard deviation of reported probabilistic expectations) in the top or bottom 5% of expectations survey respondents, and tax refund surprises in the top or bottom 1%, as well as individuals with adjusted gross incomes below 0. Appendix Figure A1 presents visual evidence comparing the the core and outlier samples.

<sup>9</sup>As discussed in subsection 2.1, 96% of clients who completed the financial coaching session with a financial guide consented for their credit report data to be used for this research.

additional columns, suggesting that attrition across surveys or data sources is largely unrelated to tax status or demographic characteristics that could bias our results. Column 3 restricts to the 429 taxpayers in the core sample who completed the asset survey, with almost no change in mean characteristics. Column 4 restricts to the smaller sample of 361 filers for whom consumption proxies could be measured in credit report data, and column 5 restricts to the smaller sample of 235 taxpayers who responded to the follow-up consumption survey. Although the column 4 sample has modestly higher adjusted gross income and debt, other demographics between this sample and the core sample are broadly comparable, and similarities are even stronger between the column 5 sample and the core sample. Despite a 46 percent response rate, individuals that responded to the follow-up consumption survey in column 5 are nearly identical in terms of their average characteristics to individuals in the core sample in column 2. Finally, column 6 restricts to taxpayers in the core sample who filed their taxes with a Boston Tax Help Coalition tax site in the previous year (2015). This subsample again has modestly higher adjusted gross income and debt than the core sample but remains broadly similar to the core sample in terms of the economic and demographic variables in the table.

Table 1 additionally shows that refund amounts are large relative to income, savings, and debt levels. The mean refund of \$1,446 in the core sample is nearly seven percent of the average individual’s adjusted gross income and is about triple the average individual’s savings at tax filing.

### 3 Tax Refund Expectations and Realizations

We surveyed Dorchester House taxpayers to elicit their beliefs about the tax refund they would receive after filing. Since consumption responses to refund amounts may depend on both the expected refund amount and the uncertainty about that amount, we used probabilistic survey questions to elicit both aspects of filers’ beliefs. This section describes the belief survey, explains how we converted survey responses to smooth belief distributions, and compares taxpayer beliefs about refunds to both realized refunds and surprises. Although taxpayers reported substantial uncertainty about their refunds, their mean expectations were, on average, correct. In addition, filers reporting greater uncertainty saw larger refund surprises. These facts suggest that most taxpayers had an accurate sense of the refund amount they could expect to receive and the uncertainty they faced. However, when we restrict the sample to filers whose income or family status changed in the past year we see (mean) inaccurate expectations, suggesting that taxpayers are imperfectly aware of how after-credit tax rates change as they move to different parts of the income tax schedule.

### 3.1 Belief Elicitation Survey

The survey was administered at the beginning of the financial counseling session at Dorchester House, which took place prior to the tax preparation session. We view this as the ideal time to survey program participants on their refund expectations: taxpayers had not yet received any information about their refunds. However, taxpayers had collected their tax documents, come to the tax site, and filled out a detailed economic and demographic survey for use during the tax preparation session.

The final question in this survey elicited probabilistic refund expectations. Respondents were asked the percent chance that their refund would fall in each of six bins: negative (they would have to pay taxes), \$0-\$500, \$500-\$1,000, \$1,000-\$2,500, \$2,500-\$5,000, over \$5,000. We asked for points in a probability mass function rather than moments such as the mean and standard deviation because subjective probabilities are easier to understand and calculate. In addition, probabilistic survey questions can provide richer information about beliefs. We would have ideally constructed bins around each filer’s point estimate to obtain comparable uncertainty measures across individuals. The need to conduct the survey quickly made this approach too difficult to implement, so we used fixed intervals. Nevertheless, we show in the next section that the fitted distributions accurately capture both expected refund amounts and uncertainty.

Appendix Table A2 describes features of the elicited belief distributions. The first column presents statistics for all taxpayers in our main analysis sample, and the remaining columns disaggregate those statistics into subgroups. Forty percent of respondents put nonzero probability on three or more bins, while sixty percent did so on only one or two bins.

### 3.2 Fitting Belief Distributions

To summarize beliefs and to quantify both mean expectations and uncertainty, we convert each probabilistic elicitation into a smooth probability distribution following Engelberg et al. (2009) (hereafter EMW). Our goal is to use all information available in respondents’ subjective probabilities and to smooth between points of the cumulative density function in a reasonable way. We fit a distribution which depends on the number of bins on which the respondent placed positive probability. Single bin reports are fit with a scalene triangle; the support is the full bin, and the mode is the point estimate. In this case, we depart from EMW by using additional information from the respondent’s point estimate, fitting a scalene triangle rather than an isosceles triangle. Meanwhile, two-bin reports are fit with an isosceles triangle with the widest possible support that is consistent with the probabilities for each bin. These sets of assumptions uniquely pin down a distribution for one- and

two-bin responses. For three or more bins, we follow EMW in fitting a beta distribution to the reported quantiles. Triangle and beta distributions are appropriate for our setting because they have finite support, and because beta distributions can match a wide range of distributional shapes that might be implied by probabilistic survey questions.<sup>10</sup> The maximum refund amount was a little below \$20,000, and the lowest refund amount was approximately -\$500 (the taxpayer had \$500 due). We take these two values as the endpoints of the support of the highest (over \$5,000) and lowest (negative) bins.

The triangle distributions are exactly identified and fit using analytical formulas. To fit the beta distributions, we follow EMW and minimize the sum of squared differences between the reported cumulative probabilities at each point in the distribution’s support and those of a beta distribution with the same support. Let  $\mathcal{X}$  denote the support points of the response to the probabilistic survey question. Let  $Z$  denote a beta-distributed random variable governed by parameters  $(\alpha, \beta)$  and normalized to have support on  $\mathcal{X}$ . Finally, let  $p_x$  denote the reported cumulative probability at each point  $x \in \mathcal{X}$ . We find the  $(\hat{\alpha}_i, \hat{\beta}_i)$  for the elicited distribution from each individual  $i$  which solves

$$\min_{\alpha, \beta} \sum_{x \in \mathcal{X}_i} [p_{x,i} - P(Z \leq x \mid \alpha, \beta)]^2$$

The fitted distributions reveal large variation in the expected refund amounts and in uncertainty across taxpayers. Appendix Table A2 shows that the average mean expectation is \$1,686, and the average standard deviation is \$611. The average coefficient of variation is 0.51 – so refund uncertainty is, on average, large relative to the expected amount. These averages mask an enormous amount of variation across taxpayers in their refund expectations. The standard deviation across taxpayers of their mean expectations is \$2,291, and the standard deviation of subjective uncertainty (where uncertainty is measured using the standard deviation of each taxpayer’s fitted distribution) is \$714.

It is illustrative to compare self-reported measures of qualitative and quantitative uncertainty as a validity check on these survey responses. Table 2 summarizes the coefficients of variation of respondents’ belief distributions depending on whether they were “very sure,” “somewhat sure,” or “not sure at all” about whether their refund would be within \$500 of their point estimate. The most uncertain individuals have much larger coefficients of variation. Two-sample t-tests of equal means strongly reject equal quantitative uncertainty for any two qualitative responses. The next subsection provides additional evidence that the quantitative measures of uncertainty meaningfully capture taxpayers’ subjective beliefs.

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<sup>10</sup>We also depart from EMW by not constraining the estimated beta densities to be single-peaked.

### 3.3 Beliefs and Realizations

Our unique institutional setting allows us to compare applicants’ refund expectations to what they actually received. This comparison shows not only that applicants have correct mean expectations, but also that they understand the degree of uncertainty they face, at least on average.

Figure 2 compares mean expectations from survey responses to actual refund amounts. Mean expectations closely track realized amounts. The slope of the regression line is close to one, though beliefs are slightly attenuated: those with the most extreme realizations had slightly less extreme expectations. The strongly linear relationship between expected and actual refund amounts does not imply that taxpayers faced little uncertainty, or that any individual had unbiased beliefs. Rather, it shows that beliefs tracked realized refund amounts on average, suggesting that the probabilistic survey question does contain meaningful quantitative information.

Figure 3 performs a similar exercise for the degree of self-reported uncertainty. It compares the magnitude of each taxpayer’s refund “surprise” – the difference between the realized and expected refund amounts – to the fitted standard deviation of their belief distribution. There is a clear linear relationship between subjective uncertainty and realized absolute errors.<sup>11</sup> Thus, taxpayers face substantial refund uncertainty, and they seem to be aware of the degree of uncertainty that they face. The next section investigates the determinants of refund uncertainty and shows that some but not all of the variation in refund uncertainty across individuals can be explained by observed characteristics.

### 3.4 Predictors of Refund Uncertainty and Surprises

In this section we investigate the predictors of refund uncertainty and the magnitude and direction of refund surprises. We find that current income and family structure are highly predictive of refund uncertainty, while demographic variables such as age, gender, and education are less predictive. Filers whose income or family structure changed from previous years are somewhat more uncertain, though not significantly so. Furthermore, the characteristics that predict greater uncertainty are associated with larger surprises, suggesting that these relationships reflect real differences in uncertainty across taxpayers. Even after controlling for demographic characteristics and changes in tax situation, there is substantial variation in both uncertainty and surprises.

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<sup>11</sup>Note that the slope of the line should not necessarily be one – a standard deviation is the square root of the expected squared error, not the expected absolute error – and the conditional expectation function need not be linear.

To analyze determinants of subjective refund uncertainty, we first regress three of measures of refund uncertainty on a range of economic and demographic characteristics. Our specifications take the form

$$y_i = X_i\beta + \epsilon_i \quad (1)$$

where  $y_i$  is a measure of uncertainty, and  $X_i$  includes sociodemographic variables capturing age, education, and gender; demographic variables including marital status and number of dependents; and dummy variables for each quartile of adjusted gross income (AGI). Results from a series of these regressions are shown in Table 3. Columns 1-3 use the standard deviation of the taxpayer’s parametric belief distribution as the measure of uncertainty,  $y_i$ ; columns 4-6 use the absolute value of the refund surprise (refund amount - mean expectation); and columns 7-9 use the value of the refund surprise.

Column 1 shows that the number of dependents and income quartile are quite predictive of refund uncertainty, as measured by the standard deviation of beliefs. Taxpayers in the third income quartile report greater uncertainty, as do taxpayers with more dependents. These differences are large: for example, an additional dependent is associated with \$333 more in refund uncertainty (as measured by the standard deviation of an individual’s fitted belief distribution), and filers in the third AGI quartile report \$327 greater uncertainty than filers in the first quartile. In contrast, the demographic variables capturing age, education, and gender are less predictive of uncertainty. These patterns are consistent with a model in which cognitive ability and cumulative experience with the tax system are less important determinants of refund uncertainty than are current economic characteristics that directly determine tax liabilities.

Columns 2 and 3 add several variables related to changes in financial and family status: whether the filer received unemployment insurance payments in the past year; whether their filing status changed, e.g. from single to married; the (absolute or level) change in their AGI; and the (absolute or level) change in the number of dependents. The sample size in these columns is lower, reflecting the fact that we only observe these changes for filers who filed at a Boston tax site in previous years. Column 2 controls for indicators for, and magnitudes of, these year-to-year changes, while column 3 replaces absolute changes with level (signed) changes.

Our results in these two columns provide mixed evidence on whether changes in financial and family status contribute to refund uncertainty. In column 2, the magnitude of change in AGI is positively related to uncertainty but not statistically significant. There is no significant correlation between uncertainty and either the absolute or level change in number of dependents. These results however are noisy enough to be consistent with taxpayer

uncertainty being partially driven by changes in financial or family situations, which may result from how after-credit tax rates depend directly on family size and structure as well as income. In both columns 2 and 3, the coefficient estimates on third quartile of AGI and number of dependents remain statistically significant and of similar magnitudes as seen previously in column 1.

A natural question is whether the taxpayers who reported greater uncertainty actually saw higher variance in their refund surprises. Columns 4-6 of Table 3 repeat the regressions in columns 1-3 with the absolute value of the taxpayer’s refund surprise as the dependent variable. Most variables which significantly predict refund uncertainty in columns 1-3 significantly predict absolute errors in the corresponding specification in columns 4-6, with the same sign and similar magnitudes. Number of dependents and income quartile remain the main predictors of refund surprise magnitudes, while demographic variables are less predictive. However, changes in a household’s financial or family situation are stronger predictors of refund surprises than of subjective uncertainty. Column 5 shows that taxpayers with larger AGI changes saw larger surprises (a surprise of \$18 for each \$1,000 change in AGI), as did filers with changes in number of dependents (surprises higher by \$1,050). In addition, surprise size is predicted by the direction of these changes. Taxpayers with increases in the number of dependents actually saw smaller surprise magnitudes. Taken together, these results suggest that individuals of different household types may recognize the greater uncertainty they face as a result of changing characteristics, but they may not fully update their subjective uncertainty based on changes in income and family structure.

Finally, columns 7-9 of Table 3 regress the surprise amount, rather than the magnitude, on the same sets of predictors to investigate whether individuals in certain types of households systematically over- or under-estimate the size of their tax refunds beliefs. Consistent with the finding in section 3.3 that expected refund amounts track realizations, most of the coefficient estimates on current taxpayer characteristics are statistically insignificant. In particular current AGI, which was predictive of refund uncertainty and surprise magnitudes, does not systematically predict the direction of mistakes. Though the coefficient on the second income quartiles are marginally statistically significant in column 7, it becomes less significant after controlling for the change covariates.

There are two demographic variables which significantly predicts bias: married taxpayers systematically overestimate their refund amounts by more than \$1,000 relative to unmarried filers, and taxpayers with dependents underestimate their refund amount by about \$700 on average relative to taxpayers without dependents. Additionally, we find in columns 8 and 9 that changes in financial status are predictive of under- or over-estimates: filers whose AGI rose had lower surprises, by 2.3 cents per dollar of change in AGI. This is consistent

with taxpayers underestimating the slope of their refund with respect to characteristics: for example, the EITC claw-back rate as incomes rise.

The above discussion yields several takeaways regarding tax refund expectations. First, the relationship between uncertainty and variables directly relevant to a individual’s tax liability, but not sociodemographic variables, suggests that uncertainty about how financial characteristics map to tax liabilities is common across a range of households with varied levels of sophistication and experience. Second, the types of households who report greater uncertainty also see larger refund surprises. Third, current taxpayer characteristics do not predict the direction of mistakes, with the exception of marital status and the presence of dependents; however, taxpayers do not fully update about how changes in income and family structure affect their tax liabilities. A final observation is that even this broad set of taxpayer attributes fails to explain all of the variation in uncertainty. The R-squared in column 3 – the highest across all specifications – is 0.327 leaving substantial unexplained variation.

## 4 Borrowing and Consumption Responses to Tax Refunds

In this section we study how individuals’ borrowing and consumption behavior around the time of tax filing responds to their expectations about, and actual realizations of, their tax refunds. In our sample of low-income taxpayers, we find that roughly 15 cents per dollar of expected tax refund is used to repay revolving debt after tax refund receipt. In contrast, the unexpected (“surprise”) component of tax refunds has a near-zero effect on revolving debt repayment. These results are consistent with individuals borrowing out of their expected tax refunds to smooth consumption over the course of the year, while also having a high propensity to consume out of windfall income in the form of tax refund surprises. Furthermore, we find that individuals exhibit precautionary behavior in their willingness to borrow out of expected tax refunds, as post-refund revolving debt repayment is significantly more pronounced for individuals who report being less uncertain of their refund amount ex-ante.

Further exploring the effects of tax refund surprises, we find that surprises have a significantly positive effect on installment debt balances: unexpectedly high refunds lead to higher installment debt levels. This result is consistent with tax refunds partly being used to fund downpayments for newly financed durable purchases, such as new autos purchased partly on credit. We use our follow-up survey of consumption behavior to corroborate this possible mechanism, finding that individuals with higher tax refund surprises indeed more



frequently report that they bought a new car or initiated home repairs after tax filing. Summing the effects of refund surprises across both installment balances and revolving balances, we estimate that an additional dollar of refund surprise leads to an additional 35 cents of debt. While noisy, this estimate is significantly greater than zero and suggests a mechanism whereby medium-run MPCs can lie above 1 when windfall income is used to relax collateral constraints for new borrowing.

Finally, we test whether ex-ante uncertainty about tax refunds affects individuals' propensity to consume out of tax refund surprises. If individuals behave precautionarily and if the consumption function is concave in cash on hand, as predicted under a broad set of conditions (Zeldes, 1989; Carroll and Kimball, 1996), then individuals with more ex-ante uncertainty should have lower propensities to consume out of tax refund surprises. Our results are consistent with this prediction in sign, but underpowered, and we fail to reject the null that MPCs out of surprises are the same for different levels of ex-ante uncertainty.

## 4.1 Revolving Debt Repayment

We begin by examining financial behavior around tax filing by studying revolving debt balances.<sup>12</sup> These loans are sensible to examine first, as their balances are most readily adjustable over a short time horizon; we defer until Section 4.2 a discussion of less easily adjustable installment debt.<sup>13</sup>

Using the linked panel of credit report data, we calculate the change in each taxpayer's revolving debt balance between the credit report drawn just prior to tax filing and credit reports at subsequent two-month and six-month horizons. These provide short- and medium-run measures of responses to tax refunds. We then regress these two-month and six-month changes on three features of taxpayers' beliefs and realizations of tax refunds: (1) their expectation of their tax refund amount, (2) their uncertainty about their tax refund amount as measured by the standard deviation of their elicited subjective probability distribution over refund amounts, and (3) the surprise in their realized tax refund relative to their expected refund. Debt changes are signed so that a negative change is a decrease in debt levels.<sup>14</sup> Refund surprise is defined as realized tax refund minus expected tax refund; thus, a positive

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<sup>12</sup>Revolving debt includes all loans with a flexible repayment schedule and an open line of credit that can be used flexibly over time and over purchases, including credit cards, retail store cards, and home equity lines of credit (HELOCs).

<sup>13</sup>Installment debt includes all loans with a fixed repayment schedule. These loans are often used to fund one-time purchases, including car loans, student loans, and mortgages.

<sup>14</sup>For sake of computing these changes, individuals who open or close accounts between the baseline and the follow-up horizon have those accounts included as zeros when they are closed; for example, an individual with no credit card at baseline and a credit card balance of \$500 six months later has a balance change of \$500. Individuals with no open accounts at either horizon are not included in the relevant regressions.

surprise is “good news” for the taxpayer. We estimate regressions of the form

$$\Delta b_i = \alpha + \beta_1 \mu_i + \beta_2 \text{surprise}_i + \beta_3 \sigma_i + \gamma Z_i + \eta_i \quad (2)$$

where  $i$  indexes a taxpayer;  $\Delta b_i$  denotes change in balances;  $\mu_i$  is  $i$ ’s mean expected refund;  $\sigma_i$  is their subjective standard deviation; and  $\text{surprise}_i$  is their refund surprise. The vector  $Z_i$  controls for a range of interacted taxpayer characteristics because household debt paths may differ at different stages of the lifecycle: we include fully interacted fixed effects for age group, income quartile, marital status, and whether an individual has dependents.<sup>15</sup> These interaction terms aim to absorb differences in leveraging or delevering over time that are due to differences between, for example, a young unmarried parent in the middle of our sample’s income distribution, and a married elder at the bottom of our sample’s income distribution. All residual variation is within a set of individuals who have similar lifecycle circumstances.<sup>16</sup> We also add controls for whether an individual received their refund by direct deposit or by paper check, and for an individual’s treatment status in the randomized trial being conducted simultaneously at the tax site as discussed in Section 2.1. Additionally, in order to avoid results being driven by outliers in the dependent variable, changes in balances are top and bottom-coded at the 95th and 5th percentiles of their distribution respectively.<sup>17</sup>

Table 4 reports estimates from specifications without and with lifecycle controls at a two-month horizon (columns 1 and 2) and a six-month horizon (columns 3 and 4). Column 1 indicates that for every dollar of expected tax refund, our sample repays roughly 14 cents in revolving balances after refund receipt. While these estimates become slightly attenuated with the inclusion of lifecycle controls at the two-month horizon (column 2), we again see an estimate of roughly 13-14 cents with and without lifecycle controls at the six-month horizon, which is significantly different from zero in the uncontrolled specification. These results quantify how revolving lines of credit are used to transfer a moderate share of expected tax refunds forward in time to fund earlier consumption.

Turning to the second row of the table, we see that surprises in tax refunds are *not* used to repay revolving debt. After including lifecycle controls (columns 2 and 4), we can reject more than 12 cents of refund surprise being put toward revolving debt repayment at a two-month horizon, and 22 cents at a six-month horizon. This suggests that individuals

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<sup>15</sup>We group individuals into three age bins based on whether they are younger than 25, between 26 and 50, or over 50.

<sup>16</sup>The most notable omission from these lifecycle controls is arguably the variability of individuals’ labor income. In future work, additional data cleaning of individuals’ self-reported industry and/or occupation, together with our data on age, income level, and history of unemployment insurance receipt, will make it possible to impute a measure of labor income uncertainty using data such as the Panel Study of Income Dynamics (PSID) or Current Population Survey (CPS) for long-run or short-run income risk, respectively.

<sup>17</sup>Throughout this section, results are qualitatively robust but less precise when instead top- and bottom-coding at the 99th and 1st percentiles.

have a marginal propensity to consume (MPC) of close to one out of windfall income such as surprises in tax refunds.<sup>18</sup> This is consistent with existing evidence of high MPCs from windfall income among low-income consumers (Jappelli and Pistaferri, 2014). We further explore such propensities to consume in Section 4.2.

In the final row of the table we test for the presence of precautionary behavior in borrowing out of tax refunds. If taxpayers are less certain of their tax refund amount ex-ante, they may borrow less of their expected refund before filing. We find that revolving balances are repaid less after refund receipt for more uncertain taxpayers; for every dollar of standard deviation in a taxpayer’s subjective beliefs about their tax refund amount ex-ante, we estimate 28 to 35 cents less is used to repay debt ex-post. This pattern is consistent with uncertain taxpayers precautionarily taking on less debt prior to filing their taxes. The estimated relationship between uncertainty and debt changes remains stable across both horizons and with the inclusion of lifecycle controls, although standard errors become larger at the six-month horizon. In dollar terms (results not shown), we estimate that having above-median refund uncertainty predicts roughly \$336 less repaid toward revolving debt after refund receipt.

## 4.2 Installment Debt Repayment and Durable Consumption

We now turn our attention from revolving debt balances, such as credit card borrowing, to non-mortgage installment debt such as auto loans, retail loans, and student loans. We conduct the same analyses as in table 4 for installment debt instead of revolving debt, again estimating equation 2 with and without taxpayer controls at two-month and six-month horizons. We present these results in table 5.

We find that higher (more positive) tax refund surprises lead to relative *increases* in installment debt. The effect of surprises on installment debt is near zero at a two-month horizon, but at a six-month horizon each additional dollar of tax refund surprise leads to an additional 68 cent increase in installment debt.<sup>19</sup> This estimated effect remains stable as lifecycle controls are added in column 4. We reject a zero effect on installment debt changes in columns 3 and 4 with 99% and 95% confidence, respectively.

Other coefficient estimates for installment debt are noisier than for revolving debt. While we estimate that a smaller share of expected refunds is used for installment debt repayment than for revolving debt repayment, the estimates are not significantly different from zero or

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<sup>18</sup>Note that a coefficient of -1 on refund surprise would indicate an MPC of zero; taxpayers would then be spending their entire refund surprise to pay down debt rather than changing consumption.

<sup>19</sup>More than half of new auto loans originated during the tax season are not reported to the credit bureau within 2 months of the loan opening date. Hence, the fact that this effect appears after 6 months and not after 2 months is more reflective of delays in credit reporting than delays in individuals’ origination of new auto loans after tax refund receipt.

from the revolving debt estimates at reasonable confidence levels.<sup>20</sup> Similarly, the effect of uncertainty on borrowing behavior for installment debt cannot be distinguished from zero or from the estimated effects for revolving debt.

The result that positive refund surprises lead to rising installment balances is intriguing. We corroborate this relationship visually in figure 4, using a binned scatter plot to show conditional means of the dependent variable across bins of refund surprise after partialling out the controls in column 4 of table 5. The visual evidence strongly confirms the relationship between refund surprises and changes in installment debt. Across large and small, positive and negative surprises, an approximately linear relationship holds between surprises and installment debt changes, confirming that this pattern is not driven by non-linearity or outliers.

Given that installment debt is less adjustable over short horizons than revolving debt – it has a fixed repayment schedule, and taking out additional debt typically must coincide with a new purchase – this result suggests that positive tax refund surprises may be used to fund downpayments on newly financed durable purchases. Conversely, a negative tax refund surprise may make an anticipated durable purchase no longer possible due to collateral constraints. This mechanism is illustrative of a case where medium-run MPCs out of windfall income can in fact be above 1, when such income is used to relax collateral constraints for new durable financing.

To investigate the durable purchases explanation, table 7 examines the relationship between tax refund surprises and self-reported new car purchases or newly initiated home repairs in the follow-up durable consumption survey we conducted approximately two months after tax filing. See Section 2 for a survey description. This table follows a similar format to tables 4 and 5, although all four columns correspond to a 2-month follow-up horizon. Columns 1 and 2 use a binary outcome for whether a respondent reported any new car purchase or home repair at all, while columns 3 and 4 use the respondent’s reported dollar value of their new purchase or repair. While the coefficient estimates on refund surprise are only marginally significant, they are consistent with the interpretation that higher refund surprises lead to a greater likelihood of or dollar value of new durable purchases after refund receipt ( $p = .116$  for the null of no effect of a refund surprise in column 4;  $p = 0.239$  for the null of no effect of a refund surprise in column 2).

Finally, we pool both revolving and installment debt balances together and estimate the effects of tax refund expectations, uncertainty, and surprises on overall non-mortgage debt

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<sup>20</sup>Greater rates of borrowing out of tax refunds through installment rather than revolving debt would be consistent with optimal consumption smoothing behavior when installment debt interest rates are lower than revolving debt interest rates (and when installment borrowing is sufficiently fungible to substitute for revolving debt).

balances. We estimate the same specifications as in tables 4 and 5, but with the total change in installment and revolving debt balances as the dependent variable.<sup>21</sup> Estimates for these specifications are shown in table 6. A moderate amount of each dollar of expected refund is used to repay debt shortly after refund receipt, suggesting that individuals use both revolving and installment debt to smooth consumption by borrowing out of refunds ex-ante. We also find evidence that individuals behave precautionarily in borrowing out of tax refunds, as this borrowing is less pronounced for individuals with more uncertainty ex-ante. However, unlike in our specification using only revolving debt, these differences are not statistically significant. Finally, we again find that more positive refund surprises lead to significantly higher total debt at a six-month horizon. Our preferred estimate when including lifecycle controls in column 4 is an additional 38 cents of total debt for each additional dollar of refund surprise. The modest amount of delevering on revolving debt does not overwhelm the larger, positive effect on installment debt balances. On net, positive surprises appear to lead to higher indebtedness in the medium term.

### 4.3 Further Tests of Precautionary Behavior

In this final subsection, we study the relationship between ex-ante uncertainty about tax refunds and individuals' later consumption out of tax refund surprises. This provides a further test of precautionary behavior. Here, we test a central prediction of the buffer stock consumption-savings model: the consumption function should be concave in cash on hand (Carroll and Kimball, 1996; Zeldes, 1989).

The logic of our test is that conditional on other characteristics, refund uncertainty is an instrument for initial debt levels. Suppose two taxpayers have identical characteristics, mean refund expectations, and refund surprises, but have different levels of refund uncertainty at filing. With a precautionary savings motive, the filer with greater uncertainty should enter tax season with lower debt or higher assets to maintain a buffer against lower-than-expected tax refund realizations. Since the two filers are identical after refund uncertainty is realized, they should have the same consumption function, but the measured MPC<sup>22</sup> will be evaluated at different wealth levels. As a result, we should estimate a negative interaction between refund surprise and uncertainty after controlling for mean expectations and mean taxpayer characteristics. We implement this test by adding an interaction between refund surprise

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<sup>21</sup>Individuals are included in this regression sample if they ever have either revolving loans or installment loans over our panel horizon, so the sample differs from that in our analyses of revolving debt and installment debt alone.

<sup>22</sup>Precisely, we measure changes in debt balances, and invoke the low levels of saving (in either real or financial assets) in our sample to translate from changes in debt balances to consumption. See also Section 2.

and the subjective standard deviation of ex-ante expectations to equation 2:

$$\Delta b_i = \alpha + \beta_1 \mu_i + \beta_2 \text{surprise}_i + \beta_3 \sigma_i + \beta_4 \text{surprise}_i \times \sigma_i + \gamma Z_i + \eta_i \quad (3)$$

Estimates from these specifications are shown in Table 8. Each pair of columns shows changes in debt at two-month and six-month horizons, and the three pairs of columns respectively show results for revolving debt, non-mortgage installment debt, and both debt categories together. The estimates are noisy, reflecting the fact that uncertainty is measured with error. However, we generally estimate negative signs on the interaction term that are consistent with precautionary behavior having induced lower MPCs. We conclude that this test for precautionary behavior is underpowered in our setting.

## 5 Conclusion

In this paper we used a rich dataset linking administrative tax and credit data to surveys on taxpayer expectations and consumption behavior to shed new insight on low- and moderate-income households' choices to pay down debt, save, and consume. We showed that simple questions about an individual's expected tax refund can be used to generate rich probabilistic distributions that are informative about both mean expectations and uncertainty. We then showed that, in our sample of low-income filers, individuals face substantial uncertainty about the size of their tax refund. This is true despite the fact that annual refunds make up a substantial part of individuals' annual income and is true even for individuals whose tax situation has not changed since they last filed. Finally, we showed that refund expectations and surprises influence household financial decisions after tax filing. Taxpayers use roughly fifteen cents per dollar of expected tax refund to repay revolving debt after tax refund receipt. In contrast, refund surprises are not used to pay down debt, but rather, lead to higher borrowing through installment credit such as auto loans, consistent with MPCs potentially lying above one due to relaxed collateral constraints for financed durables. Post-refund debt repayment is most pronounced for less uncertain individuals, suggesting precautionary behavior.

There are two key limitations to our work. First, because of the small size of our sample, we are unable to generate precise estimates of the impact of uncertainty on consumption decisions. In particular, while our results are in line with buffer-stock consumption theory's predictions about how uncertainty should affect ex-ante borrowing out of expected refunds and ex-post propensities to consume out of surprises, our estimates remain somewhat noisy, especially in our tests for heterogeneous MPCs. Second, because we focus on individuals

who take advantage of the BTHC and OFE’s free tax preparation services, our results may be specific to this population of low-income filers. The fact that these individuals sought out nonprofit services suggests that they may be in a more distressed financial situation than some of their peers, or conversely, their use of free tax preparation services may indicate greater wherewithal in financial planning; both of these circumstances could differentiate our sample from the broader population of low-income taxpayers.

One possible direction for future work would be to study how uncertainty and expectations evolve over time. While we were only able to collect one year of expectations data, it would be interesting to examine whether individuals’ beliefs about their refunds become more precise if they file similar returns for several years. A different possibility would be to consider a broader sample of tax filers, who may have higher incomes or who may not take advantage of free government-provided tax filing services. Finally, given the recent changes to the U.S. tax code, a complementary question is how taxpayers update their beliefs about their tax liabilities when the tax code itself – in addition to their own financial status – has changed.

## References

- Aaronson, Daniel, Sumit Agarwal, and Eric French**, “The spending and debt response to minimum wage hikes,” *American Economic Review*, 2012, *102* (7), 3111–39.
- Agarwal, Sumit, Chunlin Liu, and Nicholas S Souleles**, “The Reaction of Consumer Spending and Debt to Tax Rebates—Evidence from Consumer Credit Data,” *Journal of Political Economy*, 2007, *115* (6), 986–1019.
- Aghion, Philippe, Ufuk Akcigit, Matthieu Lequien, and Stefanie Stantcheva**, “Tax Simplicity and Heterogeneous Learning,” Technical Report, Harvard University 2017.
- Aguiar, Mark and Erik Hurst**, “Deconstructing Life Cycle Expenditure,” *Journal of Political Economy*, Jun 2013, *121* (3), 437–492.
- Allcott, Hunt and Judd B Kessler**, “The Welfare Effects of Nudges: A Case Study of Energy Use Social Comparisons,” *American Economic Journal: Applied Economics*, 2018.
- Armantier, Olivier, Scott Nelson, Giorgio Topa, Wilbert Van der Klaauw, and Basit Zafar**, “The Price Is Right: Updating Inflation Expectations in a Randomized Price Information Experiment,” *Review of Economics and Statistics*, 2016, *98* (3), 503–523.
- Ballard, Charles L, Sanjay Gupta et al.**, “Perceptions and realities of average tax rates in the federal income tax: evidence from Michigan,” Technical Report, Working paper (August) 2017.
- Baugh, Brian, Itzhak Ben-David, Hoonsuk Park, and Jonathan A Parker**, “A Test of Consumption Smoothing and Liquidity Constraints: Spending Responses to Paying Taxes and Receiving Refunds,” Technical Report, Massachusetts Institute of Technology March 2018.
- Benzarti, Youssef**, “How Taxing Is Tax Filing? Using Revealed Preferences to Estimate Compliance Costs,” Technical Report, National Bureau of Economic Research 2017.
- Broda, Christian and Jonathan A Parker**, “The Economic Stimulus Payments of 2008 and the Aggregate Demand for Consumption,” *Journal of Monetary Economics*, 2014, *68*, S20–S36.
- Campbell, John Y**, “Household finance,” *The journal of finance*, 2006, *61* (4), 1553–1604.
- Carroll, Christopher D**, “Buffer Stock Saving: Some Theory,” Technical Report, Johns Hopkins University September 1996.
- , “Buffer-Stock Saving and the Life Cycle/Permanent Income Hypothesis,” *The Quarterly Journal of Economics*, 1997, *112* (1), 1–55.
- **and Andrew A Samwick**, “How Important Is Precautionary Saving?,” *Review of Economics and Statistics*, 1998, *80* (3), 410–419.



- **and Miles S Kimball**, “On the Concavity of the Consumption Function,” *Econometrica*, 1996, pp. 981–992.
- **, Karen E Dynan, and Spencer D Krane**, “Unemployment Risk and Precautionary Wealth: Evidence from Households’ Balance Sheets,” *Review of Economics and Statistics*, 2003, *85* (3), 586–604.
- Chetty, Raj and Emmanuel Saez**, “Teaching the Tax Code: Earnings Responses to an Experiment with EITC Recipients,” *American Economic Journal: Applied Economics*, 2013, *5* (1), 1–31.
- **, John N Friedman, and Emmanuel Saez**, “Using Differences in Knowledge Across Neighborhoods to Uncover the Impacts of the EITC on Earnings,” *American Economic Review*, 2013, *103* (7), 2683–2721.
- Cookson, Anthony, Erik Gilje, and Rawley Heimer**, “Shale Shocked: The Long Run Effect of Non-Labor Income on Consumer Credit,” 2018.
- Deaton, Angus**, “Saving and Liquidity Constraints,” *Econometrica*, 1991, *59* (5), 1221–1248.
- Delavande, Adeline and Susann Rohwedder**, “Individuals’ Uncertainty about Future Social Security Benefits and Portfolio Choice,” *Journal of Applied Econometrics*, 2011, *26* (3), 498–519.
- **, Xavier Giné, and David McKenzie**, “Measuring Subjective Expectations in Developing Countries: A Critical Review and New Evidence,” *Journal of Development Economics*, 2011, *94* (2), 151–163.
- Dominitz, Jeff and Charles F Manski**, “Measuring and Interpreting Expectations of Equity Returns,” *Journal of Applied Econometrics*, 2011, *26* (3), 352–370.
- Dornhelm, Ethan**, “US Average FICO Score Hits 700,” Jul 2017.
- Dynan, Karen E**, “How Prudent are Consumers?,” *Journal of Political Economy*, 1993, *101* (6), 1104–1113.
- Engelberg, Joseph, Charles F Manski, and Jared Williams**, “Comparing the Point Predictions and Subjective Probability Distributions of Professional Forecasters,” *Journal of Business & Economic Statistics*, 2009, *27* (1), 30–41.
- Fujii, Edwin T and Clifford B Hawley**, “On the accuracy of tax perceptions,” *The Review of Economics and Statistics*, 1988, pp. 344–347.
- Fulford, Scott L**, “How important is variability in consumer credit limits?,” *Journal of Monetary Economics*, 2015, *72*, 42–63.
- Gourinchas, Pierre-Olivier and Jonathan A Parker**, “The Empirical Importance of Precautionary Saving,” *American Economic Review*, 2001, *91* (2), 406–412.

- Hubbard, R Glenn, Jonathan Skinner, and Stephen P Zeldes**, “Precautionary Saving and Social Insurance,” *Journal of Political Economy*, 1995, 103 (2), 360–399.
- Jappelli, Tullio and Luigi Pistaferri**, “Using Subjective Income Expectations to Test for Excess Sensitivity of Consumption to Predicted Income Growth,” *European Economic Review*, 2000, 44 (2), 337–358.
- and —, “Fiscal Policy and MPC Heterogeneity,” *American Economic Journal: Macroeconomics*, 2014, 6 (4), 107–36.
- Johnson, David S, Jonathan A Parker, and Nicholas S Souleles**, “Household Expenditure and the Income Tax Rebates of 2001,” *American Economic Review*, 2006, 96 (5), 1589–1610.
- Jones, Damon**, “Inertia and Overwithholding: Explaining the Prevalence of Income Tax Refunds,” *American Economic Journal: Economic Policy*, 2012, 4 (1), 158–85.
- Kimball, Miles S**, “Precautionary Saving in the Small and in the Large,” *Econometrica: Journal of the Econometric Society*, 1990, pp. 53–73.
- Manski, Charles F**, “Measuring Expectations,” *Econometrica*, 2004, 72 (5), 1329–1376.
- Parker, Jonathan A and Bruce Preston**, “Precautionary saving and consumption fluctuations,” *American Economic Review*, 2005, 95 (4), 1119–1143.
- , **Nicholas S Souleles, David S Johnson, and Robert McClelland**, “Consumer Spending and the Economic Stimulus Payments of 2008,” *American Economic Review*, 2013, 103 (6), 2530–53.
- Rees-Jones, Alex and Dmitry Taubinsky**, “Measuring Schmeduling,” 2018.
- Romich, Jennifer L and Thomas Weisner**, “How Families View and Use the EITC: Advance Payment Versus Lump Sum Delivery,” *National Tax Journal*, 2000, pp. 1245–1265.
- Skinner, Jonathan**, “Risky Income, Life Cycle Consumption, and Precautionary Savings,” *Journal of Monetary Economics*, 1988, 22 (2), 237–255.
- Smeeding, Timothy M, Katherin Ross Phillips, and Michael O’Connor**, “The EITC: Expectation, Knowledge, Use, and Economic and Social Mobility,” *National Tax Journal*, 2000, pp. 1187–1209.
- Souleles, Nicholas S**, “The Response of Household Consumption to Income Tax Refunds,” *American Economic Review*, 1999, 89 (4), 947–958.
- Wiswall, Matthew and Basit Zafar**, “Determinants of College Major Choice: Identification Using an Information Experiment,” *The Review of Economic Studies*, 2014, 82 (2), 791–824.

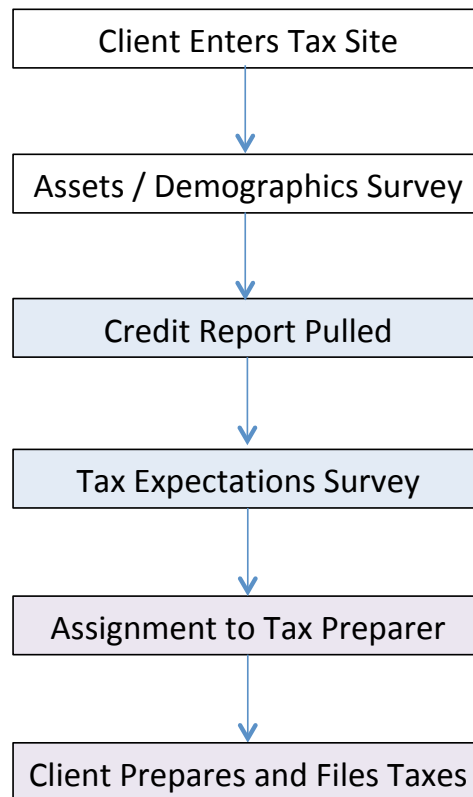
**Zafar, Basit**, “How Do College Students Form Expectations?,” *Journal of Labor Economics*, Apr 2011, *29* (2), 301–348.

**Zeldes, Stephen P**, “Optimal Consumption with Stochastic Income: Deviations from Certainty Equivalence,” *The Quarterly Journal of Economics*, 1989, *104* (2), 275–298.

**Zwick, Eric**, “The Costs of Corporate Tax Complexity,” 2018.

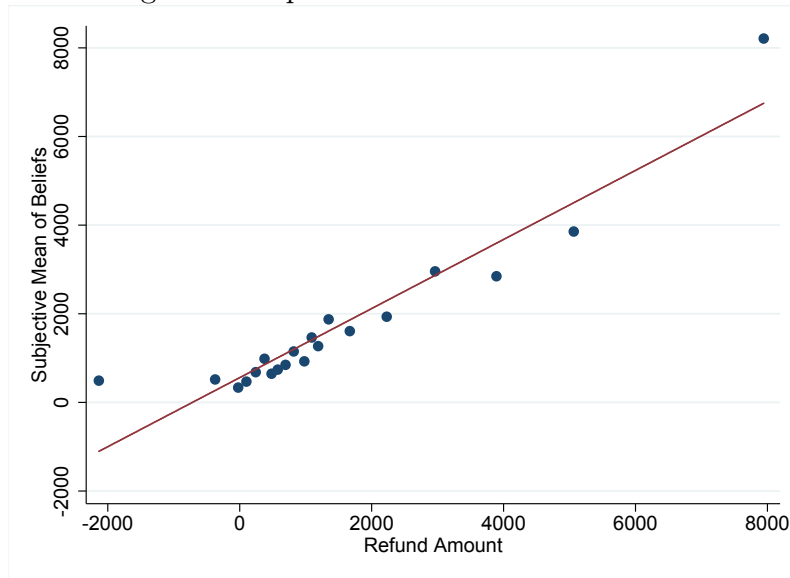
## 6 Figures and Tables

Figure 1: Dorchester House Tax Site Flow



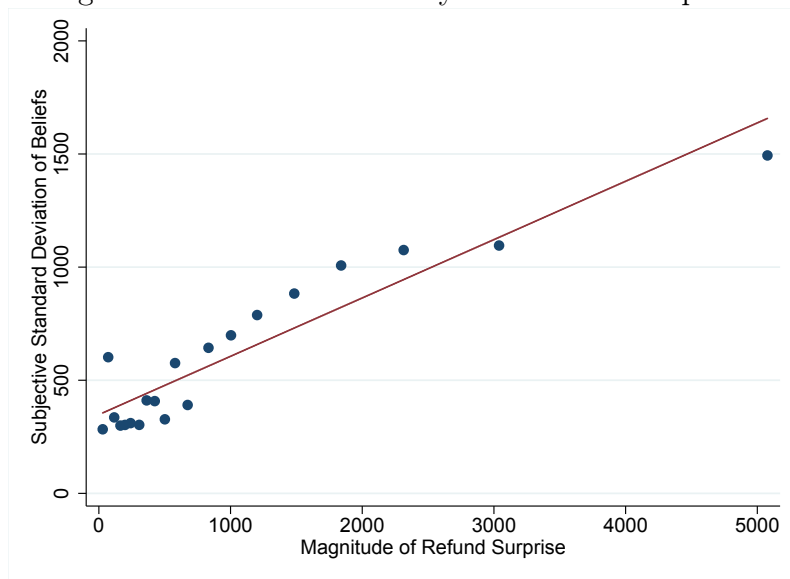
Note: This figure shows the steps a Dorchester House tax client would go through upon arriving at the center. The steps in white occur before a client has met with a financial guide or tax preparer. The steps in blue are completed in collaboration with one of Dorchester House's financial guides. The steps in purple are completed with the help of a volunteer tax preparer.

Figure 2: Expected Versus Actual Refunds



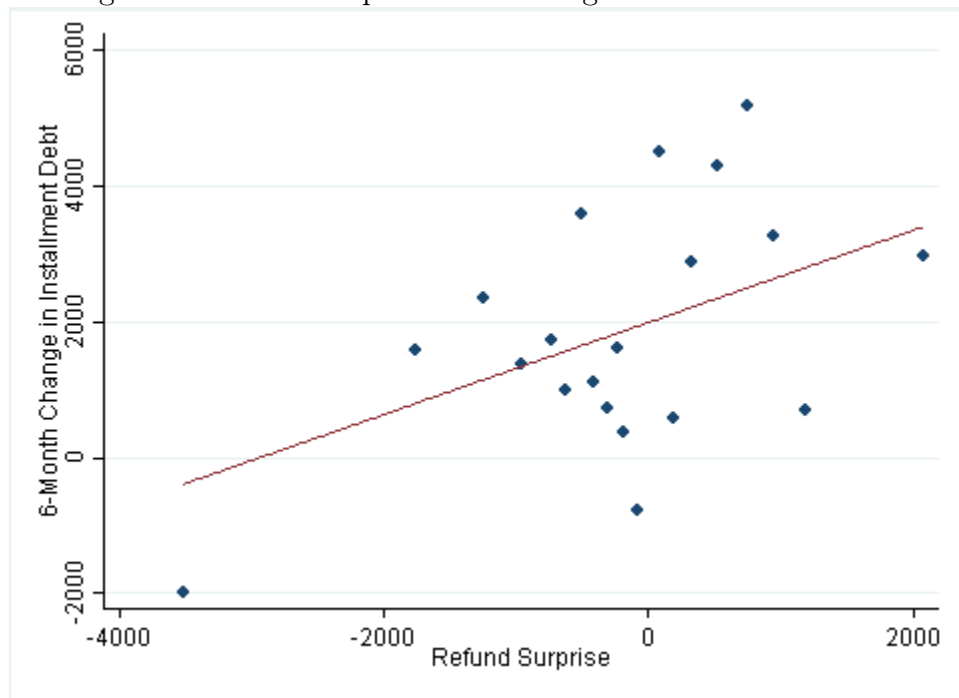
Note: This figure plots a binned scatterplot of mean expectations against actual refund amounts. The expected refunds are the means of the distributions calculated using the procedure described in Section 3.

Figure 3: Refund Uncertainty and Refund Surprises



Note: This figure plots the size of the refund “surprise” (actual refund - mean expectation) against the standard deviation of beliefs.

Figure 4: Refund Surprises and Changes in Installment Debt



Note: This figure plots a binned scatterplot of 6-month changes in installment balances against tax refund surprises. Surprises are defined as realization minus expectation, such that a positive surprise is “good news” for the taxpayer. These data are plotted after partialling out the other controls included in column 4 of Table 5.

Table 1: Descriptive Statistics

	Expectations Data and Tax Data (1)	Expectations, Tax and Credit Report Data ("Core Sample") (2)	Core Sample plus Asset Survey Data (3)	Core Sample plus Credit-Report- derived Consumption (4)	Core Sample plus Durable Consumption Survey Data (5)	Core Sample plus Past-Year Tax Data (6)
Female	0.62	0.62	0.62	***	0.62	0.66
Age	39.86 (15.65)	* 40.03 (15.68)	40.03 (15.58)	40.28 (15.67)	40.40 (16.40)	42.29 (15.73)
Adjusted Gross Income (\$)	\$21,038 (\$15,897)	*** \$21,822 (\$15,961)	\$21,874 (\$16,029)	\$24,008 (\$16,291)	\$21,183 (\$16,523)	\$23,831 (\$15,840)
Has Dependents	30%	30%	30%	30%	28%	32%
Filing Status						
Married	8%	8%	7%	**	10%	6%
Single Head of Household	25%	26%	26%	25%	23%	29%
Filed Schedule C	8%	7%	7%	8%	9%	7%
Refund Size	\$1,428 (\$2,208)	\$1,446 (\$2,188)	\$1,469 (\$2,198)	\$1,519 (\$2,309)	\$1,414 (\$2,309)	\$1,678 (\$2,308)
Received EITC	35%	34%	33%	29%	32%	35%
EITC Credit (If >0)	\$1,555 (\$1,647)	\$1,548 (\$1,597)	\$1,558 (\$1,633)	\$1,843 (\$1,731)	\$1,574 (\$1,755)	\$1,731 (\$1,702)
Chose Direct Deposit	60%	60%	60%	65%	56%	65%
Estimated Savings Balance	\$523 (\$580)	\$535 (\$582)	\$535 (\$582)	\$593 (\$596)	\$627 (\$609)	\$570 (\$600)
High School or Above	83%	84%	84%	87%	85%	86%
Some College or More	17%	18%	18%	23%	16%	21%
FICO Score	665 (88)	665 (88)	665 (89)	672 (85)	673 (89)	674 (88)
Credit Card Balances (\$)	\$1,675 (\$5,190)	\$1,675 (\$5,190)	\$1,765 (\$5,456)	\$2,255 (\$5,914)	\$1,471 (\$4,063)	\$1,940 (\$6,103)
Installment Balances (\$) (non-mortgage)	\$9,919 (\$23,814)	\$9,919 (\$23,814)	\$10,249 (\$24,668)	\$13,353 (\$26,795)	\$9,476 (\$23,473)	\$12,449 (\$27,831)
Has Mortgage	4%	4%	4%	5%	5%	5%
Observations	530	486	429	361	235	285
Obs. with Asset Survey	468	429	429	318	206	254

Note: This table provides descriptive statistics on our population of low-income taxpayers. The first column shows individuals who filed taxes at Dorchester House and completed the expectations survey. The second column, our "Core Sample," restricts the sample to the population for whom we additionally have both initial and follow-up credit reports. The third column shows the part of the Core Sample that additionally responded to the demographics and asset survey; the fourth column shows the part of the Core Sample for which nondurable consumption proxies were observable in the credit report data; the fifth column shows the part of the Core Sample that additionally completed the follow-up survey on nondurable consumption; and the sixth column shows the part of the Core Sample that additionally could be matched to the preceding year's tax return by virtue of being repeat clients. In each column, gender, savings balance, and education are reported for the subset of individuals in that column who also completed the demographics and asset survey. All columns in this table exclude individuals with subjective uncertainty (as measured by standard deviation of reported probabilistic expectations) in the top or bottom 5% of expectations survey respondents, and tax refund surprises in the top or bottom 1%, as well as individuals with adjusted gross incomes below 0. See Appendix Table A1 for further description of these outlier observations.

Table 2: Comparison of Qualitative and Quantitative Uncertainty

Qualitative Uncertainty		Quantitative Uncertainty			
	N	Coefficient of Variation		p-Value from t-test for Equality of Means	
		Mean	S.D.	Not Sure	Somewhat Sure
Not Sure at All	114	0.83	3.94		
Somewhat Sure	207	0.46	0.69	0.00723	
Very Sure	160	0.37	0.74	0.00100	0.00000

Note: This table compares the coefficient of variation calculated for the parametric belief distributions to the qualitative uncertainty responses. The sample includes all individuals in the Core Sample defined in Table 1 who responded to both the qualitative and quantitative questions eliciting tax refund uncertainty.



Table 3: Correlates of Refund Uncertainty and Surprises

	Elicited Standard Deviation of Refund Amount			Magnitude of Refund Surprise			Refund Surprise		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
25 or Younger	74.01 (84.24)	-25.92 (128.2)	-13.11 (129.7)	-22.64 (152.2)	55.03 (234.2)	36.84 (239.8)	12.91 (205.3)	79.81 (336.3)	186.7 (338.6)
Older than 50	-118.4 (74.27)	-121.9 (97.51)	-121.5 (97.39)	-216.6 (134.2)	-148.3 (178.1)	-148.2 (180.1)	275.1 (181.0)	394.3 (255.8)	347.4 (254.3)
Any College	-54.95 (65.06)	-52.92 (89.96)	-50.20 (90.16)	103.1 (117.5)	130.1 (164.3)	145.1 (166.7)	99.21 (158.6)	153.4 (236.0)	97.19 (235.4)
Female	-116.7* (68.35)	-36.52 (97.02)	-29.14 (96.62)	-157.8 (123.5)	-201.7 (177.2)	-194.9 (178.7)	256.4 (166.6)	301.3 (254.5)	313.7 (252.3)
Has Dependent	198.4 (128.7)	236.7 (166.2)	199.9 (165.3)	703.4*** (232.6)	984.1*** (303.6)	791.9** (305.7)	691.8** (313.8)	744.5* (436.0)	716.7* (431.7)
Number of Dependents	333.6*** (71.46)	318.0*** (95.67)	367.7*** (93.17)	227.9* (129.1)	147.5 (174.7)	444.2** (172.3)	-76.13 (174.2)	-14.16 (250.9)	-20.43 (243.3)
Married	208.0* (120.8)	317.8 (203.3)	341.9* (202.0)	219.4 (218.3)	186.3 (371.3)	195.0 (373.5)	-1030.1*** (294.5)	-1280.2** (533.3)	-1355.6** (527.5)
AGI in 2nd Quartile	43.18 (86.00)	-7.559 (131.5)	-20.39 (134.9)	153.1 (155.4)	122.8 (240.2)	-23.32 (249.4)	469.3** (209.6)	470.9 (344.9)	650.0* (352.2)
AGI in 3rd Quartile	327.2*** (87.64)	246.4* (129.4)	238.2* (134.6)	494.5*** (158.3)	420.5* (236.2)	260.2 (248.8)	-141.6 (213.6)	-85.04 (339.3)	110.8 (351.4)
AGI in 4th Quartile	141.8 (90.59)	67.52 (135.5)	74.30 (143.1)	255.6 (163.7)	-37.62 (247.5)	-183.5 (264.6)	-338.4 (220.8)	-38.65 (355.5)	201.3 (373.6)
Received UI in Past Year		-139.0 (168.5)	-139.9 (168.0)		-173.4 (307.7)	-137.2 (310.7)		637.8 (441.9)	586.6 (438.8)
Change in Filing Status		-205.1 (193.3)	-142.1 (149.0)		-988.1*** (353.0)	-246.2 (275.6)		-16.64 (507.0)	42.28 (389.2)
Magnitude of Change in AGI (\$1,000)		2.996 (5.302)			17.53* (9.683)			-7.128 (13.91)	
Any Change in Number of Dependents		100.3 (167.2)			1050.0*** (305.4)			77.96 (438.7)	
Change in AGI (\$1,000)			-1.201 (4.437)			8.700 (8.204)			-22.54* (11.59)
Change in Number of Dependents			-111.3 (78.23)			-463.6*** (144.7)			178.1 (204.3)
Constant	385.7*** (88.20)	403.5*** (136.5)	409.7*** (134.1)	551.8*** (159.4)	518.5** (249.2)	689.3*** (247.9)	-589.0*** (215.0)	-836.5** (357.9)	-963.1*** (350.1)
N	429	254	254	429	254	254	429	254	254
R-squared	0.295	0.323	0.327	0.205	0.302	0.289	0.105	0.122	0.136

Note: This table reports estimates from ordinary least squares regressions of refund uncertainty and surprises on taxpayer characteristics. The sample in columns 1, 4, and 7 is all Dorchester House taxpayers in the Core Sample who additionally responded to the assets and demographics survey (see column (3) of Table 1). The sample in the remaining columns is the subset of those taxpayers who could be linked to the previous year's tax return by virtue of being a repeat client. The Elicited Standard Deviation of Refund Amount (columns 1-3) is the standard deviation of the parametric belief distribution fit to each taxpayer's probabilistic survey question response, described in Section 3.2. Magnitude of Refund Surprise (columns 4-6) is the absolute value of the difference between each taxpayer's refund amount and the mean of their parametric belief distribution. Refund Surprise (columns 7-9) is the (signed) level of the same quantity. AGI is Adjusted Gross Income as reported on the tax return. Change in Filing Status is an indicator for whether a tax filer's filing status changed from the previous year of filing. Standard errors are in parentheses. \*  $p < .1$  \*\*  $p < 0.05$  \*\*\*  $p < 0.01$

Table 4: Impact of Refund Surprise on Revolving Debt Balances

	Dependent Variable: Change in Revolving Debt (\$)			
	2-Month Follow-Up		6-Month Follow-Up	
	(1)	(2)	(3)	(4)
Mean Expectation (\$1,000)	-137.2*** (42.87)	-72.96 (53.41)	-139.7** (65.04)	-129.0 (79.50)
Surprise (\$1,000)	-67.66* (36.28)	-32.94 (45.10)	-86.09 (55.06)	-85.22 (67.34)
S.D. of Beliefs	347.6** (141.3)	281.5* (153.9)	357.0* (214.4)	312.1 (228.8)
Controls for Taxpayer Characteristics		X		X
R-Squared	0.039	0.194	0.021	0.212
N	314	314	312	312

Note: This table reports estimates from ordinary least squares regressions of changes in revolving debt balances on taxpayer expectations, refund surprises, and characteristics. The sample in all columns is the Core Sample for which nondurable consumption proxies were observable in the credit report data; this excludes individuals with no open, revolving credit accounts at either baseline or the follow-up horizon. In columns 1 and 2, the dependent variable is the change in revolving debt between the week of tax filing and the two-month credit report follow-up. Column 1 controls for the mean and standard deviation of each taxpayer's parametric belief distribution, fit as described in Section 3.2, as well as their refund surprise. Column 2 adds controls for taxpayer characteristics. Columns 3 and 4 repeat these specifications for the six-month change in revolving debt. All columns additionally control for whether the taxpayer received their refund via direct deposit or with a paper check, and for the taxpayer's treatment status in the randomized controlled trial conducted simultaneously at the tax site (see Section 2.1). Taxpayer characteristics are fully interacted bins of age less than 25, 25-50, and over 50; adjusted gross income (AGI) quartile; marital status; and an indicator for any dependents. Standard errors are in parentheses. \*  $p < .1$  \*\*  $p < 0.05$  \*\*\*  $p < 0.01$

Table 5: Impact of Refund Surprise on Installment Debt Balances

	Dependent Variable: Change in Installment Debt (\$)			
	2-Month Follow-Up		6-Month Follow-Up	
	(1)	(2)	(3)	(4)
Mean Expectation (\$1,000)	-75.73 (109.4)	-121.2 (140.8)	21.54 (303.2)	-256.9 (381.9)
Surprise (\$1,000)	76.52 (93.15)	81.97 (117.2)	675.1*** (258.3)	677.3** (319.8)
S.D. of Beliefs	-246.4 (344.3)	-88.16 (370.9)	-555.8 (954.6)	-412.6 (1004.9)
Controls for Taxpayer Characteristics		X		X
R-Squared	0.031	0.218	0.043	0.263
N	226	226	224	224

Note: This table reports estimates from ordinary least squares regressions of changes in installment debt balances on taxpayer expectations, refund surprises, and characteristics. The sample in all columns is the Core Sample for which consumption proxies were observable through installment loans in the credit report data; this excludes individuals with no open installment loan accounts at either baseline or the follow-up horizon. In columns 1 and 2, the dependent variable is the change in installment debt between the week of tax filing and the two-month credit report follow-up. Column 1 controls for the mean and standard deviation of each taxpayer’s parametric belief distribution, fit as described in Section 3.2, as well as their refund surprise. Column 2 adds controls for taxpayer characteristics. Columns 3 and 4 repeat these specifications for the six-month change in installment debt. All columns additionally control for whether the taxpayer received their refund via direct deposit or with a paper check, and for the taxpayer’s treatment status in the randomized controlled trial conducted simultaneously at the tax site (see Section 2.1). Taxpayer characteristics are fully interacted bins of age less than 25, 25-50, and over 50; adjusted gross income (AGI) quartile; marital status; and an indicator for any dependents. Standard errors are in parentheses. \*  $p < .1$  \*\*  $p < 0.05$  \*\*\*  $p < 0.01$

Table 6: Impact of Refund Surprise on Non-Mortgage Debt Balances

	Dependent Variable: Change in All Non-Mort. Debt (\$)			
	2-Month Follow-Up		6-Month Follow-Up	
	(1)	(2)	(3)	(4)
Mean Expectation (\$1,000)	-151.5** (69.86)	-89.18 (87.07)	-183.1 (193.3)	-316.3 (240.5)
Surprise (\$1,000)	-14.82 (60.22)	29.46 (76.17)	379.0** (166.7)	358.6* (211.0)
S.D. of Beliefs	152.5 (226.7)	118.6 (240.9)	528.2 (627.6)	640.1 (664.7)
Controls for Taxpayer Characteristics		X		X
R-Squared	0.024	0.161	0.020	0.163
N	359	359	357	357

Note: This table reports estimates from ordinary least squares regressions of changes in total non-mortgage debt balances on taxpayer expectations, refund surprises, and characteristics. The sample in all columns is the Core Sample for which consumption proxies were observable through either revolving or installment loans in the credit report data (see column (4) of Table 1); this excludes individuals with no open revolving or installment loan accounts at either baseline or the follow-up horizon. In columns 1 and 2, the dependent variable is the change in debt between the week of tax filing and the two-month credit report follow-up. Column 1 controls for the mean and standard deviation of each taxpayer's parametric belief distribution, fit as described in Section 3.2, as well as their refund surprise. Column 2 adds controls for taxpayer characteristics. Columns 3 and 4 repeat these specifications for the six-month change in debt. All columns additionally control for whether the taxpayer received their refund via direct deposit or with a paper check, and for the taxpayer's treatment status in the randomized controlled trial conducted simultaneously at the tax site (see Section 2.1). Taxpayer characteristics are fully interacted bins of age less than 25, 25-50, and over 50; adjusted gross income (AGI) quartile; marital status; and an indicator for any dependents. Standard errors are in parentheses. \*  $p < .1$  \*\*  $p < 0.05$  \*\*\*  $p < 0.01$

Table 7: Impact of Refund Surprise on Durable Purchases

	Dependent Variable: Survey- Reported New Car Purchase or New Home Repair (1 or 0)		Dependent Variable: Self-Reported Value of New Car Purchase or Home Repair (\$)	
	2-Month Follow-Up		2-Month Follow-Up	
	(1)	(2)	(3)	(4)
Mean Expectation (\$1,000)	1.716 (2.046)	1.007 (2.556)	30.74 (23.41)	16.27 (28.45)
Surprise (\$1,000)	0.774 (1.700)	2.614 (2.212)	17.42 (19.46)	38.91 (24.61)
S.D. of Beliefs	-9.130 (7.077)	-7.013 (7.801)	-137.8* (80.98)	-112.4 (86.81)
Controls for Taxpayer Characteristics		X		X
R-squared	0.011	0.185	0.019	0.236
N	235	235	235	235

Note: This table reports estimates from ordinary least squares regressions of an indicator for durable purchases between tax filing and the two-month follow-up consumption survey. Controls are taxpayer expectations, refund surprises, and characteristics. The sample in all columns includes individuals with non-missing data on demographics as measured in the asset survey, expectations, and a response to the follow-up consumption survey conducted approximately two months after tax refund receipt. Column 1 controls for the mean and standard deviation of each taxpayer's parametric belief distribution, fit as described in Section 3.2, as well as their refund surprise. Column 2 adds controls for taxpayer characteristics. All columns additionally control for whether the taxpayer received their refund via direct deposit or with a paper check, and for the taxpayer's treatment status in the randomized controlled trial conducted simultaneously at the tax site (see Section 2.1). Taxpayer characteristics are fully interacted bins of age less than 25, 25-50, and over 50; adjusted gross income (AGI) quartile; marital status; and an indicator for any dependents. Standard errors are in parentheses. \*  $p < .1$  \*\*  $p < 0.05$  \*\*\*  $p < 0.01$

Table 8: Testing Concavity of the Consumption Function

Dependent Variable  Horizon	Change in Revolving Debt		Change in Installment Debt		Change in All Non-Mort. Debt	
	2-Mo.	6-Mo.	2-Mo.	6-Mo.	2-Mo.	6-Mo.
	(1)	(2)	(3)	(4)	(5)	(6)
Surprise (\$1,000)	-61.75 (55.33)	-115.6 (82.74)	125.5 (146.0)	945.7** (397.8)	23.48 (95.09)	532.2** (263.1)
Surprise * S.D. of Beliefs	37.45 (41.64)	39.27 (62.01)	-53.33 (106.0)	-325.2 (286.8)	7.184 (68.19)	-207.4 (187.9)
S.D. of Beliefs	303.2* (155.8)	335.0 (231.9)	-123.9 (378.3)	-631.3 (1022.5)	123.6 (246.1)	492.6 (677.8)
Controls for Taxpayer Characteristics	X	X	X	X	X	X
Controls for Mean Expectation	X	X	X	X	X	X
R-squared	0.196	0.213	0.219	0.268	0.161	0.166
N	314	312	226	224	359	357

Note: This table reports estimates from ordinary least squares regressions of changes in debt balances on taxpayer expectations, refund surprises, and taxpayer characteristics. The sample in all columns is the Core Sample for which consumption proxies were observable through either revolving loans (columns (1) and (2)), or installment loans (columns (3) and (4)), or either (columns (5) and (6)), in the credit report data; this excludes individuals with no open loan accounts at either baseline or the follow-up horizon. In columns 1 and 2, the dependent variable is change in two- and six-month revolving debt balances, respectively. Both columns control for the mean and standard deviation of each taxpayer's parametric belief distribution, fit as described in Section 3.2, as well as their refund surprise, an interaction between the surprise and belief standard deviation, and taxpayer characteristics. Columns 3 and 4 repeat these specifications for changes in installment debt balances, and columns 5 and 6 do the same for all non-mortgage debt. All columns additionally control for whether the taxpayer received their refund via direct deposit or with a paper check, and for the taxpayer's treatment status in the randomized controlled trial conducted simultaneously at the tax site (see Section 2.1). Taxpayer characteristics are fully interacted bins of age less than 25, 25-50, and over 50; adjusted gross income (AGI) quartile; marital status; and an indicator for any dependents. Standard errors are in parentheses. \*  $p < .1$  \*\*  $p < 0.05$  \*\*\*  $p < 0.01$

## A Appendix Tables and Figures

Table A1: Descriptive Statistics (Including Outliers)

	Expectations Data and Tax Data	Expectations, Tax and Credit Report Data ("Core Sample")	Core Sample plus Asset Survey Data	Core Sample plus Credit-Report- derived Consumption	Core Sample plus Durable Consumption Survey Data	Core Sample plus Past-Year Tax Data
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.62	0.62	0.62	0.68	0.61	0.65
Age	40.39 (15.85)	40.73 (15.86)	40.57 (15.78)	40.59 (15.79)	40.69 (16.22)	42.65 (15.81)
Adjusted Gross Income (\$)	\$20,920 (15,931)	\$21,627 (15,987)	\$21,544 (15,807)	\$23,758 (16,244)	\$21,134 (16,225)	\$24,061 (16,031)
Has Dependents	32%	33%	33%	34%	31%	36%
<u>Filing Status</u>						
Married	8%	8%	7%	8%	9%	6%
Single Head of Household	27%	28%	29%	29%	27%	31%
Filed Schedule C	7%	6%	6%	7%	8%	6%
<u>Refund Size</u>						
	\$1,592 (2,377)	\$1,635 (2,386)	\$1,651 (2,386)	\$1,754 (2,525)	\$1,545 (2,443)	\$1,845 (2,483)
Received EITC	35%	35%	34%	31%	32%	35%
EITC Credit (If >0)	\$1,730 (1,703)	\$1,760 (1,673)	\$1,750 (1,679)	\$2,027 (1,749)	\$1,718 (1,756)	\$1,921 (1,715)
Chose Direct Deposit	58%	59%	58%	64%	56%	64%
Estimated Savings Balance	\$519 (571)	\$525 (572)	\$525 (572)	\$577 (588)	\$600 (598)	\$564 (590)
High School or Above	82%	83%	83%	86%	84%	85%
Some College or More	15%	15%	15%	20%	15%	18%
FICO Score	664 (87)	664 (87)	664 (87)	671 (84)	671 (88)	672 (87)
Credit Card Balances (\$)	\$1,677 (4,852)	\$1,677 (4,852)	\$1,746 (5,048)	\$2,292 (5,547)	\$1,537 (3,960)	\$1,891 (5,596)
Installment Balances (\$) (non-mortgage)	\$9,159 (22,081)	\$9,159 (22,081)	\$9,411 (22,782)	\$12,514 (24,989)	\$9,341 (22,437)	\$11,197 (25,554)
Has Mortgage	4%	4%	5%	5%	5%	6%
Observations	687	623	556	456	286	362
Obs. with Asset Survey	611	556	556	405	251	327

Note: This table provides descriptive statistics on our population of low-income taxpayers, analogously to Table 1. Unlike Table 1 this table includes individuals with subjective uncertainty (as measured by standard deviation of reported probabilistic expectations) in the top or bottom 5% of expectations survey respondents, and tax refund surprises in the top or bottom 1%, as well as individuals with adjusted gross incomes below 0. The first column shows individuals who filed taxes at Dorchester House and completed the expectations survey. The second column, our “Core Sample” including outliers, restricts the sample to the population for whom we additionally have both initial and follow-up credit reports. The third column shows the part of the Core Sample (including outliers) that additionally responded to the demographics and asset survey; the fourth column shows the part of the Core Sample (including outliers) for which nondurable consumption proxies were observable in the credit report data; the fifth column shows the part of the Core Sample (including outliers) that additionally completed the follow-up survey on nondurable consumption; and the sixth column shows the part of the Core Sample (including outliers) that additionally could be matched to the preceding year’s tax return by virtue of being repeat clients. In each column, gender, savings balance, and education are reported for the subset of individuals in that column who also completed the demographics and asset survey.



Table A2: Elicited Beliefs by Tax Filer Group

Features of Probabilistic Survey Question Responses									
	Full Sample	Has Dependents		Marital Status		Adjusted Gross Income (AGI)		Education	
		Yes	No	Married	Single	Above \$20,000	Below \$20,000	Some College	No College
Number of Bins with Positive Probability									
1 Bin	15.2%	20.0%	13.2%	30.0%	13.9%	18.6%	12.4%	14.6%	15.7%
2 Bin	43.6%	46.2%	42.5%	32.5%	44.6%	39.1%	47.4%	42.2%	44.6%
3 Bin	23.0%	16.6%	25.8%	12.5%	24.0%	20.9%	24.8%	21.4%	24.3%
4 Bin	12.1%	11.0%	12.6%	12.5%	12.1%	14.1%	10.5%	15.0%	10.0%
5 Bin	4.5%	4.8%	4.4%	10.0%	4.0%	5.5%	3.8%	5.3%	3.9%
6 Bin	1.4%	1.4%	1.5%	2.5%	1.3%	1.8%	1.1%	1.5%	1.4%
Qualitative Uncertainty									
Very Sure	32.9%	29.7%	34.3%	50.0%	31.4%	27.7%	37.2%	31.1%	34.3%
Somewhat Sure	42.6%	48.3%	40.2%	30.0%	43.7%	45.5%	40.2%	39.8%	44.6%
Not Sure at All	23.5%	21.4%	24.3%	20.0%	23.8%	25.5%	21.8%	27.2%	20.7%
Quantitative Responses									
Point Estimate	1,623	3,308	906	2,238	1,568	2,124	1,208	1,519	1,699
Minimum	-555	928	-1,185	-250	-582	-348	-726	-752	-409
Maximum	5,493	9,621	3,738	7,238	5,336	6,966	4,274	5,684	5,352
Features of Parametric Distribution									
Mean	1,686	3,566	886	2,575	1,606	2,259	1,211	1,611	1,741
Median	1,766	3,586	992	2,460	1,703	2,334	1,296	1,706	1,810
Std. Dev.	611	1,102	402	900	585	783	468	610	612
Coefficient of Variation	0.51	0.29	0.61	0.34	0.53	0.36	0.64	0.59	0.45

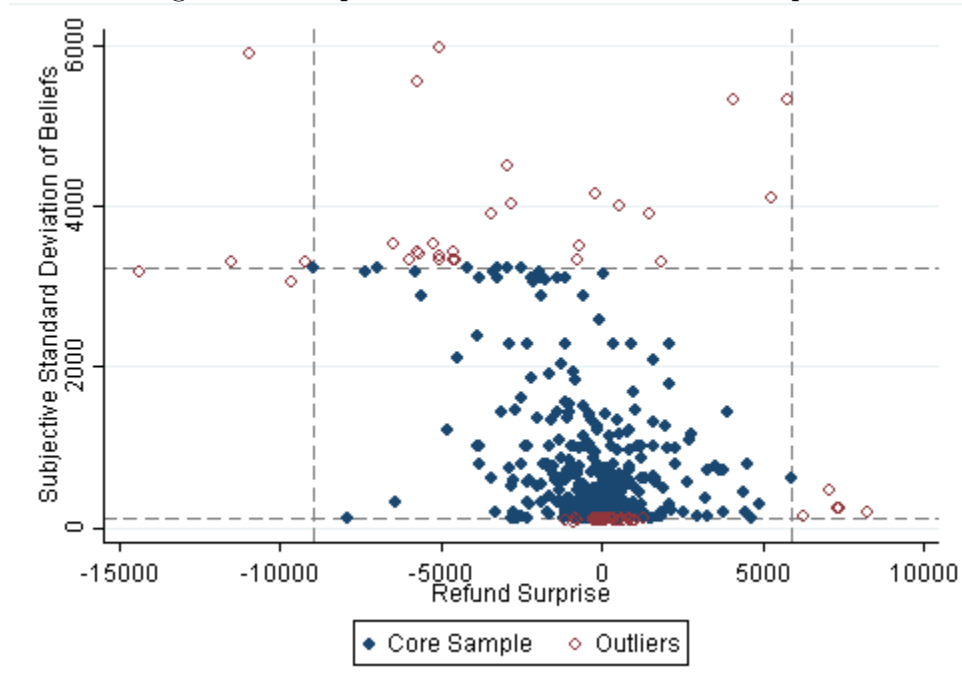
Notes: This table reports responses to the beliefs survey. All statistics are means within each group. The last panel contains statistics based on the parametric distributions fit to the probabilistic survey question described in Section 3.

Table A3: Parametric Belief Distributions

Features of Elicitations under Alternative Parametric Assumptions and Sample Restrictions												
	Baseline		Uniform		Lower Bound		Upper Bound		Omitting Only Top/Bottom Bin		Omitting 50-50 Reports	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Mean	1,686	2,291	2,024	2,829	1,001	1,265	3,046	4,435	1,438	1,568	1,739	2,400
Median	1,766	2,793	1,789	2,679	893	1,298	2,718	4,647	1,534	2,325	1,833	2,957
Std. Dev.	611	714	2,095	2,668					546	574	656	755
Minimum	475	1,124	455	1,126					363	820	467	1,169
Maximum	4,712	6,064	5,493	6,849					4,370	5,570	5,137	6,408

Notes: This table reports features of parametric belief distributions under alternative assumptions. Statistics are aggregated across all taxpayers in the main analysis sample. The first pair of columns contains statistics based on the parametric distributions fit to the probabilistic survey question described in Section 3. Uniform assumes a uniform distribution within each bin with nonzero probability. Lower (Upper) bound calculates the lowest (highest) value of each taxpayer's subjective mean and median expectation that is consistent with their subjective probabilities. The last two pairs of columns implement sample restrictions using the baseline parametric assumptions.

Figure A1: Expectation Outliers and Core Sample



Note: This figure is a scatterplot of the fitted standard deviation of subjective beliefs about refund size, against the realized surprise in refund size. Dotted lines denote the thresholds at which the top and bottom 1% of refund surprise and the top and bottom 5% of subjective standard deviations are excluded as outliers. Solid circles represent the core sample excluding outliers and hollow circles represent the outliers. See tables 1 and A1 for summary statistics on these two groups.

## B Survey Appendix

### B.1 Expectations Survey

The expectations survey consisted of four questions, printed below. The survey was administered by the financial guides at Dorchester House, after obtaining written consent to the statement, “I consent for tax, credit, and survey information (including follow-up surveys) to be released to OFE to be used to improve OFE services and for academic research in conjunction with researchers at MIT. This information will be stored securely at OFE, will only be accessed by OFE employees, and will be kept confidential. I understand that participation is voluntary and that my consent will not affect the security or confidentiality of my information or my eligibility for services offered by OFE. I understand that I may decline to answer any questions and that I may stop participation without consequences. I understand that if I participate in follow-up surveys for academic purposes, I will be mailed a \$10 gift card for each survey.”

- 1) If you get a tax refund this year, how much do you think it will be? Please choose an amount:

\$\_\_\_\_\_

*(Financial Guide volunteer: please write \$500 above this number, and \$500 below this number, in the two blank lines in the question below)*

- 2) How sure are you that your refund will be between \$\_\_\_\_\_ and \$\_\_\_\_\_? Please circle one:

NOT SURE AT ALL

SOMEWHAT SURE

VERY SURE

- 3) Suppose you want to make some extra money by working more hours next week. Do you think you could you get your manager/supervisor to schedule you for more hours?

YES

NO

I AM NOT WORKING RIGHT NOW

I AM NOT PAID HOURLY

- 4) We have one final question about your tax refund. Below we show six possible amounts that your refund could be (for example, "between \$1000 and \$2500"). For each of the six possibilities, please say what is the "percent chance" that you think your refund could be that amount:

**Could my refund be... (Please Enter % Chance for Each)**

Over \$5000	%
Between \$2500 and \$5000	%
Between \$1000 and \$2500	%
Between \$500 and \$1000	%
Between \$0 and \$500	%
Negative: I will owe taxes	%

## B.2 Follow-Up Survey

The follow-up survey was conducted via phone by a Dorchester House volunteer. After introducing herself and reading the consent statement, the volunteer went through a pre-specified script and coded the answers into a spreadsheet. Individuals who completed the survey were mailed a \$10 gift card.

**Consent Statement:** The survey information will be stored securely at the City of Boston's Office of Financial Empowerment, will be kept confidential, and will only be accessed by OFE employees. The information will also be used as part of ongoing research with researchers at MIT. All survey questions are voluntary and you can stop the survey at any time. Participation will not affect your eligibility for city services. The survey should take about 4 minutes. To thank you for your participation, you will be given a \$10 gift card at the end of the survey.

### Questions

1. Have you made any of the following large purchases in 2016?
  - (a) Car or motorcycle
  - (b) Large household appliance, for example a dishwasher, refrigerator, or clothes dryer
  - (c) A major repair to your home or the place you live
  - (d) Television or computer
  - (e) Car repairs
  - (f) Wedding, funeral, or party expenses
  - (g) [Repeat for each of the items purchased:]
    - i. About when was it that you purchased? How certain are you of this date?
    - ii. How much did it cost?
    - iii. How did you pay for it? (cash/check/credit...)
2. Have you faced any unexpected expensive life events, such as job loss, job change, or medical bills, in 2016?
  - (a) [Repeat for each event:]
    - i. About when did — happen? How certain are you of this date?
    - ii. If applicable: how much did the expense cost, and how did you pay for it?
3. About what time did you receive your tax refund this year?
  - (a) How long was it after you first came to Dorchester House to file taxes?

4. Did you use your tax refund to put more money in a savings or checking account?
5. OK, now I have just one last question about the things we've discussed so far.

(a) [Repeat for each large purchase or life event in Questions 1 and 2:]

- i. Do you recall if — was before or after you got your tax refund?
- ii. Do you recall if that was before or after you came to Dorchester House to file taxes?