Tax Refund Uncertainty: Evidence and Welfare Implications*

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Abstract

Transfers paid through annual tax refunds are a large but uncertain source of income for poor households. We document that low-income tax-filers have substantial subjective uncertainty about these refunds. We investigate the determinants and consequences of refund uncertainty by linking survey, tax, and credit bureau data. On average, filers' expectations track realized refunds. More uncertain filers have larger differences between expected and realized refunds. Filers borrow in anticipation of their refunds, but more uncertain filers borrow less, consistent with precautionary behavior. A simple consumption-savings model suggests that refund uncertainty reduces the welfare benefits of the EITC by about 10 percent.

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1 Introduction

The tax system is used both to raise revenue and to redistribute income from richer to poorer households. Much of this redistribution is done through large tax credits paid out in annual tax refunds, such as the Earned Income Tax Credit (EITC) and Child Tax Credit (CTC). These credits are a substantial portion of income for many recipients,[1] but the rules determining these credits are complex. This complexity may lead individuals to be uncertain about their tax liability or refund amount even after other income-related uncertainty is resolved (Chetty et al., 2013; Kleven, 2020).

This paper studies tax refund uncertainty and its welfare consequences among low-income tax filers. We make three contributions. First, we quantify substantial tax-refund uncertainty among low-income filers, many of whom are EITC recipients. Second, we show that, despite facing considerable uncertainty, filers have correct mean expectations on average, and seem to update their expectations from year to year in response to new information. Third, we show that refund uncertainty distorts individuals' consumption-savings choices and is large enough to cause welfare losses on the order of 10 percent of the value of the EITC.

The starting point for our analysis is a unique survey of tax filer beliefs that we conducted at a Boston Volunteer Income Tax Assistance (VITA) site. The survey elicited filers' expectations and uncertainty just before they filed their taxes. We link the survey to administrative tax data for the tax returns filed at the VITA site, to a panel of filers' credit reports, and to a demographic survey.

Refund uncertainty is large in both absolute and relative terms, roughly 4.5 times larger than prior estimates of transitory income uncertainty (Guvenen et al., 2019). A quarter of filers in our sample report that they are, at the time of tax filing, not at all certain that their refund will fall within a $1000-interval around their best guess. The median filer's subjective standard deviation is more than one quarter the size of their expected refund amount. Tax filers are more uncertain if their income has changed substantially, if they have dependents, and if they are married, suggesting that some of this uncertainty could relate to more complex parts of the tax code, such as the EITC schedule.

Despite reporting substantial uncertainty, filers' beliefs are highly predictive of the refunds they receive: mean expectations closely track average realizations. This is not simply because filers remember last year's refund; expectations also strongly predict how their refund will change. In fact, we show that filers' beliefs incorporate new information over the course of the year in a manner consistent with Bayesian updating. The level of uncertainty also varies

[1] The typical EITC recipient sees an average refund equal to 12% of their annual income (Jones, 2012). As noted by Gelman et al. (2019), EITC filers' refunds are necessarily large because the EITC cannot be claimed in advance.

across individuals in sensible ways. More uncertain individuals make larger prediction errors, or differences between realized and expected tax refunds. These patterns suggest that our survey measure of uncertainty corresponds to actual subjective uncertainty.

In the last part of the paper, we examine how tax refund uncertainty impacts financial behavior and welfare. Such impacts arise for two main reasons. First, variability in refund amounts reduces ex-ante welfare for risk-averse filers. Second, uncertainty can increase variability in average consumption *over time* via precautionary behavior, such as borrowing less before refund receipt to insure against receiving a small refund (Zeldes, 1989; Carroll and Kimball, 1996).

Using a panel of consumer credit reports, we find that uncertainty is reflected in individuals' financial decisions in the months leading up to and following tax filing. Controlling for refund size, more uncertain individuals borrow less in advance of filing, consistent with standard precautionary savings models. The pattern is robust to including demographic controls and to instrumenting our measure of subjective uncertainty with two qualitative measures.

Finally, using a simple two-period consumption model and a range of assumptions about household risk aversion, we find that tax refund uncertainty is large enough to have significant welfare costs. The average filer in our sample would be willing to give up roughly \$80 to remove uncertainty and \$160 to remove both uncertainty and variability. While these numbers may seem small in absolute terms, for the average tax filer in our sample they are equivalent to 5 and 9 percent of the filer's total refund, respectively; for EITC recipients, the corresponding welfare costs are 9 and 17 percent of EITC credit amounts. Total 2017 EITC payments were \$66 billion, suggesting aggregate welfare losses on the order of \$6-11 billion annually for EITC recipients.[2]

To our knowledge, this paper is the first to quantify uncertainty about annual tax refunds and estimate its welfare costs. While there is extensive work on limited understanding of and behavioral responses to the tax code, less is known about tax-related income uncertainty. Prior work has emphasized how individuals may misunderstand the difference between marginal and average tax rates in general (Rees-Jones and Taubinsky, 2018; Ballard et al., 2017; Fujii and Hawley, 1988) and may be unaware of EITC rules and incentives (Chetty and Saez, 2013; Chetty et al., 2013; Romich and Weisner, 2000; Smeeding et al., 2000). This limited understanding contributes to limited take-up of tax refunds and credits (Abeler and Jäger, 2015; Zwick, 2018) and may dampen labor-supply responses to the EITC

[2] We divide by EITC credit in our sample and then scale by total EITC credit among the 27 million households who received any in 2017; a similar exercise would use total refund amount both in our sample and in the population, but the latter is unavailable in public IRS statistics.

(Kleven, 2020). Part of this failure to optimize may be due to the costs of acquiring relevant information (Aghion et al., 2017; Chetty et al., 2013; Jones, 2010) or inattention and inertia (Jones, 2012). Beyond the tax context, other research has emphasized the welfare consequences of uncertainty about program rules or benefits in settings such as health insurance (Handel and Kolstad, 2015), food stamps (Finkelstein and Notowidigdo, 2019), and FAFSA financial aid applications (Bettinger et al., 2012).

2 Data and Empirical Setting

Our analysis relies on a unique combination of administrative tax data, credit bureau data, and survey data on household demographics and refund expectations. The data are collected through one of the largest Volunteer Income Tax Assistance (VITA) tax preparation centers in Boston, MA.

2.1 The Tax Site

Boston residents in 2016 were eligible to receive free tax preparation services at the tax site if they worked in the prior year, earned less than $54,000, and did not own their own business. At the site, tax filers typically go through three stations. First, they complete an intake survey, which includes questions on demographics and savings behavior. Second, they are offered a free "financial check-up" from a volunteer "financial guide." The guide offers the filer a free credit report and provides information on city services.[3] Finally, a tax preparer electronically prepares and submits the filer's tax return.

We partnered with the tax site to field a survey of tax filers' expectations about their refund (detailed in Appendix B.1) at the second of the three stations. The survey therefore measures filers' refund uncertainty just before tax preparation and filing. We view this as ideal timing: filers had not yet received any direct information about their refund, but uncertainty about pre-tax income had been resolved, and any efforts to reduce refund uncertainty – such as understanding their withholding, tax liability, and credit eligibility – had already been made. Research consent was also provided at this stage. Figure A1 describes the sequence of data collection at the site.

Because of financial guide shortages, many filers skipped the financial check-up during busy periods. As a result, we obtained consent from only 60% of tax filers at the site.

[3] The site implemented a randomized controlled trial in 2016 where some filers were given a detailed explanation of their credit report and financial advice. We control for treatment status in our analysis of borrowing behavior. An analysis by Navin Associates (2017) shows the treatment and control groups are balanced.

Because consent rates were high (96%) among filers who did access the financial check-up station, we do not believe consent was a major source of selection into our research sample.

2.2 Elicitation and Demographic Surveys

We elicited beliefs in two ways. First, we directly asked each filer for a point estimate of their refund amount. We also asked them if they were "sure", "very sure", or "not at all sure" that the refund would fall within $500 of their guess. Second, we elicited probabilistic beliefs by asking individuals the probability that their refund would fall within six bins: negative (they would have taxes due), $0-$500, $500-$1,000, $1,000-$2,500, $2,500-$5,000, and over $5,000 (see Appendix B.1 for details).

We asked for points in a probability mass function rather than moments such as the mean and variance because subjective probabilities may be easier for respondents to understand and calculate (Manski, 2004; Morgan and Henrion, 1990). Eighty-five percent of respondents put positive probability on more than one bin. Forty percent put positive probability on exactly two bins. Table A3 provides more detail on the elicited belief distributions, broken down by demographic group.

We obtained information on tax filers' demographic characteristics and financial assets from the intake survey, which nearly ninety percent of filers at the site completed.

2.3 Administrative Tax and Credit Data

We link the survey data to tax return data for consenting tax filers.[4] These data include information on income, filing status, number of dependents, and refund amount. We also observe prior-year tax returns for individuals who previously used the site's tax preparation services, nearly sixty percent of our core sample.

We merge these administrative tax records with a short panel of consumer credit reports for tax filers who provided consent. We have four reports for each individual in our sample: one pulled when they visited the tax site, and three pulled one, two, and six months later.

2.4 Descriptive Statistics

Our core analysis sample consists of 618 filers who both completed the tax refund expectations survey and filed their taxes at the site during the spring of 2016. Their characteristics are described in column 1 of Table 1 and in Table A1. Most filers are unmarried, twenty-seven percent file as a single head of household, and thirty-two percent have dependents.

[4]All data are accessed on-site through the data partner. No statistics representing fewer than 10 tax returns are provided to researchers outside the partner.

Eighty-two percent of filers have at least a high school degree, but only fifteen percent have attended college. The average age is forty years, and the average annual adjusted gross income (AGI) is about $21,000.

Tax refunds are large relative to income, savings, and debt levels. The mean refund of $1,542 in our core sample is nearly seven percent of the mean AGI and about triple the average savings balance.[5] For the 35 percent of filers who received the EITC, the average refund is nearly $1700, about half of which comes from the EITC itself.

Our main analysis samples exclude outlier observations that correspond to filers who reported extreme levels of tax refund uncertainty or income realizations. Table A1 compares this sample with the complete set of tax filers and with the subset of filers for whom we have prior year tax information and credit data.[6] The economic and demographic statistics in the table are largely stable across samples, suggesting that attrition across surveys and data sources is largely unrelated to tax status or demographic characteristics.

3 Tax Filer Beliefs

3.1 Fitting Belief Distributions

We convert individuals' probabilistic beliefs into smooth probability distributions following Engelberg et al. (2009). Our main estimates fit the elicited bin probabilities to normal distributions. This allows our fitted beliefs to be consistent with the updating model specification in Section 4.2. In Appendix Section E we show that our results are robust to fitting beta distributions, which are also common in the subjective expectations literature (Engelberg et al., 2009; Armantier et al., 2016).[7]

To fit a normal distribution to each tax filer's beliefs, we penalize the distance between the quantiles of their elicited distribution and those of a normal distribution. Because a normal distribution has full support while the elicited probabilities are over a finite support, we penalize mass in excess of a certain amount α outside of the bin's assigned positive mass.[8]

[5] Savings data are elicited using the intake survey 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. We mapped intervals to their midpoints, and "More than $1,000" to $1,500.

[6] Outlier observations are individuals with subjective uncertainty (the standard deviation of fitted beliefs) in the top or bottom 5% of respondents, and tax refund prediction errors in the top or bottom 1%, as well as individuals with adjusted gross incomes below 0.

[7] This is not surprising because the means and standard deviations from fitted normal and beta distributions track each other closely. These are the only moments in our regressions. Other research fitting beliefs to normal distributions includes Wiswall and Zafar (2014).

[8] Because some filers reported bin probabilities down to the precision of a single percentage point, we use $\alpha = .01$, the largest value consistent with rounding error.

We treat the filer's "best guess" of their refund as their subjective mean.

Formally, let $\mathcal{X}$ denote the interior support points of the response to the probabilistic survey question, and p_x denote the reported cumulative probability at each interior point $x \in \mathcal{X}$. Let $(\underline{x}, \overline{x})$ be the minimum and maximum support points. We find the $(\hat{\mu}_i, \hat{\sigma}_i)$ for the elicited distribution from each individual i which solves,

$$\min_{\mu,\sigma} \sum_{x \in \mathcal{X}_i} \left[p_{x,i} - \Phi\left(\frac{x-\mu}{\sigma}\right)\right]^2 + \left(\max\{0, 1 + \Phi\left(\frac{\underline{x}-\mu}{\sigma}\right) - \Phi\left(\frac{\overline{x}-\mu}{\sigma}\right) - \alpha\}\right)^2 \qquad (1)$$

Appendix E provides more information and examples.

3.2 Validating Fitted Beliefs

Before describing the distribution of beliefs, we verify that tax filers provided meaningful answers to the probabilistic survey questions. We do this by comparing subjective beliefs to received refunds. The blue binned scatterplot in Panel A of Figure 1 shows that, on average, mean expectations closely track realized refunds. The slope of the regression line is close to one, though respondents with the most extreme realizations had slightly less extreme expectations. Appendix Figure A4 also shows the kernel density plots of the realized refund amounts and mean expectations are strikingly similar.

Beliefs do not simply track realized refunds because individuals receive the same refund each year. The purple line in Panel A of Figure 1 shows the same binned scatterplot controlling for prior-year refund. There is still a strong positive relationship between the *residual* variation in expected refunds and realized refunds. This suggests that tax filers' beliefs incorporate additional information about changes in refunds relative to prior years.

Tax filers' reported uncertainty is also consistent with the distribution of realizations. Panel B of Figure 1 shows that more uncertain individuals see larger gaps between their expected and realized refund.[9] Many filers make large prediction errors; roughly a quarter are more than $1500.

The average expected refund is large, relative to annual income, as is uncertainty. The average mean expectation is $1,605, which is eight percent of average annual income. Subjective uncertainty is large in absolute terms—the mean of individuals' standard deviations is $426—and is also substantial relative to labor income uncertainty. The baseline estimates in Guvenen et al. (2019), for example, imply that the standard deviation of transitory income

[9] The slope should not necessarily be one – a standard deviation is the square root of the expected squared error, not the expected absolute error.

shocks for a typical worker each year is six percent of income.[10] The median filer perceives their refund as having a standard deviation equal to twenty-seven percent of expected refund size and two percent of annual pre-tax income.

4 Belief Heterogeneity

This section investigates belief heterogeneity as a first step toward understanding the underlying mechanisms driving refund uncertainty. We first describe which types of tax filers report the greatest uncertainty, and then show that filers incorporate new information about their current-year refund in a manner consistent with Bayesian updating.

4.1 Subjective Uncertainty and Prediction Errors

A natural hypothesis is that refund uncertainty is driven by tax code complexity. While our data cannot definitively distinguish alternative mechanisms, heterogeneity in subjective uncertainty and prediction errors is consistent with the tax complexity hypothesis.

We regress measures of refund uncertainty and tax circumstances on a range of economic and demographic characteristics. Our specifications take the form

$$y_i = X'_{1,i}\beta_1 + X'_{2,i}\beta_2 + \epsilon_i \,. \tag{2}$$

$X_{1,i}$ includes characteristics that we term "tax determinants" because they directly affect tax credits or liabilities, such as marital status and number of dependents. $X_{2,i}$ includes other demographics, such as gender and education. Appendix Table A5 shows that the main results are robust to separately controlling for tax determinants or demographic characteristics.

Column 2 of Table 1 presents results from a specification where the dependent variable is the standard deviation of an individual's elicited beliefs. Filers with dependents have subjective standard deviations $479 higher than other filers. Uncertainty is also higher for filers with a larger absolute change in their annual income relative to the preceding tax year. Filers above age 50 are less uncertain, with subjective standard deviations $140 lower than otherwise similar filers.

Columns 3 and 4 examine how the same variables are correlated with two proxies for tax complexity: (1) the magnitude of the change in an individual's tax refund relative to the prior year, and (2) the magnitude of the change in an individual's marginal tax rate (MTR) (Gale et al., 2001).[11] Across both proxies, groups that report higher refund uncertainty also

[10]See column 8 of their Table IV.
[11]MTRs are calculated using NBER TAXSIM (Feenberg and Coutts, 1993).

face greater complexity. In particular, the primary recipients of credits such as the EITC and CTC – tax filers with dependents – are exposed to both higher uncertainty and higher complexity.

Column 5 shows that some types of filers reporting greater uncertainty also make larger prediction errors. Prediction errors are \$830 larger in magnitude for filers with dependents and \$196 lower for filers over age 50. However, this correspondence does not hold for all filer types; for example, filers whose number of dependents changed since the prior year make larger forecast errors than other filers but do not report greater uncertainty.

4.2 Belief Updating

Belief updating has implications for the underlying causes of refund uncertainty and the effects of tax simplification reforms. We ask to what extent beliefs depend on last year's refund rather than new information realized during the current tax year.

We examine the gap between an individual's expected refund ($m_{1,i}$) and their prior year refund ($r_{0,i}$). We call this the filer's "update." Table 2 presents estimates from regressions of updates on realized refund changes ($r_{1,i} - r_{0,i}$). The realized change is interacted with economic and demographic characteristics X_i:

$$m_{1,i} - r_{0,i} = (r_{1,i} - r_{0,i})\, X_i' \beta + \eta_i.$$

The coefficients β describe how aggressively tax filers with different characteristics update their beliefs toward the actual refund they receive.

This specification can be micro-founded by a model, presented in Appendix C, of Bayesian updating where filers receive potentially noisy signals about this year's refund. Its key prediction is that filers should shade their beliefs toward last year's refund if it informs their prior. Partial updating implies that beliefs are biased conditional on the *realized* refund amount: filers whose refund increased ($r_{i1} > r_{i0}$) should, on average, underestimate their refund, while filers whose refund decreased should overestimate it. Filers who update more aggressively suffer from less ex-post bias in their beliefs. Each filer's beliefs are, nonetheless, unbiased ex-ante.[12]

Our results are consistent with these predictions. All specifications reported in Table 2 strongly reject the null that individuals do not learn about refund changes. We also reject full updating by all subgroups; every subgroup updates by strictly less than the mean realized

[12] Ex-post bias is consistent with mean expectations being unbiased *on average* when averaged across filers because the distribution of refund changes is centered at zero for most filer types in our sample. Details available upon request.

refund change. We reject no heterogeneity in updating rates in columns 2 and 3, where we focus on heterogeneity by tax determinants (the variables denoted $X_{1,i}$ in Table 1), but we fail to reject no heterogeneity across demographic groups in column 4.

Figure A5, which plots the density of "updates" as a fraction of the actual refund change $(r_{1,i} - r_{0,i})$, shows that most filers (76 percent) update in the "correct" direction: if their refund increased relative to last year, their expected refund is also higher than last year's refund.

Filers who saw larger changes in income and marginal tax rates (MTRs) update more aggressively. Column 2 of Table 2 indicates that an additional \$1,000 change in AGI predicts a 1.2 percentage point increase in $X_i'\beta$. This relationship is statistically and economically significant: the mean absolute AGI change is \$6,120, with a standard deviation of \$8,780. A similar relationship holds for marginal tax rates: a 10 percent change in MTR predicts a 4.6 percent higher updating rate. The mean (standard deviation of) change in MTR is 8.6 (14.7) percentage points. Other variables that predict subjective uncertainty, changes in MTR, and forecast errors – such as age and number of dependents – are less strongly associated with updating rates after controlling for change in MTR.

Columns 3 and 4 estimate the same specification including only tax determinants and demographic variables, respectively. The strong relationships between income changes and MTRs and updating rates continue to hold with only tax controls. Demographic variables weakly predict updating rates even after excluding tax determinants.

The finding that individuals with larger AGI and MTR changes also update more aggressively is consistent with filers exerting more effort to reduce uncertainty when the stakes are higher, but also with other changes (e.g., filing status) being more difficult to understand.

5 Consequences of Refund Uncertainty

In this section we assess the consequences of refund uncertainty for financial behavior and welfare.

5.1 Evidence of Precautionary Behavior

If tax filers behave precautionarily toward expected tax refunds, more uncertain filers will, all else equal, borrow less out of their expected refund in advance. Similar to precautionary saving, this reduced borrowing insures uncertain filers against the risk of a smaller than expected refund realization (Zeldes, 1989; Carroll and Kimball, 1996).

We test for such precautionary behavior using our panel of credit report data. We use the amount of debt repaid after refund receipt as a reasonable measure of how much a filer borrowed out of their refund ex-ante, regardless of the precise timing of that borrowing.

Specifically we focus on changes in non-installment debt balances between just prior to filing and two months post-filing, by which time a filer should have received their refund.[13] A negative change in balances (i.e., a decrease in debt) indicates that the filer repaid debt shortly after tax refund receipt.

While we do not observe consumption or the timing of ex-ante borrowing directly, this form of borrowing allows households to smooth consumption out of their refund across time. If more uncertain households are precautionarily less likely to engage in such borrowing, this suggests that refund uncertainty may lead them to *under*-consume prior to refund receipt.

Main Results We estimate regressions of the form

$$\Delta B_i = \omega m_{1,i} + \gamma \sigma_i + X_i' \beta + \epsilon_i, \tag{3}$$

where ΔB_i denotes the change in balances; $m_{1,i}$ is the filer's mean refund expectation; and σ_i is the standard deviation of their elicited belief distribution. The key parameter of interest is γ. A positive estimate is consistent with precautionary behavior. X_i includes economic and demographic controls which may affect filers' borrowing or capture heterogeneity in preferences over time and risk. The identifying assumption is that unobserved determinants of the change in balances are, conditional on the included covariates, uncorrelated with σ_i.

Table 3 presents regression estimates from equation 3 and related specifications. The first column shows a univariate model with only the first term in equation 3, filers' mean refund expectations $\alpha m_{1,i}$. Column 2 adds subjective uncertainty; column 3 adds demographic controls; and column 4 adds controls for tax determinants.[14]

The negative estimates in the first row of Table 3 show that filers who have higher mean refund expectations indeed borrow more ex-ante.[15] The positive estimates of σ_i are evidence of precautionary behavior: filers with higher subjective standard deviations of their refund expectations borrow less ex-ante. The estimates imply that, for a given expected refund, a \$1000 increase in the subjective standard deviation leads individuals to borrow over \$200 less before filing. The coefficient on uncertainty remains virtually unchanged moving across

[13]Non-installment debt is predominantly credit card debt, which, unlike installment debt such as student loans, can be adjusted relatively easily over short time horizons. Credit card debt is a primary means of consumption smoothing for low-score consumers (Fulford, 2015), among whom over ninety percent of credit card holders borrow on credit cards (Nelson, 2020).

[14]The tax determinants include indicators for being married, having dependents, and receiving unemployment insurance; the demographic controls indicate whether a filer is female, over 50, or a college graduate.

[15]The estimates of ω are close to Baugh et al. (2020)'s estimate that 13% of tax refunds are used for debt repayment or savings; see their Table 4.

columns 2-4.[16] Figure A6 depicts a binned scatterplot corresponding to the regression in column 4.

Robustness In Tables 3 and A7 we present results that suggest mismeasurement of either σ_i or change in balances is unlikely to drive our results.

We address the concern that there is measurement error in σ_i first by running two-stage least squares models where we instrument for σ_i using our qualitative measures of uncertainty, as reported in Table 3 columns 5-7. We also consider measures of beliefs that were computed by fitting beliefs to beta (rather than normal) distributions, as reported in Table A7. In both cases, our qualitative findings hold.

Mismeasurement in change in balances could arise due to classical or non-classical measurement error. Classical measurement error on the left-hand side would simply lead to larger standard errors. For non-classical error, a potential concern is that individuals may endogenously self-insure against low refund realizations through channels not observed in credit report data, for example by changing their savings or labor supply. We address this concern by, first, examining two sub-populations that are less likely to have savings – those who did not receive their refund via direct deposit, and those who have no savings account with more than \$100 – and second, examining a subpopulation of individuals who indicated in our survey data that they are unable to change their labor income when desired. Table A7 shows the same positive relationship between uncertainty and borrowing in these subgroups as in our baseline specification.

5.2 Welfare Costs

Motivated by the evidence that uncertainty may affect consumption smoothing through borrowing behavior, we use a simple model to quantify the welfare cost of uncertainty. This exercise does not depend directly on the estimates in the prior section, given the strong assumptions required to directly estimate households' preferences. Instead, we report welfare costs for a range of standard preferences.

We consider a two-period model where households make $t = 0$ borrowing decisions with uncertainty about $t = 1$ income. Households have two income sources: known take-home pay c received in both periods, and tax refunds y received in $t = 1$. At $t = 0$, the household's belief about their refund is given by $F(y)$. They can borrow or save at rate R and choose

[16] We estimate the same regression at a six-month rather than two-month horizon and cannot reject equality between the two-month and six-month estimates. While this test is low-powered given our sample size, it is consistent with our qualitative findings not being driven by unobserved heterogeneity.

debt b to maximize their expected discounted utility, yielding ex-ante welfare

$$V^u \equiv \max_b \; u(c+b) + \beta \int_y u(c+y-Rb)dF(y)$$

By comparison, a household that knows y can adjust their $t=0$ debt in anticipation of their actual refund. Their ex-ante welfare is

$$V^{nu} \equiv \int_y \left[\max_b u(c+b) + \beta u(c+y-Rb)\right] dF(y) \; .$$

In the no-uncertainty case, the household still faces refund *variability*, perhaps due to changes in tax policy or income shocks not fully realized by the end of the year. To benchmark the welfare cost of uncertainty, we consider the deterministic case where each household receives a refund equal to their mean expectation:

$$V^d \equiv \max_b u(c+b) + \beta u\left(c + \int_y ydF(y) - Rb\right)$$

A predictable policy such as universal basic income would affect households' income processes similarly to the deterministic case.

This setup abstracts away from a number of issues that likely lead us to underestimate the welfare cost of refund uncertainty. Refund-related uncertainty and variability exist on top of other sources of income variability, leading us to underestimate the likelihood of states with a high marginal utility of income. Furthermore, our welfare calculations ignore any costly effort households exert to learn about their tax liability.

On the other hand, we may overstate welfare costs if we underestimate filers' abilities to smooth consumption. However, empirical evidence that low-income households have low savings and cannot fully consumption smooth even for small shocks (FRB, 2019) suggests that our model may be a reasonable approximation.

Compensating Variation We measure the welfare cost of uncertainty by computing households' compensating variation: their willingness-to-pay to be in the no-uncertainty and deterministic cases instead of the uncertainty case. Let CV^{nu} be the per-period CV for no uncertainty, and CV^d the per-period CV for a deterministic refund. Formally,

$$\int_y \left[\max_b u(c_{0,i}+b-CV_i^{\mathrm{nu}}) + \beta u(c_{1,i}+y-Rb-CV_i^{\mathrm{nu}})\right] dF_i(y) \;=\; V_i^u \tag{4}$$

$$\max_b u(c_{0,i}+b-CV_i^{\mathrm{d}}) + \beta u(c_{1,i} + \int_y [y]dF_i(y) - Rb - CV_i^{\mathrm{d}}) \;=\; V_i^u \tag{5}$$

We interpret CV^* as the per-period cost of refund uncertainty. Because this allows the household to re-optimize b given CV, it is likely a conservative estimate.

We take a period to be one quarter. To compute CV^* for each tax filer, we need information on preferences $\{u(.), \beta\}$, take-home pay c, beliefs $F(.)$, and the interest rate R. Elicited beliefs provide a measure of $F(.)$. Take-home pay, c, comes from tax returns and is held fixed across realizations of y. Following the literature estimating risk aversion in insurance markets (Brown and Finkelstein, 2008), our preferred specification assumes constant relative risk aversion utility with $\gamma = 3$. In robustness checks we consider alternative values of γ. We assume individuals discount the future at $\beta = .98$ and face a quarterly interest rate of $R = 1.05$. Appendix D provides details about how CV^d and CV^{nu} are calculated. Our reported estimates scale CV to equal the total, not per-period, compensation required to make individuals as well off as they are in the no-uncertainty or deterministic benchmark.

Welfare Losses Figure 2 presents the mean CV across filers. The gold (blue) bars represent CV for the no-uncertainty (deterministic) case.

The average filer would give up \$85 per year to eliminate tax refund uncertainty, more than 5 percent of the average tax refund in our sample. The mean CV^{nu} is \$171 per year for EITC filers, \$136 for filers with above-median uncertainty, and \$106 for households earning below 200 percent of the federal poverty line. CV^d is consistently about twice as large as CV^{nu}.

Welfare losses are especially large for filers whose refund uncertainty is large relative to income. The median CV^{nu} is \$11 for all filers and only \$33 for EITC filers, far lower than the respective means, but a long right tail of filers face a high cost of uncertainty. The standard deviation of CV^{nu} across filers is consistently two to three times the mean, \$250 for all filers and nearly \$400 for EITC filers.

The estimated welfare losses depend on the assumed level of risk aversion. Appendix Table A8 compares CV assuming $\gamma = 1$ and $\gamma = 5$ to those for $\gamma = 3$. With modest risk aversion ($\gamma = 1$), mean CV^{nu} is \$22 per year for all filers and \$43 per year for EITC recipients. These are about one fourth of the baseline values, but still more than one percent of the value of the EITC. Conversely, with very high risk aversion ($\gamma = 5$), mean CV^{nu} is \$128 for all filers and \$238 for EITC filers.

These welfare losses are large relative to the size of the average refund, particularly for EITC recipients; our results suggest welfare costs on the order of 10% of the value of the EITC. Scaling this by the size of the federal EITC in 2017 suggests aggregate annual welfare costs of \$6-11 billion. Our results show that the structure of the EITC — which provides individuals with a large, but *uncertain* transfer — leads to lower welfare gains than a transfer that is easy to anticipate. These numbers may be useful when comparing the EITC with equally large but certain transfers, such as a universal basic income.

6 Conclusion

This paper uses a unique survey of tax filers' refund expectations, linked to administrative tax and credit data, to quantify tax refund uncertainty and estimate its consequences. In our sample of low-income filers, individuals face substantial uncertainty about the size of their tax refund, even though this refund is often a significant portion of annual income. This uncertainty affects financial decisions: more uncertain filers borrow less before filing, consistent with precautionary behavior. A simple consumption-savings model suggests that refund uncertainty significantly reduces the efficiency of redistribution through the tax code.

Our results establish that tax refund uncertainty is quantitatively important. However, more work is needed to understand underlying mechanisms and their policy implications. Why households fail to resolve uncertainty could inform the design of tax simplification policies and may be important for predicting behavioral responses to, and welfare consequences of, other tax reforms. Tax-related uncertainty may also affect other economic decisions, such as labor supply. Combining survey and administrative data, as our study does, is a promising avenue for future work.

References

Abeler, Johannes and Simon Jäger, "Complex tax incentives," *American Economic Journal: Economic Policy*, 2015, *7* (3), 1–28.

Aghion, Philippe, Ufuk Akcigit, Matthieu Lequien, and Stefanie Stantcheva, "Tax Simplicity and Heterogeneous Learning," Technical Report, Harvard University 2017.

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, "Asymmetric Consumption Smoothing," Technical Report, National Bureau of Economic Research 2020.

Bettinger, Eric P, Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu, "The role of application assistance and information in college decisions: Results from the H&R Block FAFSA experiment," *The Quarterly Journal of Economics*, 2012, *127* (3), 1205–1242.

Brown, Jeffrey R and Amy Finkelstein, "The interaction of public and private insurance: Medicaid and the long-term care insurance market," *American Economic Review*, 2008, *98* (3), 1083–1102.

Carroll, Christopher D and Miles S Kimball, "On the Concavity of the Consumption Function," *Econometrica*, 1996, pp. 981–992.

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.

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.

Feenberg, Daniel and Elisabeth Coutts, "An introduction to the TAXSIM model," *Journal of Policy Analysis and management*, 1993, *12* (1), 189–194.

Finkelstein, Amy and Matthew J Notowidigdo, "Take-up and targeting: Experimental evidence from SNAP," *The Quarterly Journal of Economics*, 2019, *134* (3), 1505–1556.

FRB, "Report on the Economic Well-Being of US Households in 2018, May 2019," *Board of Governors of the Federal Reserve System, Washington, DC*, 2019.

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.

Gale, William G et al., "Tax simplification: issues and options," *Tax Notes*, 2001, *92* (11), 1463–1483.

Gelman, Michael, Shachar Kariv, Matthew D Shapiro, and Dan Silverman, "Rational Illiquidity and Consumption: Theory and Evidence from Income Tax Withholding and Refunds," Technical Report, National Bureau of Economic Research 2019.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song, "What do data on millions of US workers reveal about life-cycle earnings dynamics?," *FRB of New York Staff Report*, 2019, (710).

Handel, Benjamin R and Jonathan T Kolstad, "Health insurance for" humans": Information frictions, plan choice, and consumer welfare," *American Economic Review*, 2015, *105* (8), 2449–2500.

Jones, Damon, "Information, preferences, and public benefit participation: Experimental evidence from the advance EITC and 401 (k) savings," *American Economic Journal: Applied Economics*, 2010, *2* (2), 147–63.

_ , "Inertia and Overwithholding: Explaining the Prevalence of Income Tax Refunds," *American Economic Journal: Economic Policy*, 2012, *4* (1), 158–85.

Kleven, Henrik, "The EITC and the Extensive Margin: A Reappraisal," Technical Report, National Bureau of Economic Research 2020.

Manski, Charles F, "Measuring Expectations," *Econometrica*, 2004, *72* (5), 1329–1376.

Morgan, Millett Granger and Max Henrion, *Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis*, Cambridge university press, 1990.

Navin Associates, "Wealth Building at Tax Time," *https://owd.boston.gov/wp-content/uploads/2017/07/DES-89-Financial-Check-up-Evaluation-2017-Web.pdf*, 2017.

Nelson, Scott, "Private Information and Price Regulation in the US Credit Card Market," *Unpublished Working Paper*, 2020.

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.

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.

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.

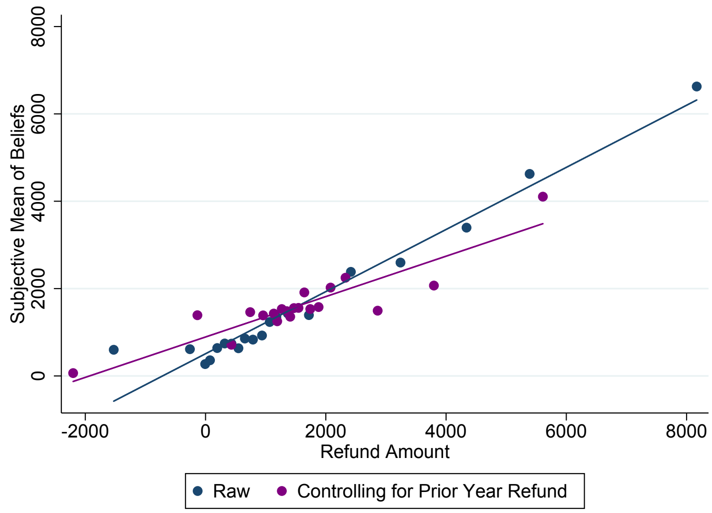
Zeldes, Stephen P, "Consumption and Liquidity Constraints: An Empirical Investigation," *Journal of Political Economy*, 1989, *97* (2), 305–346.

Zwick, Eric, "The Costs of Corporate Tax Complexity," 2018.

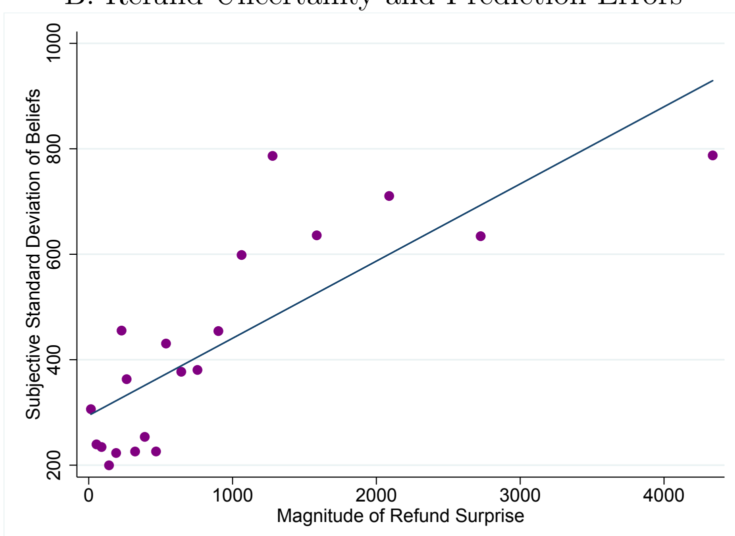
7 Figures and Tables

Figure 1: Variation in Fitted Beliefs

A. Expected Refunds Versus Actual Refunds

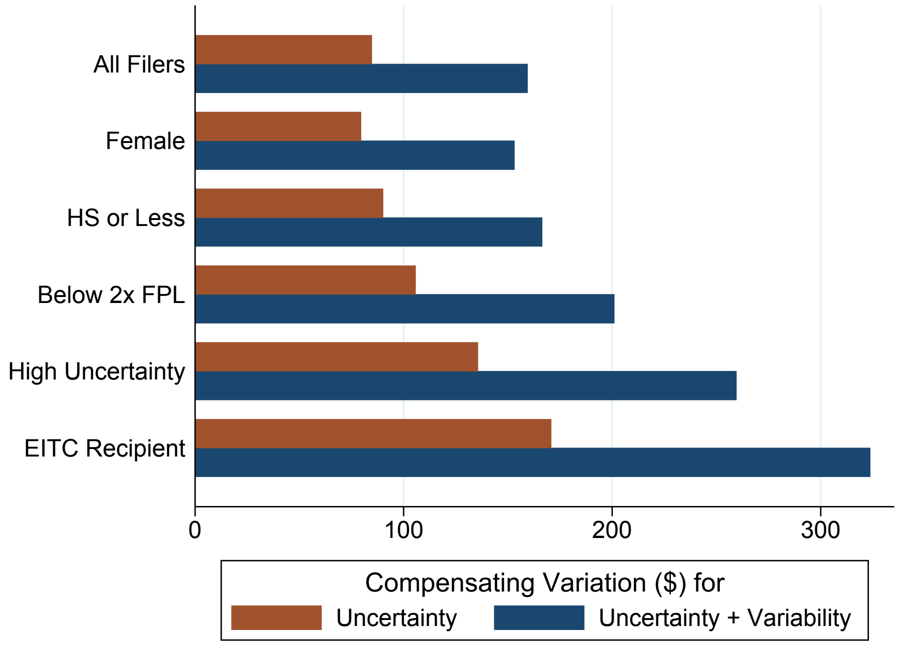


B. Refund Uncertainty and Prediction Errors



Note: Panel A shows binned scatterplots of mean expectations against actual refund amounts. The expected refunds are the means of the distributions calculated using the procedure described in Section 3. The blue binscatter corresponds to the unconditional correlation. The purple binscatter was computed after controlling for the amount of the prior-year refund. Panel B shows a binned scatterplot of the size of each filer's prediction error (actual refund - mean expectation) against the subjective standard deviation of beliefs.

Figure 2: Compensating Variation by Demographic Group



Note: This figure shows the mean compensating variation (CV) for different demographic groups under two scenarios. Under the "uncertainty" (gold) scenario, individuals are given per-period transfers such that they are as well off as they are when they choose debt and consumption levels, knowing their future refund. Under the "uncertainty+variability" (blue) scenario, individuals are given per-period transfers such that they are as well off as they are when they face a deterministic refund equal to the expected refund. These numbers are computed assuming a CRRA utility function with $\gamma = 3$. In the figure labels, high uncertainty is defined as having above-median subjective standard deviation, FPL abbreviates federal poverty level, and HS abbreviates high school. More information on how we compute CV is provided in Section 5.2. Results for a wider range of utility functions are presented in Appendix Table A8.

Table 1: Characteristics of Filers and Beliefs

		Tax Circumstances and Beliefs			
	Sample Mean	S.D. of Elicited Beliefs	Abs. Change in Refund	Abs. Change in MTR	Abs. Forecast Error
	(1)	(2)	(3)	(4)	(5)
Absolute Change in AGI	6.15	10.43**	48.05***	0.00462***	-0.481
	(8.79)	(4.517)	(10.83)	(0.00156)	(6.413)
Has Dependents	0.32	478.5***	554.7***	0.0754***	829.6***
	(0.00)	(50.55)	(142.4)	(0.0208)	(106.7)
Change in No. Dependents	-0.04	-84.03	1660.1***	0.0586	973.0***
	(0.55)	(106.7)	(373.7)	(0.0366)	(338.4)
Married	0.08	176.8*	-143.2	-0.0446	-41.38
	(0.00)	(90.30)	(244.8)	(0.0382)	(158.1)
Change in Filing Status	0.09	-46.52	-64.57	0.0350	-537.2*
	(0.29)	(111.1)	(415.3)	(0.0428)	(301.1)
Received UI during Past Year	0.08	-16.94	-38.53	0.0199	72.14
	(0.00)	(66.57)	(276.3)	(0.0367)	(141.2)
Age 25 or Younger	0.22	-25.92	-331.4**	0.00295	-112.1
	(0.42)	(42.85)	(156.2)	(0.0176)	(98.24)
Above Age 50	0.28	-139.6***	-338.8***	-0.0217	-196.4**
	(0.45)	(38.26)	(126.3)	(0.0164)	(92.50)
Any College	0.15	1.789	11.53	-0.000560	122.9
	(0.00)	(42.69)	(135.9)	(0.0163)	(87.52)
Female	0.62	-38.92	35.51	-0.00378	-133.9
	(0.49)	(38.68)	(133.6)	(0.0172)	(83.64)
Constant	---	303.1***	374.5***	0.0310*	672.2***
		(48.92)	(136.5)	(0.0177)	(94.72)
Observations	618	618	337	337	618
R-squared	---	0.255	0.442	0.231	0.221

Note: The first column describes the characteristics of filers in our core sample. Columns 2-5 examine heterogeneity in filers' beliefs and tax situations, presenting estimates from regressions corresponding to equation 2 in the text. Each of these four columns shows estimates for the dependent variable indicated in the column header. The dependent variables are in dollar units; Absolute Change in AGI is in \$1,000 units. Absolute Forecast Error is the absolute difference between each filer's refund amount and their mean elicited belief. All specifications include the listed covariates, plus controls for whether a given demographic variable was missing. Table A1 presents additional descriptive statistics and Table A5 presents additional specifications. Robust standard errors are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 2: Updating Rates

Dependent Variable: Difference between Mean Expectation and Last Year's Refund				
	No Heterogeneity	Full Heterogeneity	Tax Determinants Only	Demographics Only
	(1)	(2)	(3)	(4)
Change in Refund Amount over Last Year	0.597***	0.233	0.264**	0.580***
	(0.0722)	(0.149)	(0.122)	(0.140)
Interacted with Change in Refund Amount				
Absolute Change in AGI		0.0118**	0.0113**	
		(0.00491)	(0.00486)	
Absolute Change in MTR		0.457*	0.476*	
		(0.246)	(0.250)	
Has Dependents		-0.180	-0.0277	
		(0.160)	(0.144)	
Any Change in No. Dependents		0.0127	0.0416	
		(0.144)	(0.140)	
Married		0.0305	-0.0174	
		(0.153)	(0.173)	
Change in Filing Status		0.184	0.194	
		(0.146)	(0.153)	
Received UI during Past Year		-0.316	-0.221	
		(0.225)	(0.222)	
Age 25 or Younger		-0.403		-0.514**
		(0.285)		(0.250)
Above Age 50		0.0207		0.0133
		(0.115)		(0.177)
Any College		0.112		0.0231
		(0.131)		(0.152)
Female		0.205*		0.0469
		(0.119)		(0.158)
Observations	337	337	337	337
R-squared	0.336	0.411	0.395	0.348
No Updating (p-value)	<.01	<.01	<.01	<.01
No Heterogeneity in Updating Rates (p-value)	<.01	<.01	<.01	0.31
Full Updating (p-value)	<.01	<.01	<.01	<.01

Notes: Estimated coefficients from equation 2 in the main text. Each control is interacted with the tax filer's change in refund amount. The sample includes all filers for whom tax refund information is available from the prior tax year. Specifications with demographic and economic controls (columns 2-4) also control for missing value indicators for each variable; these coefficients are omitted for brevity. The last three rows present p-values from F-tests of the hypotheses of no updating ($\beta = 0$); no updating rate heterogeneity by filer characteristics; and complete updating ($X_i\beta = 1\,\forall i$). Robust standard errors are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

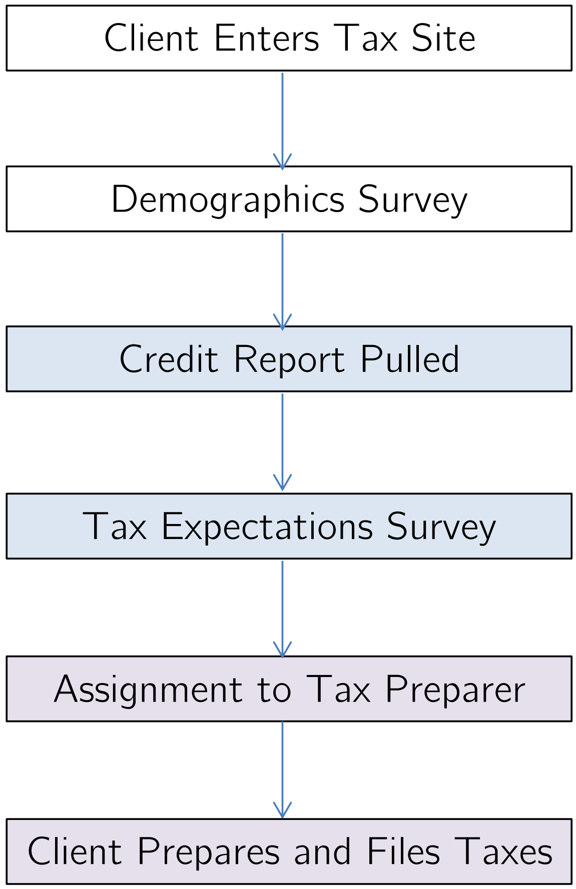
Table 3: Impact of Uncertainty on Borrowing

	Baseline Model (OLS)				2SLS Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	2-Month Change in Balances						
Expected Refund Amount	-39.94	-79.23**	-44.23	-40.38	-271.7*	-199.4	-199.3
	(27.59)	(33.69)	(38.21)	(38.07)	(140.3)	(131.0)	(146.0)
Subjective Standard Deviation		227.0*	237.2*	259.3**	1339.1*	1194.6	1243.0
		(135.0)	(128.4)	(131.5)	(806.3)	(769.9)	(866.9)
					First Stage		
"Somewhat Sure" of Refund Amount					-0.154**	-0.154**	-0.140**
					(0.0598)	(0.0613)	(0.0604)
"Very Sure" of Refund Amount					-0.185***	-0.181***	-0.156***
					(0.0598)	(0.0596)	(0.0586)
Controls							
Demographics			X	X		X	X
Tax Determinants				X			X
First-stage F-stat	--	--	--	--	4.89	4.73	3.67
Observations	359	359	359	359	359	359	359
R-squared	0.009	0.018	0.079	0.096	--	--	--

Note: This table investigates how uncertainty affects filers' borrowing behavior with regard to their tax refund. The regressions include all filers for whom we have expectations data, demographic surveys, and credit report data. The dependent variable is a 2-month change in non-installment debt balances, and coefficients are scaled to be per-$1000 of the regressors. Columns 1-4 provide results from OLS regressions of the dependent variable on the expected refund amount and other covariates as listed. Columns 5-7 provide 2SLS estimates, where we use the qualitative uncertainty measures as instruments for subjective uncertainty. The demographic controls include controls for whether a filer is female, over 50, a college graduate, married, or has dependents. The tax determinants include controls for the (absolute value of the) change in AGI, a dummy for any change in the number of dependents, a dummy for a change in filing status, and a dummy for whether the filer received UI this year. Robust standard errors are in parentheses. * $p < .1$ ** $p < 0.05$ *** $p < 0.01$

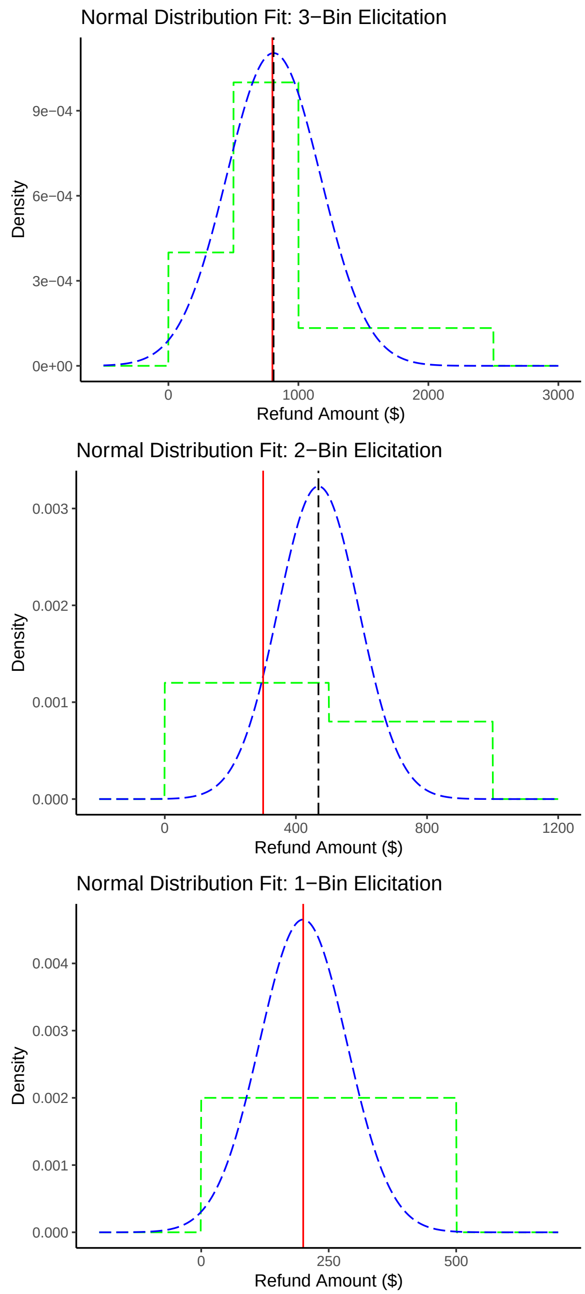
A Appendix Tables and Figures

Figure A1: Tax Site Client Flow



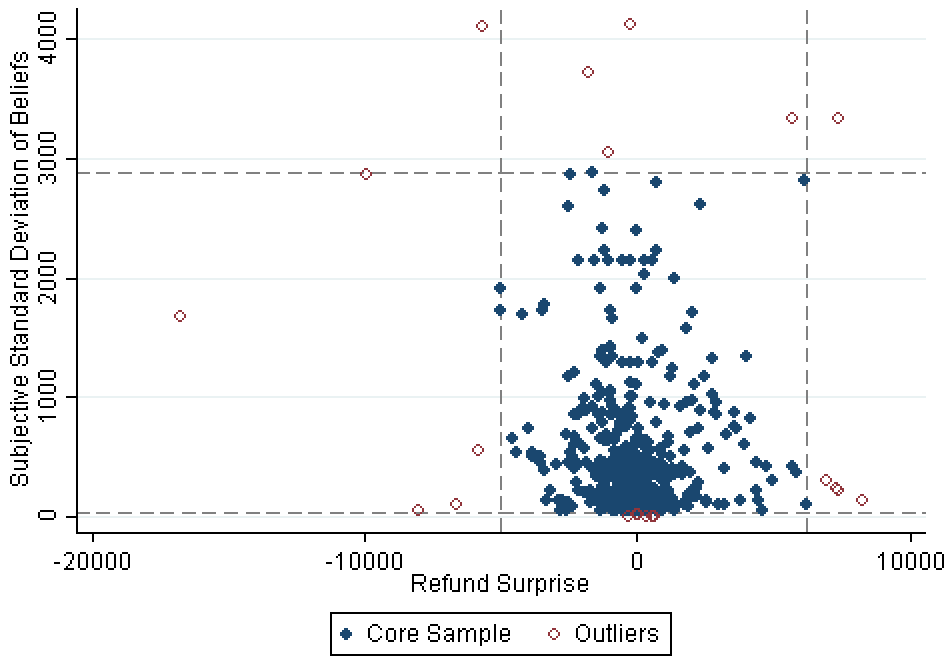
Note: This figure shows the steps a tax filer would go through upon arriving at the center. The steps in white occur before a filer has met with a financial guide or tax preparer. The steps in blue are completed in collaboration with one of the site's financial guides. Filers provided consent for their tax, credit, and survey information to be used for research purposes immediately prior to the tax expectations survey. The steps in purple are completed with the help of a volunteer tax preparer.

Figure A2: Fitting Beliefs to Normal Distributions



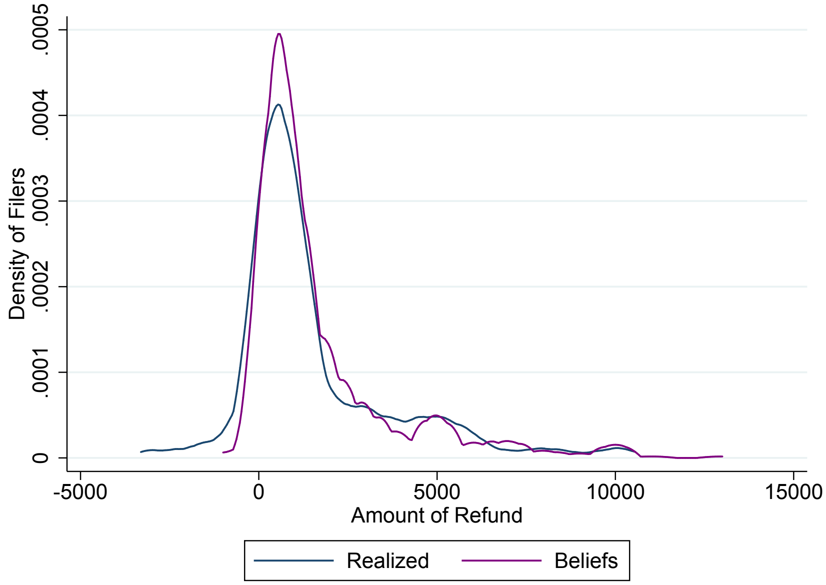
Note: This figure shows how we fit probabilistic beliefs to normal distributions if the individual places positive mass in 3 or more bins (top), in 2 bins (middle) or 1 bin (bottom). Solid lines denote data; dashed lines denote fitted distributions. The green dashed lines report the distribution of beliefs, assigning a uniform density over the density in each bin. The red line denotes the point estimate. The dashed blue curves show the density of the fitted distribution and the dashed black line shows the mean of this distribution. More information on how we fit beliefs to normal distributions is provided in Section 3. Graphs describing how we fit beliefs to beta distributions are provided in Figure A8. Table A3 presents descriptive statistics on the fitted beliefs.

Figure A3: Expectation Outliers and Core Sample



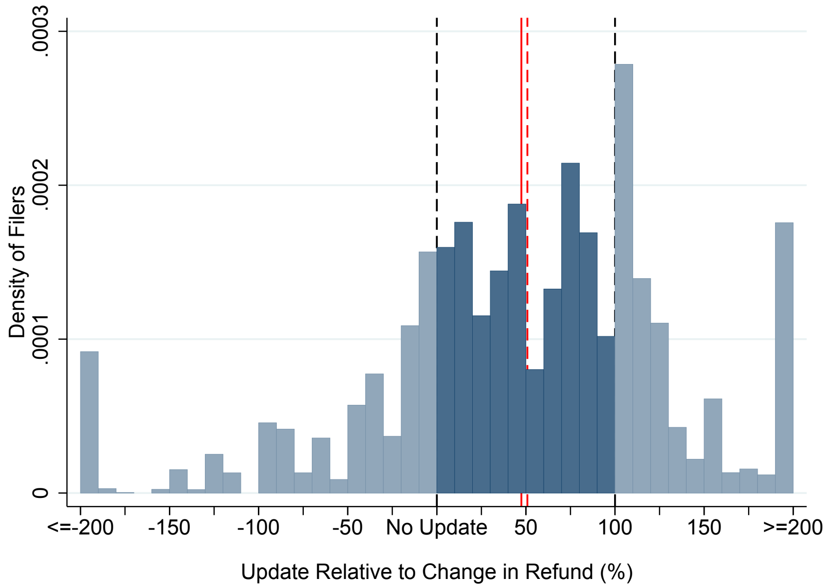
Note: This figure plots the fitted standard deviation of subjective beliefs about refund size, against the realized refund prediction errors. Dotted lines denote the thresholds at which the top and bottom 1% of refund prediction errors and the top and bottom 5% of subjective standard deviations are excluded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

Figure A4: Distribution of Refund Expectations



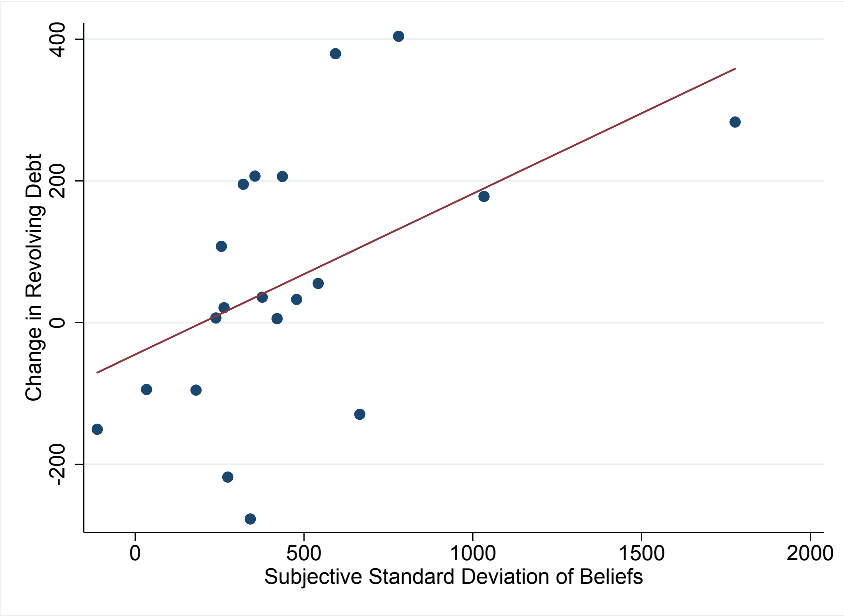
Note: This figure shows kernel density plots of filers' observed refunds (blue) and mean expectations (purple). The densities were computed using an Epanechnikov kernel with the optimal (Gaussian) bandwidth, which here is $318.

Figure A5: Belief Updating



Note: This figure plots the distribution of $\frac{m_1 - y_0}{y_1 - y_0} \times 100$, the amount an individual updates relative to his/her past year refund, as a percentage of the actual changes in refund. Negative values indicate the individual's mean estimate moved (relative to their prior year refund) in the wrong direction. Numbers between 0 and 100 indicate beliefs that fall in between the prior-year refund and the current-year refund. Numbers over 100 indicate beliefs that moved in the same direction as the refund, but which "overshot". Updates are bottom- and top-coded at -200 and 200 percent. Observations are weighted by the size of refund. The solid red line shows the mean and the dashed red line shows the median.

Figure A6: Refund Uncertainty and Borrowing Behavior



Note: This figure shows a binned scatterplot of 2-month changes in non-installment balances against subjective uncertainty corresponding to the regression specification in equation 3. These data are plotted after partialling out the demographic and tax filer characteristics included in column 4 of Table 3.

Table A1: Descriptive Statistics

	All Filers	Sample Excluding Outliers			
	Tax Data & Expectations Data	Tax Data & Expectations Data	Tax Data, Expectations Data, & Demographics	Tax Data, Expectations Data, & Demographics	Tax Data, Expectations Data, & Credit Card Data
	(1)	(2)	(3)	(4)	(5)
Demographic Characteristics					
Female	0.62	0.62	0.62	0.65	0.67
	(0.15)	(0.15)	(0.15)	(0.18)	(0.20)
Age	40.46	40.21	40.15	42.85	41.66
	(15.90)	(15.92)	(15.82)	(15.70)	(15.87)
High School or Above	0.82	0.82	0.82	0.85	0.86
	(0.39)	(0.38)	(0.38)	(0.36)	(0.35)
Some College or More	0.15	0.15	0.15	0.18	0.20
	(0.36)	(0.36)	(0.36)	(0.38)	(0.40)
Economic and Tax Characteristics					
Adjusted Gross Income ($)	20,998	20,637	20,705	23,475	24,081
	(15,941)	(15,930)	(15,752)	(16,228)	(16,356)
Has Dependents	0.32	0.32	0.32	0.36	0.34
	(0.47)	(0.47)	(0.47)	(0.48)	(0.47)
Married	0.08	0.08	0.07	0.07	0.08
	(0.28)	(0.27)	(0.26)	(0.25)	(0.28)
Single Head of Household	0.27	0.27	0.27	0.31	0.29
	(0.45)	(0.44)	(0.45)	(0.46)	(0.45)
Filed Schedule C	0.07	0.08	0.07	0.07	0.07
	(0.26)	(0.27)	(0.26)	(0.25)	(0.26)
Lost Job	0.08	0.08	0.07	0.07	0.06
	(0.26)	(0.27)	(0.26)	(0.25)	(0.24)
Tax Refund					
Refund Amount ($)	1,585	1,542	1,552	1,846	1,746
	(2,372)	(2,207)	(2,194)	(2,385)	(2,311)
Received EITC	0.35	0.35	0.35	0.35	0.31
	(0.48)	(0.48)	(0.48)	(0.48)	(0.46)
EITC Credit (If >0)	1,730	1,654	1,623	1,985	1,891
	(1,703)	(1,661)	(1,664)	(1,796)	(1,713)
EITC share	0.50	0.50	0.49	0.53	0.46
	(0.42)	(0.43)	(0.38)	(0.43)	(0.40)
Chose Direct Deposit	0.58	0.59	0.58	0.64	0.65
	(0.49)	(0.49)	(0.49)	(0.48)	(0.48)
Observations	692	618	548	337	359
with Demographics	692	548	548	303	319

Note: This table provides descriptive statistics on our sample of low-income filers. The first column describes filers who completed the expectations survey. The remaining columns focus on our core sample, which excludes outlier observations. These are individuals with subjective uncertainty in the top or bottom 5% of expectations survey respondents, and tax refund prediction errors in the top or bottom 1%, as well as individuals with adjusted gross incomes below 0. The second column describes non-outlier tax filers who completed the expectations survey. Columns 3-5 present similar descriptive statistics for individuals for whom we have additional information from the demographic survey (column 3), prior year tax return (column 4), or credit reports (column 5). Individuals do not appear in column 5 if either they did not provide consent for us to pull a credit report (96% did), or if they do not have credit. Additional descriptive statistics are provided in Table A2.

Table A2: Descriptive Statistics

	All Filers	Sample Excluding Outliers			
	Tax Data & Expectations Data	Tax Data & Expectations Data	Tax Data, Expectations Data, & Demographics	Tax Data, Expectations Data, & Demographics	Tax Data, Expectations Data, & Credit Card Data
	(1)	(2)	(3)	(4)	(5)
Savings and Credit					
Estimated Savings Balance	522	523	523	546	634
	(572)	(576)	(576)	(583)	(606)
FICO Score	664	666	666	675	684
	(86)	(87)	(88)	(89)	(80)
Credit Card Balances ($)	1,680	1,686	1,780	2,005	2,630
	(4,836)	(4,985)	(5,228)	(5,925)	(6,026)
Non-Mortgage Installment Balances	9,359	9,612	9,938	11,696	12,589
	(22,694)	(23,488)	(24,319)	(26,886)	(27,036)
Has Mortgage	0.05	0.04	0.05	0.06	0.06
	(0.21)	(0.21)	(0.21)	(0.23)	(0.23)
Filing Characterisstics					
Absolute Change in AGI	6.27	6.15	6.06	6.12	5.94
	(9.01)	(8.79)	(8.49)	(8.78)	(9.04)
Change in Filling Status	0.10	0.09	0.09	0.09	0.06
	(0.30)	(0.29)	(0.29)	(0.29)	(0.24)
Received UI during Past Year	0.08	0.08	0.07	0.07	0.06
	(0.26)	(0.27)	(0.26)	(0.25)	(0.24)
Change in Number of Dependents	-0.04	-0.04	-0.05	-0.04	-0.05
	(0.57)	(0.55)	(0.57)	(0.55)	(0.51)
Any Change in Number of Dependents	0.13	0.13	0.14	0.13	0.09
	(0.34)	(0.33)	(0.34)	(0.33)	(0.29)
Observations	692	618	548	337	359
with Demographics	692	548	548	303	319

Note: This table provides descriptive statistics on our sample of low-income filers. The first column describes filers who completed the expectations survey. The remaining columns focus on our core sample, which excludes outlier observations. These are individuals with subjective uncertainty in the top or bottom 5% of expectations survey respondents, and tax refund prediction errors in the top or bottom 1%, as well as individuals with adjusted gross incomes below 0. The second column describes non-outlier tax filers who completed the expectations survey. Columns 3-5 present similar descriptive statistics for individuals for whom we have additional information from the demographic survey (column 3), prior year tax return (column 4), or credit reports (column 5). Individuals do not appear in column 5 if either they did not provide consent for us to pull a credit report (96% did), or if they do not have credit. Additional descriptive statistics are provided in Table A1.

Table A3: Elicited Beliefs by Filer Group

	Core Sample	Has Dependents		Marital Status		College Education		Relative to 2x Federal Poverty Line	
		Yes	No	Married	Not Married	Yes	No	Below	Above
Number of Bins with Positive Probability									
1 Bin	22.2%	24.1%	21.3%	22.4%	22.1%	20.4%	24.4%	20.6%	25.0%
2 Bins	38.7%	39.0%	38.5%	36.7%	38.8%	38.1%	39.4%	40.9%	34.8%
3 Bins	20.7%	16.4%	22.7%	14.3%	21.3%	21.2%	20.1%	21.6%	19.2%
4 Bins	11.0%	11.3%	10.9%	12.2%	10.9%	12.1%	9.7%	10.2%	12.5%
5 Bins	5.0%	7.2%	4.0%	8.2%	4.7%	5.9%	3.9%	4.8%	5.4%
6 Bins	2.4%	2.1%	2.6%	6.1%	2.1%	2.4%	2.5%	2.0%	3.1%
Qualitative Uncertainty									
Very Certain	34.0%	30.3%	35.7%	44.9%	33.0%	31.3%	37.3%	36.5%	29.5%
Somewhat Certain	41.7%	48.2%	38.8%	36.7%	42.2%	41.0%	42.7%	40.6%	43.8%
Not Certain At All	23.5%	21.0%	24.6%	18.4%	23.9%	26.5%	19.7%	22.1%	25.9%
Quantitative Responses									
Point Estimate	1682	3520	837	2469	1614	1646	1726	1330	2303
Features of Parametric Distribution									
Mean	1605	3365	794	2378	1539	1595	1618	1251	2229
Std. Dev.	426	769	268	648	407	437	413	353	553
Observations	618	195	423	49	569	339	279	394	224

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 A4: Features of Subjective Belief Distributions

	Mean (1)	Standard Deviation (2)	25th Percentile (3)	50th Percentile (4)	75th Percentile (5)	Sample Size (6)
Qualitative Uncertainty						
Very Sure	34%	47%				618
Somewhat Sure	42%	49%				618
Not Sure	23%	42%				618
Point Forecast	1,682	2,115	400	1,000	2,000	616
Moments of Belief Distribution						
Mean	1,605.35	2,000.49	441.78	900.00	1,930.96	618
Standard Deviation	425.87	509.73	117.60	217.68	494.43	618
Coefficient of Variation	131.25	1,264.63	0.14	0.27	0.51	606
Moments as a Fraction of Income						
Mean	0.16	0.65	0.03	0.06	0.15	613
Standard Deviation	0.07	0.37	0.01	0.02	0.04	613
Change in Refund	-$92	$1,625	-$491	$12	$335	337

Note: This table presents descriptive statistics on qualitative uncertainty and on the moments of the subjective belief distributions for individuals for whom we have tax and expectations data. The sample size varies across rows because a few individuals did not report point forecasts or did not have income in the prior year. In addition, the final row, which reports the mean change in refund relative to the previous year, includes only individuals for whom we have two years of tax returns.

Table A5: What Drives Uncertainty?

	S.D. of Elicited Beliefs			Abs. Change in Refund Amount			Abs. Change in MTR			Abs. Forecast Error		
	Baseline	Tax Determinants Only	Demographics Only	Baseline	Tax Determinants Only	Demographics Only	Baseline	Tax Determinants Only	Demographics Only	Baseline	Tax Determinants Only	Demographics Only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Absolute Change in AGI	10.43**	11.22**		48.05***	49.33***		0.00462***	0.00473***		-0.481	1.121	
	(4.517)	(4.449)		(10.83)	(11.05)		(0.00156)	(0.00155)		(6.413)	(6.473)	
Has Dependents	478.5***	491.4***		554.7***	652.4***		0.0754***	0.0776***		829.6***	845.0***	
	(50.55)	(51.24)		(142.4)	(138.1)		(0.0208)	(0.0195)		(106.7)	(99.62)	
Change in No. Dependents	-84.03	-78.60		1660.1***	1650.8***		0.0586	0.0596		973.0***	973.0***	
	(106.7)	(107.6)		(373.7)	(375.2)		(0.0366)	(0.0366)		(338.4)	(339.1)	
Married	176.8*	156.5*		-143.2	-210.6		-0.0446	-0.0512		-41.38	-38.77	
	(90.30)	(91.82)		(244.8)	(228.3)		(0.0382)	(0.0372)		(158.1)	(159.9)	
Change in Filing Status	-46.52	-49.99		-64.57	-48.17		0.0350	0.0347		-537.2*	-548.7*	
	(111.1)	(112.7)		(415.3)	(419.5)		(0.0428)	(0.0424)		(301.1)	(305.2)	
Received UI during Past Year	-16.94	-19.38		-38.53	18.93		0.0199	0.0196		72.14	94.73	
	(66.57)	(65.50)		(276.3)	(272.4)		(0.0367)	(0.0365)		(141.2)	(136.2)	
Age 25 or Younger	-25.92		-177.8***	-331.4**		-595.6***	0.00295		-0.0274	-112.1		-358.2***
	(42.85)		(48.82)	(156.2)		(149.5)	(0.0176)		(0.0228)	(98.24)		(103.2)
Above Age 50	-139.6***		-242.8***	-338.8***		-653.4***	-0.0217		-0.0546***	-196.4**		-410.8***
	(38.26)		(43.25)	(126.3)		(160.2)	(0.0164)		(0.0166)	(92.50)		(99.38)
Any College	1.789		-20.05	11.53		-69.63	-0.000560		-0.00644	122.9		56.51
	(42.69)		(46.88)	(135.9)		(176.1)	(0.0163)		(0.0178)	(87.52)		(97.84)
Female	-38.92		54.01	35.51		128.1	-0.00378		0.0106	-133.9		87.28
	(38.68)		(45.54)	(133.6)		(177.5)	(0.0172)		(0.0179)	(83.64)		(93.99)
Constant	303.1***	222.9***	535.0***	374.5***	204.5***	1195.5***	0.0310*	0.0206**	0.105***	672.2***	553.4***	1033.8***
	(48.92)	(31.18)	(51.83)	(136.5)	(70.28)	(188.1)	(0.0177)	(0.00996)	(0.0172)	(94.72)	(60.11)	(95.90)
Observations	618	618	618	337	337	337	337	337	337	618	618	618
R-squared	0.255	0.240	0.057	0.442	0.427	0.062	0.231	0.226	0.029	0.221	0.209	0.049

Note: This table investigates the sources of refund uncertainty. Each column presents coefficients from a regression with a different dependent variable, indicated in the header. The dependent variables in columns 1-6 and 10-12 are in dollar units. Absolute Forecast Error is the absolute difference between each filer's refund amount and their mean elicited belief. Absolute Change in AGI is in $1,000 units. All specifications include the listed covariates, plus controls for whether a given demographic variable was missing. Robust standard errors are in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A6: Belief Updating Rates over Prior Year

	Number of Filers	Fraction with ratio of expected and realized change			Mean Ratio (%)
		< 0	[0,100]	> 100	
All	324	23.8%	48.0%	28.2%	47.4%
Male	96	18.6%	57.7%	23.7%	43.2%
Female	178	20.7%	48.9%	30.4%	58.2%
Young	151	20.7%	52.6%	26.7%	42.4%
Old	173	26.5%	44.0%	29.5%	51.8%
Has Kids	119	24.7%	48.2%	27.1%	43.0%
No Kids	205	22.4%	47.7%	29.9%	54.1%
HS or Less	138	21.6%	50.9%	27.6%	35.2%
More than HS	142	21.3%	48.6%	30.1%	62.3%
Received EITC	118	30.3%	43.1%	26.6%	38.2%
No EITC	206	18.3%	52.1%	29.6%	55.3%

Note: Numbers based on the statistic $\frac{m_{1,i}-r_{0,i}}{r_{1,i}-r_{0,i}}$, for tax filers who also filed their taxes in the previous year. As described in Section 4.2, this is the difference between an individual's expectation of this year's refund and their prior year refund, scaled by the change in realized refunds from last year to this year. The three middle columns show the fraction of filers for whom the ratio is negative, between 0 and 100, or over 100. Filers for whom the ratio is negative have expectations that moved in the opposite direction (relative to their prior year refund) than their realized refund. Filers for whom the ratio is between 0 and 100 updated in the "correct" direction, but less than 100%. Filers for whom the ratio is over 100 updated in the "correct" direction, but thought their refund would change more than it did. Mean Ratio (%) is the mean of this statistic across tax filers in each subgroup.

Table A7: Robustness of Borrowing Results

		Alternate Samples			Alternate Belief Distribution: Beta Distribution				
	Baseline	No Direct Deposit	No Savings	Can't Change Income	Full Sample	No Direct Deposit	No Savings	Can't Change Income	LIML
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expected Refund Amount	-40.38	-6.266	-35.28	-0.487	-54.92	-10.04	-68.22	-33.69	-208.5
	(38.07)	(47.30)	(79.27)	(41.61)	(44.14)	(48.67)	(93.92)	(49.81)	(155.2)
Subjective Standard Deviation	259.3**	196.4	486.0**	370.7**	154.0	48.57	329.0*	224.6*	1300.1
	(131.5)	(143.1)	(203.5)	(144.6)	(120.6)	(116.0)	(193.8)	(135.7)	(924.9)
Controls									
Demographics	X	X	X	X	X	X	X	X	X
Tax Determinants	X	X	X	X	X	X	X	X	X
Observations	359	234	91	211	359	234	91	211	359
R-squared	0.096	0.103	0.273	0.130	0.092	0.092	0.255	0.114	---

Note: This table investigates the robustness of the borrowing results in Table 3. The regressions include all of the core sample tax filers for whom we have expectations data, demographic surveys, and credit report data. Column 1 repeats the main specification in Column 4 of Table 3. Columns 2-4 present the same specification for different subsamples. The no direct deposit sample consists of filers who received their refund by mail, rather than direct deposit. The no savings sample consists of individuals who have less than \$100 in savings. The "can't change income" sample consists of individuals who, on the expectations survey, said that they could not easily change their income. Columns 5-8 present present results analogous to those in columns 1-4 where we use the means and standard deviations calculated by fitting beta distributions, rather than normal distributions. Column 9 presents LIML estimates for a regression analogous to that in column 1, where we have instrumented for the subjective standard deviation with indicators for our two qualitative measures of uncertainty. The demographic controls include controls for whether a filer is female, over 50, a college graduate, married, or has dependents. The tax determinants include controls for the (absolute value of the) change in AGI, a dummy for any change in the number of dependents, a dummy for a change in filing status, and a dummy for whether the filer received UI this year. Robust standard errors are in parentheses. * $p < .1$ ** $p < 0.05$ *** $p < 0.01$

Table A8: Compensating Variation Under Different Utility Specifications

		Baseline Specification CRRA, Gamma=3		Alternate Specifications, CRRA Utility			
				Gamma=1		Gamma=5	
	Percent of Sample	Uncertainty	Uncertainty+ Variability	Uncertainty	Uncertainty+ Variability	Uncertainty	Uncertainty+ Variability
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
All Taxfilers	100%	84.72	159.40	21.82	42.99	127.96	252.34
		[11.49]	[23.70]	[3.78]	[9.20]	[19.50]	[39.75]
		(250.73)	(481.29)	(56.24)	(102.97)	(326.69)	(655.86)
Female	56%	79.55	153.09	22.61	44.84	134.26	255.91
		[12.33]	[26.01]	[4.30]	[10.37]	[20.99]	[42.16]
		(216.68)	(404.09)	(58.92)	(107.83)	(358.90)	(647.97)
High School or Less	38%	90.15	166.41	25.48	49.46	135.33	266.15
		[11.89]	[24.50]	[4.04]	[9.09]	[20.65]	[40.32]
		(228.51)	(410.90)	(63.65)	(115.50)	(324.23)	(611.86)
Below 2xFederal Poverty Line	53%	105.74	201.01	26.14	49.94	140.42	295.84
		[11.06]	[22.18]	[3.82]	[8.10]	[19.38]	[37.20]
		(308.81)	(607.33)	(67.85)	(122.44)	(343.00)	(758.77)
High Uncertainty Filer	50%	135.59	259.57	36.29	70.81	205.73	404.37
		[35.87]	[71.83]	[11.41]	[24.51]	[59.82]	[120.90]
		(295.14)	(594.19)	(69.57)	(126.88)	(366.86)	(752.53)
EITC Filer	31%	170.74	323.71	42.94	81.54	238.44	483.73
		[33.27]	[65.77]	[10.45]	[22.69]	[57.35]	[111.76]
		(397.74)	(779.15)	(88.71)	(160.13)	(480.52)	(999.45)

Note: This table shows the mean compensating variation for different demographic groups under two scenarios. Under the "uncertainty" scenario, individuals are given per-period transfers such that they are as well off as they are when they choose debt and consumption levels, knowing their future refund. Under the "uncertainty+variability" scenario, individuals are given per-period transfers such that they are as well off as they are when they face a deterministic refund equal to the expected refund. The columns specify different assumptions on individuals' utility functions. More information on how we compute CV is provided in Section 5.2.

B Data and Empirical Setting

This appendix provides more information on the tax filer surveys, as well as information on the context in which we conducted these surveys.

B.1 Expectations Survey

The expectations survey consisted of four questions, printed on the next page. The survey was administered by the financial guides at the tax site.

The first question produces a point estimate of individuals' beliefs. The second question measures individuals' qualitative uncertainty: whether they are "not sure at all", "somewhat sure", or "very sure" that their refund would fall with a $500 window of the number they reported in the first question. The third question was used to measure labor income flexibility.

The fourth question elicits probabilistic beliefs. The number of bins was chosen in coordination with the VITA partner in order to balance the need to run the survey quickly with the desire to obtain richer information on individuals' beliefs. The boundaries of the bins were chosen using data on the distribution of refunds for filers at the site in the previous year, so that roughly an equal number of actual refunds would fall in each bin, with a smaller number in the two tail bins. In our core sample, the middle four of these six bins ultimately covered 24%, 19%, 24%, and 13% of taxfilers' actual refunds, while the two tail bins covered 20% of taxfilers' actual refunds.

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

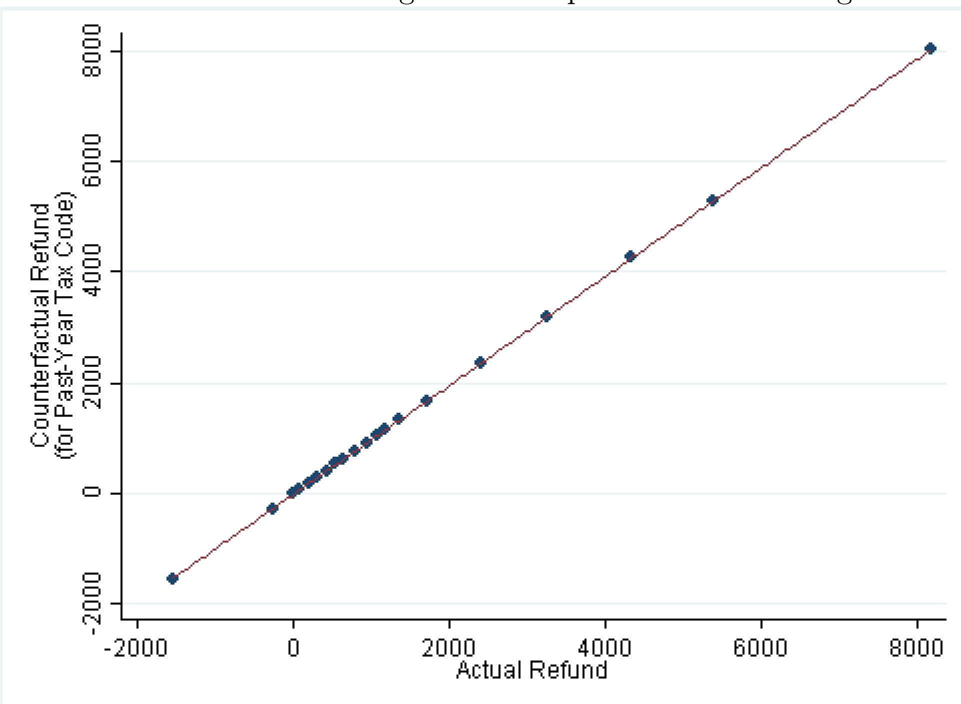
4) We have one final question about your tax refund. Below we show six possible amounts that your refund could be (for example, "between $1000 and $2500"). For <u>each</u> of the six possibilities, please say what is the "percent chance" that you think your refund could be that amount:

Could my refund be…	**(Please Enter % Chance for <u>Each</u>)**
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 Tax Environment

We conducted our survey in spring 2016, when filers were filing their 2015 tax year returns. Figure A7 shows that there were no major changes in either the federal or state tax schedule that would have resulted in large refund changes between tax years 2014 and 2015.

Figure A7: Imputed Refund Changes



Note: This figure plots a binned scatterplot of the refund an individual would have received under the 2014 tax rules (y-axis), relative to what they received under the 2015 schedule. The 2014 refunds were calculated using NBER TAXSIM (Feenberg and Coutts, 1993).

This is not surprising, because both the federal and state income schedules remained fairly stable between 2014 and 2015. The EITC and CTC also saw no major changes.

C Updating Model

Suppose filers' prior beliefs ($m_{0,i}$) are normally distributed and centered at their prior year refund ($r_{0,i}$) with precision $h_0(X_i)$, and that filers receive noisy signals of the change in their refund, $\Delta r_i + \epsilon_i$, where $\epsilon_i \sim \mathcal{N}(0, 1/h_\epsilon(X_i))$. Filers' Bayesian posterior beliefs ($m_{1,i}$) and "updates" ($m_{1,i} - r_{0,i}$) are then given by:

$$m_{1,i} = r_{0,i} + \underbrace{\frac{h_\epsilon(X_i)}{h_0(X_i) + h_\epsilon(X_i)}}_{\equiv I(X_i)}(\Delta r_i + \epsilon) \tag{6}$$

$$\underbrace{m_{1,i} - r_{0,i}}_{\text{update}} = (r_{1,i} - r_{0,i}) \times \underbrace{I(X_i)}_{X_i'\beta} + \epsilon \times I(X_i) \tag{7}$$

The amount that filers update depends on the relative precision of their prior and signal. In our regressions we parameterize the updating rate $I(X_i) = X_i'\beta$. The primary restriction is that conditional on observables, households update towards their signal at the same rate relative to their prior – in other words, they have the same ratio of their signal and prior precisions. In practice, we view our estimates as capturing an average updating rate among filers in a particular group, averaging over any possible unobserved heterogeneity in updating rates.

D Computing Compensating Variation

In order to calculate compensating variation for each individual, we have to make assumptions about the interest rate, discount rate, take-home pay, distribution of refund amounts, and form of the utility function.

- **Take-home Pay**: Take-home pay in each period, $c_{0,i}, c_{1,i}$, is equal to the individual's quarterly take home pay (adjusted annual income, minus withholding)/4.
- **Distribution of** y: We use the elicited belief distribution as our measure of $F(y)$.
- **Credit Constraints**: The borrowing limit is $c_{i,1} + E[y]$. A few households choose negative debt (positive savings) given expectations of a negative refund. Given the high levels baseline credit card debt in this population, we interpret savings as a marginal repayment of credit card debt.
- **Consumption Commitments**: Individuals must consume at least \$100 each period.
- **Interest Rate**: Individuals can borrow or save at a quarterly interest rate of $R = 1.05$. This is a realistic credit card interest rate for this population.
- **Discount Rate**: Individuals discount the future using $\beta = .98$.

Algorithm

We calculate the compensating variation for each individual. For each functional form for utility, we calculate CV as follows:

- For each s in $1, ..., B$
  1. Draw realizations of the refund amount y_{is} $\{s = 1, ..., S\}$ using the elicited belief distribution $N(\mu_i, \sigma_i^2)$.
  2. Calculate CV_i^{nu}
  3. Calculate CV_i^d assuming $y = E[y]$.
- Save the average realization of CV_i^{nu} and CV_i^d for each individual.

We average over individuals to report the mean CV^{nu} and CV^d for a given utility function and set of preference parameters. These results are presented in Table A8 and Figure 2.

E Belief Distributions

E.1 Normal Distributions

Our baseline estimates use beliefs fitted to normal distributions. Our procedure for fitting these beliefs is provided in Section 3 in the main text. As described in that section, our procedure fits reported beliefs to:

$$\min_{\mu,\sigma} \sum_{x\in\mathcal{X}_i} \left[p_{x,i} - \Phi\left(\frac{x-\mu}{\sigma}\right)\right]^2 + \left(\max\{0, 1+\Phi\left(\frac{\underline{x}-\mu}{\sigma}\right) - \Phi\left(\frac{\overline{x}-\mu}{\sigma}\right) - \alpha\}\right)^2 \tag{8}$$

Example For example, suppose a filer reports a "best guess" of \$400 and says that there is a 60% chance they will receive between \$0 and \$500 and a 40% chance they will receive between \$500 and \$1000. This corresponds to $\mathcal{X} = (\$400, \$500)$, $p = (0.5, 0.6)$, and $(\underline{x}, \overline{x}) = (\$0, \$1000)$. The middle plot in Figure A2 shows the normal distribution which best fits this elicitation. The first and third plots present analogous figures for filers who placed positive probability on three and one bins, respectively. In the single-bin case, equation 1 does not pin down σ, so we restrict the mass outside the bin to equal exactly α.

E.2 Beta Distributions

Fitting beliefs to normal distributions has the advantage of being consistent with the updating model we use in Section 4. However, normal distributions are also restrictive. For this reason, much of the literature on subjective expectations has fit probabilistic beliefs to beta distributions. Beta distributions are flexible, and allow for belief distributions that are not symmetrical and that have finite support.

In order to probe the robustness of our empirical results, we compare our baseline measures of uncertainty to those we would obtain if we fit beliefs to beta distributions.

E.2.1 Fitting Beliefs

As before, our procedure for fitting beliefs 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 Engelberg et al. (2009) by using additional information from the respondent's point estimate and by not constraining the estimated beta densities to be single-peaked.

The 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 Engelberg et al. (2009) in fitting a beta distribution to the reported quantiles. The maximum refund amount was a little below $20,000, and the lowest refund amount was approximately -$500 (the tax filer 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 Engelberg et al. (2009) 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 (α, β) 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

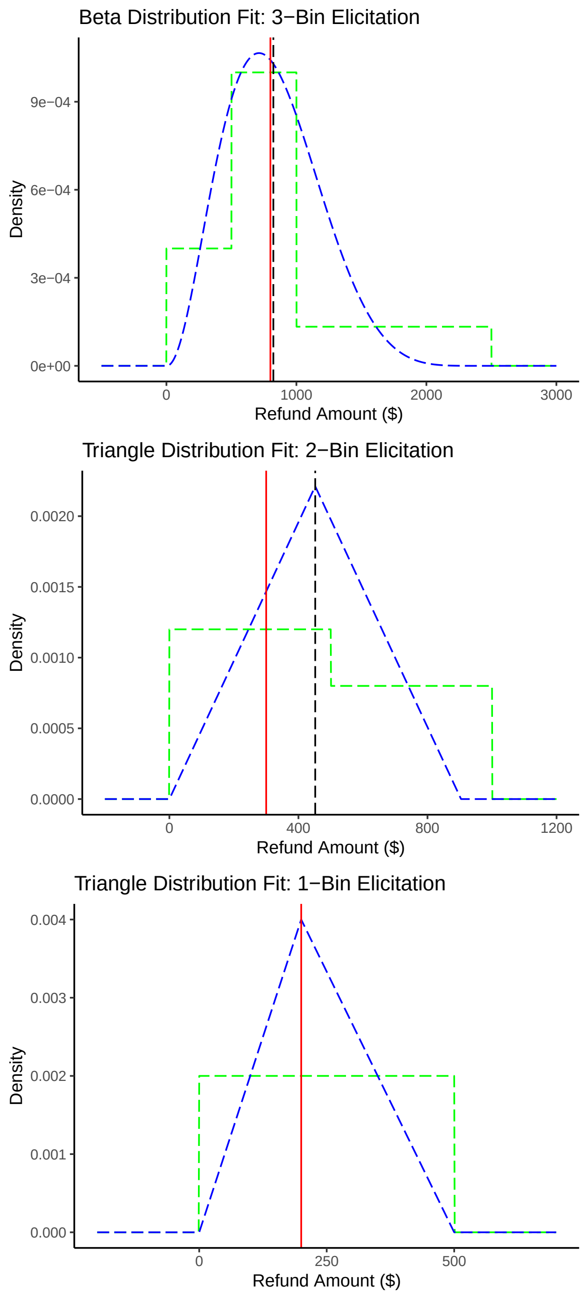
$$\min_{\alpha,\beta} \sum_{x \in \mathcal{X}_i} [p_{x,i} - P(Z \leq x \mid \alpha, \beta)]^2$$

E.2.2 Comparison with Normal Beliefs

Figure A9 compares the means and standard deviations from the normal and beta fitted belief distributions. The first panel shows that the mean beliefs track each other closely; the slope of the fitted regression line lies nearly on top of the 45-degree line. The second panel shows that the standard deviations of uncertainty also track each other closely. However, we obtain larger standard deviations when using the beta distribution. This is especially true for individuals with high absolute levels of uncertainty. This is because the more flexible beta distribution allows us to capture uncertainty that is not "symmetric". By contrast, the normal distribution smooths out uncertainty that leads to skewness in the distribution.

Table A3 presents descriptive statistics on the means and standard deviations of different groups of tax filers under different parametric assumptions. Dropping individuals that put 50/50 probability on two bins does not affect the mean or standard deviation meaningfully. Dropping individuals who placed a hundred percent probability on a single bin reduces the standard deviation somewhat, especially when we use the beta distribution. Our estimates using the normal distribution are less sensitive to the choice of sample.

Figure A8: Fitting Beliefs to Beta Distributions



Note: This figure shows how we fit probabilistic beliefs to beta distributions if the individual places positive mass in 3 or more bins (top), in 2 bins (middle) or 1 bin (bottom). Solid lines denote data; dashed lines denote fitted distributions. The green dashed lines report the distribution of beliefs, assigning a uniform density over the density in each bin. The red line denotes the point expectation. The dashed blue curves show the density of the fitted distribution and the dashed black line shows the mean of this distribution. More information on how we fit beliefs to beta distributions is provided in Appendix Section E. Graphs describing how we fit beliefs to normal distributions are provided in Figure A2. Table A3 presents descriptive statistics on the fitted beliefs.

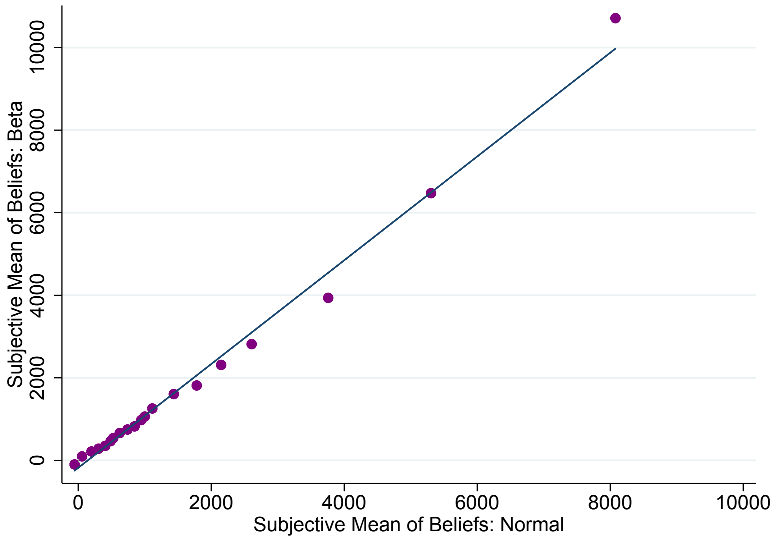
Table A9: Parametric Belief Distributions

	Normal Distribution				Beta Distribution			
	Baseline	Exclude 50/50	Exclude Single Bins	All	Baseline	Exclude 50/50	Exclude Single Bins	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean	1,605	1,641	1,322	1,678	1,837	1,905	1,435	1,932
	(2000)	(2061)	(1407)	(2187)	(2584)	(2698)	(1705)	(2796)
Median	1,605	1,641	1,322	1,678	1,943	2,026	1,582	2,068
	(2000)	(2061)	(1407)	(2187)	(3138)	(3299)	(2626)	(3407)
Std. Dev.	426	457	385	454	690	739	578	733
	(510)	(535)	(456)	(599)	(895)	(941)	(725)	(1005)
Observations	618	541	584	647	618	541	584	647

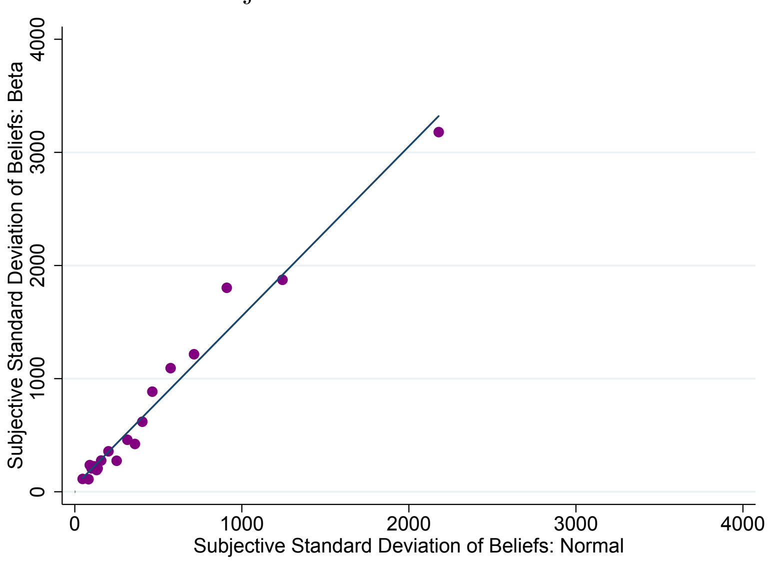
Notes: This table reports features of parametric belief distributions under alternative assumptions. Statistics are aggregated across all tax filers in the main analysis sample. The first set of four columns contains statistics based on the normal distributions fit to the probabilistic survey question described in Section 3. The second set of columns contain statistics based on beta distributions. We describe how we fit these distributions in Appendix E. The first column in each set presents our baseline sample. The second column excludes individuals who put 50/50 probability on two bins. The third column excludes individuals who put 100% probability on a single bin. The final column includes all tax filers who filled out the expectations survey.

Figure A9: Distributional Assumptions for Beliefs

A. Mean Expectation



B. Subjective Standard Deviation



Note: This figure plots the fitted mean beliefs (panel A) and fitted standard deviations of beliefs (panel B) from a normal distribution against those from a beta distribution. Section 3 describes how we fit normal distributions; Appendix Section E describes how we fit beta distributions.