Tax Refund Uncertainty: Evidence and Welfare Implications*

Sydnee Caldwell — UC Berkeley
Scott Nelson — Chicago Booth
Daniel Waldinger — NYU

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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.

*Caldwell: scaldwell@berkeley.edu; Nelson: scott.nelson@chicagobooth.edu; Waldinger: danielwaldinger@nyu.edu. Special thanks go to the City of Boston Office of Financial Empowerment, including Trinh Nguyen, Constance Martin, Mimi Turchinetz, Brian Robinson, Jason Andrade, and Joanne Evans. Ariel Duong provided invaluable assistance implementing the surveys. We thank Daron Acemoglu, Alex Bartik, Scarlet Chen, Amy Finkelstein, Damon Jones, Olivia Kim, Henrik Kleven, Patrick Kline, Jonathan Kolstad, Ilyana Kuziemko, Pascal Noel, Jonathan Parker, Ricardo Perez-Truglia, Jim Poterba, Antoinette Schoar, Lauren Taylor, Neil Thakral, Owen Zidar, and seminar audiences at the Boulder CDFM Conference, CFPB Research Conference, Harvard, MIT, the New York Fed - ECB Consumer Expectations Conference, the NTA Annual Conference, the Princeton Public Finance Lunch, Texas A&M Public and Labor Conference, and the Washington Center for Equitable Growth Grantee Conference for helpful comments. An earlier version of this paper circulated under the title "Tax Refund Expectations and Financial Behavior." IRB approval was granted by MIT (COUHES protocol 1511304889). Nelson gratefully acknowledges support from the Washington Center for Equitable Growth. Caldwell, Nelson and Waldinger each thank the George and Obie Shultz Fund at MIT for its support and the National Science Foundation for support under NSF Doctoral Dissertation Research in Economics award No. 1729822. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

1 Introduction

Tax refunds are a significant source of income for many low-income households.[1] They are also the primary means of distributing tax-based transfers such as the Earned Income Tax Credit (EITC) and Child Tax Credit (CTC). However, the complex nature of the tax code 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). Relatively little is known about this uncertainty among low-income filers, despite its potential consequences for individual income volatility and welfare, and for tax program design.

This paper studies tax refund uncertainty and its welfare consequences among low-income tax filers. In the first part of the paper, we provide survey evidence that low-income tax filers face significant uncertainty about their tax refund at the time of filing, after uncertainty about income and other tax determinants has been resolved. Uncertainty is especially high for filers who have dependents and who experienced large changes in their tax circumstances. We then show that this uncertainty matters – it affects individuals' consumption-savings choices and is large enough to cause welfare losses among EITC filers 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, by asking filers what their "best guess" of their refund was, by asking how "certain" they were about that guess, and by asking filers to report the percent chance their refund would fall in six different bins. These probabilistic responses allow us to construct full subjective belief distributions over refund outcomes and obtain quantitative measures of subjective uncertainty (Engelberg et al., 2009). 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 $1,000-interval around their best guess. The median filer's subjective standard deviation is more than one quarter the size of their expected refund.

Despite reporting substantial uncertainty, filers' beliefs are predictive of the refunds they receive: mean expectations closely track average realizations, and hypothetical refunds drawn from tax filers' subjective belief distributions closely overlap with the distribution of actual

[1] One reason these refunds are so large is that some credits cannot be claimed in advance (Gelman et al., 2019). For example, the typical Earned Income Tax Credit (EITC) recipient sees a refund equal to 12 percent of their annual income (Jones, 2012).

refunds amounts. This is not simply because filers remember last year's refund; expectations also predict changes in their refund relative to last year. The level of uncertainty also varies across individuals in sensible ways. More uncertain individuals have 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.

Two facts suggest the uncertainty we measure may come from the tax code itself – in particular, how income and withholding translate into refund amounts. First, because the survey was conducted after filers brought their tax documents to the tax preparation site, but before they learned their refunds, it measures subjective beliefs after all uncertainty about last year's income and withholding had been resolved. Second, correlates of refund uncertainty are consistent with tax code complexity contributing to uncertainty. Tax filers are more uncertain if their income has changed substantially, if they have dependents, and if they are married. These groups also experience larger annual changes in their marginal tax rates and refund amounts.

In the last part of the paper, we examine how tax refund uncertainty impacts financial behavior and welfare. Such impacts have two components. First, variability in refund amounts reduces ex-ante welfare for risk-averse filers, apart from any precautionary response. Second, when filers respond to uncertainty with precautionary behavior, such as borrowing less before refund receipt to insure against receiving a small refund, this increases intertemporal variability in consumption even as it helps tax filers reduce within-period uncertainty (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 expected refund size, more uncertain individuals borrow less in advance of filing, consistent with standard precautionary savings models.[2] The pattern is robust to including demographic controls and to instrumenting our measure of subjective uncertainty with two qualitative measures, as well as controlling flexibly for realized refunds and for income.

Finally, using a simple two-period consumption-savings model and a range of assumptions about risk aversion, we find that tax refund uncertainty is large enough to have significant welfare costs. In the model, tax filers are aware of their uncertainty about their tax refund, and they precautionarily adjust first-period consumption to insure against receiving a lower than expected tax refund in the second period. The model suggests the average filer in our sample would be willing to give up about $90 to eliminate refund uncertainty for one year. For the average tax filer in our sample, this welfare loss is equivalent to 5 percent of

[2]These results are also consistent with the precautionary behavior studied by Gelman et al. (2019) among tax filers with substantial non-labor income.

the filer's total refund; for EITC recipients, the corresponding welfare costs are 9 percent of EITC credit amounts. Total 2016 EITC payments were $69 billion, suggesting aggregate welfare losses on the order of $6 billion annually for EITC recipients.[3]

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 the extent and costs of resultant tax-related income uncertainty. Prior work has emphasized how individuals 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 unaware of EITC rules and incentives (Chetty and Saez, 2013; Chetty et al., 2013; Hall and Romich, 2016; 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 is thought to dampen labor-supply responses to the EITC (Kleven, 2020). We argue that the welfare cost of filers' refund-related income uncertainty is another quantitatively important channel through which limited tax understanding can cause welfare loss.[4] We also contribute to work on individuals' limited understanding of their taxes. Prior work has emphasized that this may be due to the costs of acquiring relevant information (Aghion et al., 2017; Chetty et al., 2013; Jones, 2010), or inattention or inertia (Morrison and Taubinsky, 2019; Taubinsky and Rees-Jones, 2018; Feldman et al., 2016; Jones, 2012).

Beyond the tax context, this paper joins a growing literature on the consequences of uncertainty about or limited understanding of program rules or benefits in settings such as Social Security (Luttmer and Samwick, 2018), health insurance (Handel and Kolstad, 2015), food stamps (Finkelstein and Notowidigdo, 2019), Medicare prescription drug plans (Abaluck and Gruber, 2011), and FAFSA financial aid applications (Bettinger et al., 2012). This literature has used either experimental variation, self-reported certainty equivalents, or choice data to quantify the consequences of uncertainty and limited understanding. In contrast, we use survey methods to directly quantify subjective uncertainty and its correlates, and we link our measures with ex-post outcomes and data on financial behavior to assess their accuracy and relevance. In this vein, we are related to more recent work on firms' macroeconomic uncertainty by Bloom et al. (2019), Coibion et al. (2018), and Coibion et al. (2020) that links measures of firm uncertainty with investment choices and outcomes.

[3] We divide by the EITC credit in our sample and then scale by total EITC credit among the 27 million households who received any in 2017. A related exercise would divide by each EITC recipient's total refund and then scale by the total refunds paid to EITC recipients, but the latter (the sum of all EITC recipients' total tax refunds) is unavailable in public IRS statistics.

[4] A complementary but distinct question is the extent of uncertainty about future *changes* in tax policy, as studied in Skinner (1988).

The paper proceeds as follows. Section 2 describes the empirical setting and data. Section 3 describes how we translate our survey measures of beliefs into probabilistic distributions, compares belief distributions to the distribution of realized refunds, and describes features of these beliefs. Section 4 uses panel data on credit reports to investigate whether filers engage in precautionary savings. It then uses a simple model to calculate the welfare losses associated with refund uncertainty and variability. Section 5 concludes.

2 Data and Empirical Setting

Our analysis relies on a unique combination of administrative tax data, credit bureau data, and survey data on 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 directed to the "financial check-up" station where they are offered a financial check-up from a volunteer "financial guide." The guide offers the filer a free credit report and provides information on city services.[5] Tax site volunteers directed filers to the check-up station even if they did not want (and did not receive) a check-up. 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. Filers may still have had *subjective* uncertainty, however, about the size of the refund they would receive: while filers could see their income and withholding on their tax statements (e.g. W2s), these statements do not contain information on refund amounts or

[5] 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.

on how the tax code determines refund amounts. 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 were directed to skip the financial check-up station during busy periods. As a result, we obtained consent from only 60% of tax filers at the site. Because consent rates were high (96%) among filers who did access the financial check-up station, and because site volunteers had no reason to exercise discretion when directing some filers to skip the check-up during busy periods, we do not believe consent was a major source of selection into our research sample.

As in other studies that use data from a single tax site, a natural question is whether our results generalize beyond the filers in our sample (Chetty and Saez, 2013; Meier and Sprenger, 2010). A comparison of our filers to those served at the thirty-six other tax sites coordinated by the data partner suggests that our filers are comparable to this broader population.[6] The average savings account balance is $523 in our sample, compared to $499 overall; sixty-two percent of our filers are female, compared to sixty-two percent overall. Finally, fifteen percent of filers in our sample have a bachelor's degree or above, compared with twenty percent of filers at all other tax sites.

2.2 Belief Elicitation and Demographic Surveys

We elicited beliefs in two ways (City of Boston Office of Financial Empowerment, 2016b). 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 a $1,000-interval around their best guess. Second, we elicited probabilistic beliefs by asking individuals the probability that their refund would fall within each of 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. We designed these bins based on prior-year tax data so that approximately equal numbers of actual refunds would fall in each bin, with a smaller number in the two tail bins (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). Section 3 describes how we fit parametric probability distributions to these elicited probabilities in order to calculate each filer's subjective mean and standard deviation.

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 (City of Boston Office of Financial Empowerment, 2016b).

[6] These sites served 12,843 taxpayers in 2016. Together, these filers were refunded $24.5 million, of which $8.8 million came from the EITC alone. See BTHC (2016).

2.3 Administrative Tax and Credit Data

We link the survey data to tax return data for consenting tax filers (City of Boston Office of Financial Empowerment, 2016a).[7] 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 (TransUnion, 2016). 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. Eighty-two percent of filers have at least a high school degree, but only fifteen percent have completed a BA. The average age is forty years, and the average annual adjusted gross income (AGI) is less than $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.[8] 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.

The remaining columns in Table 1 present descriptive statistics for filers who completed the demographic survey (column 2), for whom we have prior-year tax returns (column 3), and who appeared in credit report data (column 4).[9] 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. If anything, filers for whom we have credit data are slightly more educated (20% have a BA, relative to 15% in the overall pool).

[7] 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.

[8] 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.

[9] In the US, consumers who do not use formal credit products typically will not appear in credit bureau data (Brevoort et al., 2016).

Our main analysis samples exclude outlier observations that correspond to filers who reported extreme levels of tax refund uncertainty or income realizations, or whose elicited beliefs were internally inconsistent. Table A1 compares this sample with the complete set of tax filers, both overall and in the subset of filers for whom we have prior year tax information and credit data.[10]

Filers report substantial uncertainty about their refund amounts. Appendix Table A3 describes filers' responses to the beliefs survey overall and by demographic subgroups. Seventy-eight percent of respondents put positive probability on more than one bin. Of those, half put positive probability on exactly two bins, the remaining on three or more. These patterns are stable across filers regardless of whether they are filing with dependents, are married, have a college education, or are above twice the federal poverty level. Responses to the qualitative survey question also indicate uncertainty. A majority of filers (66 percent) are "Somewhat Certain" or "Not Certain At All," rather than "Very Certain," that their refund will fall within a $1,000-interval around their best guess. This holds for every subgroup reported in Appendix Table A3, with 55 to 70 percent reporting they were not "Very Certain."

3 Tax Filer Beliefs

This section describes how we translate tax filers' survey responses into subjective beliefs represented by smooth probability distributions, compares these beliefs to realized outcomes, and describes features of these beliefs.

3.1 Fitting Belief Distributions

We convert individuals' probabilistic survey responses into smooth probability distributions following Engelberg et al. (2009). Doing so uses all information available in respondents' elicited probabilities while smoothing between points of the cumulative distribution function in a reasonable way. Our main estimates fit the elicited bin probabilities to normal distributions. We also report results assuming beliefs follow beta or triangle distributions, which are common in the subjective expectations literature and which do not require beliefs to be symmetric or single-peaked (Engelberg et al., 2009). Under this alternative, we estimate higher subjective uncertainty but obtain qualitatively similar borrowing responses and

[10] Outlier observations are individuals with subjective uncertainty (the standard deviation of fitted beliefs) in the top or bottom 1% of respondents, or tax refund prediction errors in the top or bottom 1%, as well as individuals with adjusted gross incomes below 0. Internally inconsistent beliefs either had a point forecast that fell outside the support of the bins used to report subjective probabilities, or had subjective probabilities that did not sum to 100%. We also include in this category a few individuals whose subjective probabilities did not have contiguous support. Figure A3 provides a visualization of outliers relativer to the core sample.

similar, though higher, welfare costs.[11]

To fit a normal distribution to each tax filer's elicited beliefs, we penalize the distance between the quantiles of the filer's reported cumulative 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 bins assigned positive mass. We report results for $\alpha = .01$ because some filers reported bin probabilities down to the precision of a single percentage point. We interpret the filer's "best guess" of their refund as their subjective median, and we use it as an additional moment when fitting beliefs.

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

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

The first term in Equation 1 penalizes deviations between the interior cumulative probabilities reported by the tax filer and the value of a normal CDF; the second term penalizes mass outside the relevant bins in excess of α. Appendix E provides additional details on our procedure, describes the analogous procedure for fitting beta distributions, and compares results from the two parametric assumptions.

3.2 Validation of Belief Distributions

We verify that tax filers provided meaningful answers to our probability-based survey questions by comparing filers' subjective beliefs to realized refunds.

We first compare realized refunds to the means, μ_i, of tax filers' belief distributions. 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 (in blue) is close to one, though respondents with the most extreme realizations had slightly less extreme expectations.

We also compare the uncertainty in each tax filer's belief distribution to the filer's realized prediction error. To facilitate this comparison, we calculate each filer's expected magnitude of prediction error assuming their refund is drawn from their elicited beliefs. We then

[11]This is not surprising because the means and standard deviations from fitted normal and beta distributions are highly correlated. These two moments are the only moments used in our regressions. Other research fitting beliefs to normal distributions includes Wiswall and Zafar (2014).

compare these expected magnitudes to the magnitudes of actual prediction errors. The binned scatterplot in Figure 2 shows that actual and expected error magnitudes track each other closely. The regression line slope is close to one ($\beta = 1.01$), suggesting our measure of tax filers' subjective uncertainty accurately captures differences in uncertainty across filers.[12]

Next, we assess whether tax filers' belief distributions are consistent with the overall distribution of realized refunds in the sample. To do so, we simulate draws from filers' belief distributions and compare them to the realized refund distribution. Kernel densities for these two distributions are shown in Panel B of Figure 1. The two distributions overlap closely, showing that our sample's beliefs on aggregate track the distribution of realized refunds.

Finally, we ask whether the consistency we have shown between expectations and realizations could just be an artifact of persistence in individuals' tax refund sizes from year to year. We find this is not the case. Returning to the binned scatterplot in Panel A of Figure 1, we again plot the relationship between mean beliefs and realized refunds, this time (in purple) controlling for last year's refund. There is still a clear positive relationship between the residual variation in expected refunds and realized refunds, with a univariate R^2 of 33.4 percent. This suggests that tax filers' belief distributions incorporate additional information over the course of the year about changes in refunds relative to prior years.

To further illustrate how tax filers respond to additional information over the course of the year, Figure 3 plots the density of individual-level "updates"—differences between an individual's expected refund ($m_{1,i}$) and their prior year refund ($r_{0,i}$)—as a fraction of the individual's actual refund change ($r_{1,i} - r_{0,i}$). This distribution shows that most filers (76 percent) update in the direction of their actual refund change: if their refund increased relative to last year, their expected refund is also higher than last year's refund. This is consistent with Bayesian updating, which would require that more than 50 percent of individuals update in the direction of the change in refund.[13] In Appendix Section C, we explore heterogeneity in updating through the lens of a simple model and reject the null that individuals do not learn about refund changes, the null that individuals update fully, the null of no heterogeneity, and the null that individuals over-react (Bordalo et al., 2020). We also find suggestive evidence consistent with models of rational inattention (Coibion et

[12] The positive intercept of the regression line could be driven by several phenomena, including measurement error in mean beliefs (which would inflate the magnitude of realized prediction errors for all filers); under-estimation of actual uncertainty that causes a common, level shift in expected prediction error for all filers; or our use of normal distributions being a conservative choice for quantifying the total level of uncertainty in our sample (for related evidence, see Figure A7 and Table A4). The latter two explanations would imply that we are underestimating filers' uncertainty and the associated welfare costs.

[13] This holds so long as the distribution of signal noise is symmetric. Further statistics on the share of tax filers with various directions and magnitudes of updating rates, both overall and across demographic groups, are shown in Appendix Table A6.

al., 2018).[14]

Overall, the comparison between elicited beliefs and refund realizations helps validate the answers to the probabilistic survey question. Filers' answers predict what actually happened, suggesting their reports contain real information about their beliefs, and that the normal parametric model accurately summarizes key moments of these beliefs.

3.3 Expectations and Uncertainty

Filers expect to receive large refunds relative to annual income, but they also face substantial uncertainty. Table 2 shows that the average mean expectation in our main sample 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 shocks for a typical worker each year is six percent of income.[15] The median filer at the time of tax filing 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. Consistent with this uncertainty, many filers also face large realized prediction errors; roughly a quarter of prediction errors are more than $1500.

These patterns are qualitatively robust to alternative samples and distributional assumptions. Appendix Table A4 (column 2) shows that subjective means and standard deviations are similar if we exclude filers who put equal (50/50) probability on two bins (Fischhoff and Bruine De Bruin, 1999). Furthermore, assuming normal distributions may yield a conservative estimate of subjective uncertainty; the second group of columns in Table A4 shows results assuming beliefs follow beta and triangular distributions instead of normal distributions. The subjective standard deviations are fifty percent larger under this alternative. In section 4, we show that this leads to slightly larger average welfare costs of uncertainty, with similar qualitative comparisons across subgroups.

The remaining columns of Table 2 show that subjective uncertainty is large for a variety of demographic groups, both in absolute terms and relative to income, savings, and debt. Columns (2) and (3) show that filers with dependents, many of whom qualify for the EITC, have mean subjective standard deviation of $769, while for other filers uncertainty is smaller in magnitude but still substantial ($267). Similarly, in column (4), the 49 married filers in

[14] Prior work has found evidence that firms, as well as consumers in relatively high-income samples, form beliefs in a Bayesian manner when learning new information (Coibion et al., 2018; Armantier et al., 2016). Recent work has also emphasized the importance of better understanding belief formation among lower-income or lower-SES individuals (Das et al., 2020; Kuhnen and Miu, 2017). Our evidence on partial updating is consistent with the imperfect learning about the child tax credit schedule shown in (Feldman et al., 2016).

[15] See column 8 of their Table IV.

our sample have relatively high uncertainty ($648). Interestingly, education is not predictive of subjective uncertainty on its own; filers who attended college have similar uncertainty to those who did not (columns (6) and (7)). Households below 200 percent of the federal poverty line face more uncertainty, but also expect larger refunds, than higher-income filers (columns (8) and (9)).

Table 2 also demonstrates that the income shocks generated by higher- or lower-than-expected refunds are large enough to be economically significant for this low-income sample. For all subgroups, the subjective standard deviation is of similar magnitude to self-reported savings, and anywhere from 10 to 30 percent of non-installment debt. It is between two and three percent of *annual* income for most subgroups, and between 20 and 50 percent of the expected refund itself. In section 4.2, we quantify the welfare cost of refund uncertainty under specific assumptions about households' ability to smooth consumption in response to income shocks.

The magnitude of refund uncertainty is particularly striking because it is measured after filers plausibly know their income, withholding, and other tax characteristics – filers had collected all of their tax documents and brought them to the tax site at the moment the survey was conducted. Given this, we interpret the uncertainty we measure as being most likely driven by how the tax code maps these characteristics into refund amounts. It is natural to ask whether individuals who face more tax "complexity" – and may therefore experience higher costs of calculating their exact refund – are in fact more uncertain.[16]

We explore how uncertainty correlates with several plausible measures of tax complexity: the year-over-year change in a tax filer's marginal tax rate; the size of a tax filer's change in AGI; and whether a filer is married, has dependents, or has experienced a change in either marital status or number of dependents. Appendix Table A5 presents regressions controlling for these proxies for complexity as well as demographic variables that do not directly affect taxes. Column (1) shows that uncertainty is positively correlated with year-over-year absolute changes in marginal tax rates (MTRs). In column (2), we add other complexity proxies and find significantly higher uncertainty among tax filers with dependents and among tax filers facing larger absolute changes in their AGI. Columns (3) and (4) confirm that filers with larger changes in MTR and who have dependents also make larger prediction errors. In column (5), we move the change in MTR to the left-hand-side in order to document

[16]Complexity has been defined in a variety of ways in the literature. Gale et al. (2001) associate complexity with variable marginal tax rates; Abeler and Jäger (2015) define complexity as the "number of distinct tax rules"; and Zwick (2018) describes complexity as the existence of "many independently legislated provisions, overlapping and offsetting incentives." Rather than taking a stance on which definition of complexity is most relevant for low-income tax filers, we examine several proxies for a tax filer's exposure to tax complexity that are consistent with these definitions.

the correlation among the complexity proxies highlighted in earlier columns. We emphasize that we cannot infer causality from these associations. Nevertheless, they are consistent with tax complexity being a driver of refund uncertainty.

Overall, we find that tax filers face substantial uncertainty about their refund size. Heterogeneity across filers shows that this uncertainty is broad-based across a variety of demographic groups, and points to a potential role of tax complexity in generating uncertainty.

4 Consequences of Refund Uncertainty

In this section we assess the consequences of refund uncertainty for financial behavior and welfare. We first illustrate the importance of precautionary motives in this population using linked data from a panel of credit reports. We show that more uncertain individuals indeed borrow less prior to refund receipt, consistent with precautionary behavior. Motivated by this result, we then use a simple calibrated model that incorporates both risk aversion and a precautionary motive to calculate the welfare costs of refund uncertainty, under a range of preference parameters.

4.1 Evidence of Precautionary Behavior

If tax filers behave precautionarily toward expected tax refunds, filers who have greater refund uncertainty will 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 proxy for how much a filer borrowed out of their refund before filing. 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.[17]

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 less likely to engage in such borrowing due to precautionary motives, refund uncertainty may lead them to consume less prior to refund receipt.[18]

[17]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 accounts are used for borrowing (Nelson, 2020).

[18]While tax refund uncertainty has arguably clear predictions for comparative statics in wealth flows (i.e., saving and borrowing decisions) under precautionary behavior, there are confounding determinants of the

4.1.1 Main Results

We estimate regressions of the form

$$\Delta D_i = \omega m_{1,i} + \gamma \sigma_i + X_i' \beta + \epsilon_i, \tag{2}$$

where ΔD_i denotes the reduction in non-installment (principally, credit card) debt; $m_{1,i}$ 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. We adopt the convention that debt repayments are signed positive, so a negative estimate of γ 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 reduction in debt are uncorrelated with σ_i conditional on the included covariates. To reduce the influence of outliers we winsorize the dependent variable at the 5% level.[19]

Table 3 presents regression estimates from equation 2 and related specifications. The first column shows a univariate model with only the first term in equation 2, filers' mean refund expectations $m_{1,i}$. Column 2 adds subjective uncertainty; column 3 adds demographic controls; and column 4 adds controls for tax determinants.[20]

The positive estimates in the first row of Table 3 show that filers who have higher mean refund expectations indeed borrow less ex-ante.[21] The negative estimates of the coefficient on σ_i are evidence of precautionary behavior: filers with higher subjective standard deviations of their refund expectations borrow less ex-ante (and therefore repay less ex post). 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. While our estimates are somewhat imprecise, the coefficient on uncertainty is stable across columns 2-4 and, depending on the specification, significant at either the 5% or 10% level.[22] Figure A4

stock of wealth that make the correlation between wealth stocks and tax refund uncertainty less clear. Such determinants may include child-bearing (Nau et al., 2015), marriage (Addo, 2014), divorce (Fay et al., 2002), job loss (Sullivan, 2008), home foreclosures (Kermani and Wong, 2021), the Great Financial Crisis (Kuhn et al., 2020), and health shocks (Dobkin et al., 2018). We therefore focus on flows rather than stocks in this analysis.

[19] Specifically, the ninety-fifth percentile value of the dependent variable is assigned to observations with values above the ninety-fifth percentile (and similarly for values below the fifth percentile). We show robustness to winsorizing at the 1% level in Column 9 of Table 4.

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

[21] 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.

[22] We estimate the same regression at a six-month rather than two-month horizon and cannot reject equality

depicts a binned scatterplot corresponding to the regression in column 4. The fact that the coefficient on expected refund amount loses statistical significance once we control for demographics and tax determinants (Columns 3 and 4) reflects how expectations are non-trivially correlated with demographics.[23]

4.1.2 Robustness of Borrowing Results

Tables 3, 4, and A8 present results from a series of robustness checks.

Mismeasurement of Uncertainty We first address the concern that there is measurement error in σ_i by running two-stage least squares models where we instrument for σ_i using our qualitative measures of uncertainty. Results are reported in columns 5-7 of Table 3. The first stage results, presented in the bottom panel, confirm that individuals who report they are "somewhat sure" or "very sure" of their refund amount have smaller measures of σ_i than those who report they are "not sure at all," even after controlling for demographic characteristics and tax determinants. While the resulting estimates are noisy (the second-stage p-values on the subjective uncertainty term are respectively .1, .12, and .15 as we successively add controls), the coefficient on σ_i remains positive and is in fact larger in the 2SLS specifications presented in columns 5-7 than in the corresponding OLS estimates in columns 2-4. This suggests that our estimates of the importance of precautionary behavior may be conservative (i.e., biased toward zero).

We present another series of checks that address potential measurement error in columns 2-6 of Appendix Table A8, which is further described in Appendix Section E. These results show that our qualitative findings are robust to considering measures of beliefs that were computed by fitting beliefs to beta (rather than normal) distributions.

Errors in the Dependent Variable We use ΔD_i — the post-refund reduction in non-installment balances — as a proxy for pre-refund borrowing. Classical measurement error in ΔD_i would simply lead to larger standard errors. However, if individuals endogenously self-insure against low refund realizations through channels not observed in credit report data, ΔD_i may not be a reasonable proxy for pre-refund borrowing. This would occur if, for example, individuals change their savings or their hours worked in response to tax refund uncertainty.

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. For other evidence using subjective expectations data to test for precautionary behavior, see for example Ben-David et al. (2018), Christelis et al. (2018), Jappelli and Pistaferri (2000), or Guiso et al. (1996).

[23]The demographic controls alone explain 37.5% of the variation in the expected refund amount.

We address this concern by examining two sub-populations that are less likely to have savings and by examining filers who indicated in our survey data that they are unable to change their labor income when desired. Column 2 of Table 4 presents results for filers that did not choose to receive their refund via direct deposit. These individuals may use their savings accounts less heavily, or may not have savings accounts. Column 3 focuses on individuals who, on the demographics and assets survey, either reported that they did not have a savings account, or that they had less than $100 in such an account. Both columns show the same, negative relationship between uncertainty and borrowing: more uncertain individuals borrow less prior to refund receipt, indicating that they spent less of their refund before the resolution of uncertainty. Column 4 of Table 4 shows we obtain similar results in the subpopulation of individuals who indicated in our survey data that they are unable to change their labor income when desired.

Table A8 shows that we obtain the same negative relationship between uncertainty and borrowing in these 3 subgroups when using the alternative beta-distribution measure of beliefs, as described further in Appendix Section E. Column 9 of Table 4 shows that we obtain similar results when we winsorize the dependent variable at the 1% level, rather than the 5% level.

Omitted Variables Bias Finally, we address the concern that our results may reflect unobserved heterogeneity across filers. Such heterogeneity would have to generate a positive correlation between uncertainty and changes in borrowing over time in the absence of a causal channel from uncertainty to changes in borrowing.

Column 5 of Table 4 shows that we obtain qualitatively similar results when we restrict our sample to those without dependents, as having dependents is one of the main correlates of uncertainty in our sample. The remaining columns in this table address the concern that those with high levels of uncertainty are simply those that receive small refunds. Columns 6-8 add additional controls for refund and income, two of the main determinants of borrowing behavior. Column 6 adds a linear control for the received refund amount. Column 7 adds a linear control for AGI. Column 8 adds a third-order polynomial in both refund and AGI. The coefficient on uncertainty remains negative, and is stable across specifications. This is consistent with precautionary behavior, rather than unobserved heterogeneity, being the main driver of our results.

4.2 Welfare Costs

Motivated by the evidence that uncertainty may affect consumption smoothing through borrowing behavior, we use a simple calibrated model to quantify the welfare costs of refund uncertainty. The model is intentionally stylized; it is meant to capture whether the uncertainty we have documented is large enough to be welfare-relevant. We do not directly use the estimates from section 4.1, given the strong assumptions required to estimate households' preferences. Instead, we report welfare costs for a range of standard preferences assuming that filers save optimally given their preferences and beliefs. Our model abstracts away from a number of phenomena which could affect the welfare cost of uncertainty. We discuss several of these below.

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

$$V^u \equiv \max_b \; u(c+b) + \beta \int_y u(c+y-Rb)dF(y)\,. \tag{3}$$

Crucially, the household must choose the debt b they carry into $t = 1$ before learning their refund 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

$$V^{nu} \equiv \int_y \left[\max_b u(c+b) + \beta u(c+y-Rb)\right] dF(y)\,. \tag{4}$$

We measure the welfare cost of uncertainty by computing households' compensating variation: their willingness-to-pay to be in the no-uncertainty case instead of the uncertainty case. Let CV^{nu} be the per-period CV for no uncertainty, defined implicitly by

$$\int_y \left[\max_b u(c+b-CV^{nu}) + \beta u(c+y-Rb-CV^{nu})\right] dF(y) = V^u\,. \tag{5}$$

We interpret CV^{nu} as the per-period welfare loss due to refund uncertainty.

To implement this welfare calculation, we take a period to be one quarter. To compute CV^{nu} 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 $R = 1.05$. The latter is an approximation to the cost of typical non-installment debt like credit cards (Nelson, 2020). Appendix D provides additional details about how CV^{nu} is calculated. Our reported estimates scale CV to equal the total, not per-period, compensation required to make individuals as well-off as they would be with no uncertainty.

4.2.1 Welfare Losses

Figure 4 presents the mean CV^{nu} for different filer subgroups in our baseline specification, which assumes $\gamma = 3$ and normally distributed beliefs. The average filer would give up \$93 per year to eliminate tax refund uncertainty, more than 5 percent of the average tax refund in our sample and roughly 2 percent of quarterly income for the average filer. The mean CV^{nu} is \$165 per year for EITC filers, \$179 for filers with above-median uncertainty, and \$108 for households earning below 200 percent of the federal poverty level.

Losses are larger for filers whose refund uncertainty is large relative to income. Column 2 of Table 5 shows that the median CV^{nu} is only \$12 for all filers and only \$33 for EITC filers, far lower than the respective means. However, 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, \$272 for all filers and \$368 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 percent of the value of the EITC. Scaling this by the size of the federal EITC in 2016 suggests aggregate annual welfare costs of \$6 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, and for evaluating tax simplification policies. Of course, the costs of making taxes more understandable for recipients – be they the fiscal costs of tax code changes, welfare costs of less-precisely targeted refunds, or operational costs of educational or tax preparation services – would need to be weighed against any gains from reducing uncertainty.

4.2.2 Discussion and Robustness

This section discusses how the assumptions in our baseline model might impact our results, and explicitly considers alternative assumptions about beliefs, risk aversion, and savings.

We first consider the parametric assumptions used to translate the probabilistic survey questions to belief distributions. Column 3 of Table 5 assumes beliefs follow a beta/triangle distribution instead of a normal distribution. As shown in Appendix Table A4, beta/triangle distributions tend to estimate higher subjective uncertainty, so the estimated welfare costs are higher than in our baseline specification for most subgroups. We also consider the extent to which the welfare costs are driven by filers who place all probability mass on one bin, since we have the least information about their subjective uncertainty. When we assume that any such filer who also reports being "very sure" about their refund amount has no subjective uncertainty, the mean and median CVs reported in Column 4 are slightly lower (\$88 and \$10, respectively), but qualitatively similar for all subgroups.

The estimated welfare losses are most sensitive to the assumed level of risk aversion. Columns 5 and 6 of Table 5 compare CV^{nu} assuming $\gamma = 1$ and $\gamma = 5$, respectively. With modest risk aversion ($\gamma = 1$), mean CV^{nu} is \$24 per year for all filers and \$42 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 relatively high risk aversion ($\gamma = 5$), mean CV^{nu} is \$125 for all filers and \$217 for EITC filers.

So far, we have assumed all filers have the same level of risk aversion. If risk aversion is heterogeneous, we might expect it to be negatively correlated with subjective uncertainty, as the most risk-averse filers may exert effort to learn about their refund in advance. Assuming homogeneous risk aversion would then overstate the welfare cost of uncertainty.[24] Column 7 of Table 5 captures this idea by assuming $\gamma \sim U[1, 5]$ with a correlation of -0.5 with filers' uncertainty ranks. This strong negative correlation between uncertainty and risk aversion reduces mean welfare costs to \$83, compared to \$93 in Column 2.

Another potentially important set of assumptions in our model is that we limit households' ability to consumption smooth. Empirical evidence that low-income households have low savings and cannot fully smooth consumption even for small shocks (Federal Reserve Board, 2019) suggests that our model may be a reasonable approximation. Nevertheless, some filers may have existing savings, be able to borrow from friends or relatives, or save precautionarily over a longer period of time. While we cannot rule out all of these channels, when we allow filers to consume the savings they report on the intake survey in addition to their income (Column 8 of Table 5), this only slightly lowers the welfare cost of uncertainty.

5 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,

[24]Our calculations also do not include any costs of acquiring information to reduce uncertainty.

consistent with precautionary behavior. A simple consumption-savings model suggests that refund uncertainty significantly reduces the efficiency of redistribution through the tax code.

Our findings mirror those of a growing literature on the welfare consequences of uncertainty about and limited understanding of public benefits (see, e.g., Luttmer and Samwick (2018); Abaluck and Gruber (2011); Finkelstein and Notowidigdo (2019)). Like many papers in the tax literature, our analysis relies on data from a single tax site. One direction for future work would be to collect such data among a larger sample of filers. Another direction for future work would be to examine how filers incorporate new information throughout the course of a year. We found suggestive evidence that filers incorporate new information in a manner consistent with both Bayesian updating and rational inattention. Data from a larger sample would allow a researcher to test these models more directly.

Moreover, further 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, which in turn influence the efficiency costs of income taxation. Combining survey and administrative data, as our study does, is a promising avenue for future work.

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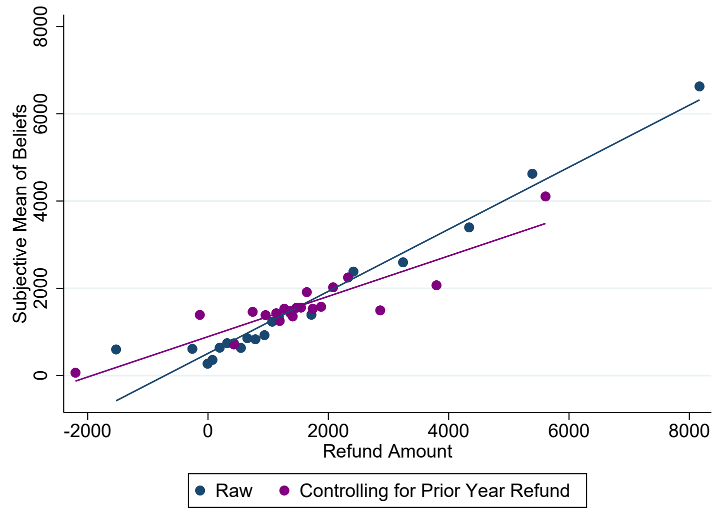
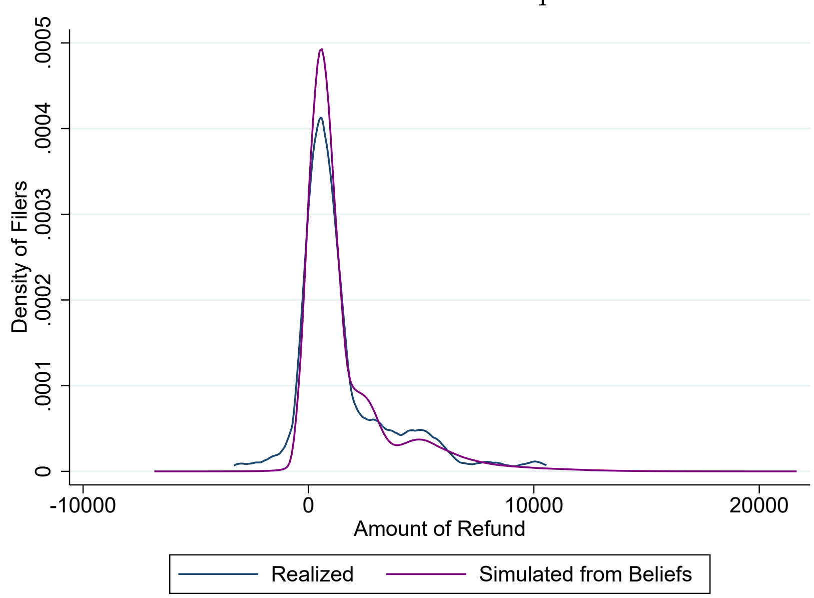
6 Figures and Tables

Figure 1: Refunds and Fitted Beliefs

A. Refunds and Expected Refunds

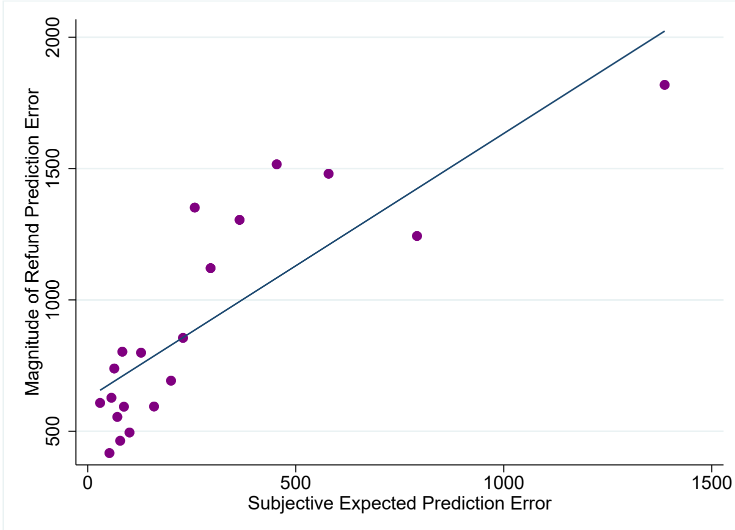


B. Distribution of Refund Expectations



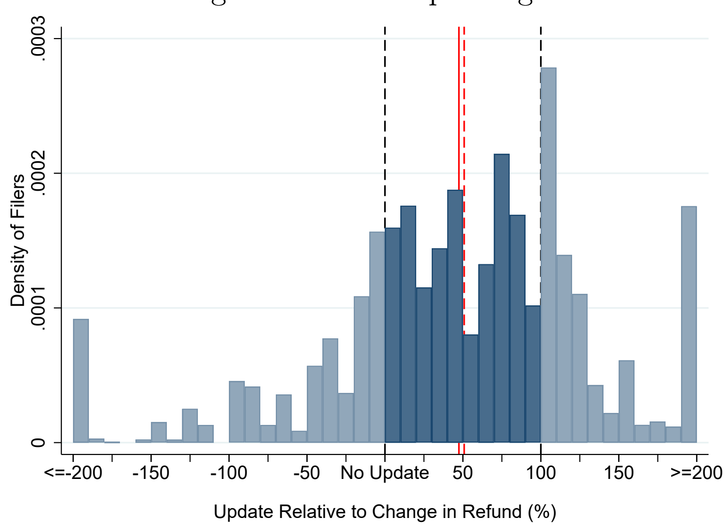
Note: Panel A shows binned scatterplots of mean expectations against actual refund amounts. The expected refunds are the means of the distributions calculated using the procedure described in Section 3. The blue binned scatterplot corresponds to the unconditional correlation. The purple binned scatterplot was computed after controlling for the amount of the prior-year refund. Panel B shows kernel density plots of filers' observed refunds (blue) and the distribution implied by filers' fitted beliefs (purple). The densities were computed using an Epanechnikov kernel with the optimal (Gaussian) bandwidth, which here is $318.

Figure 2: Refund Uncertainty and Prediction Errors



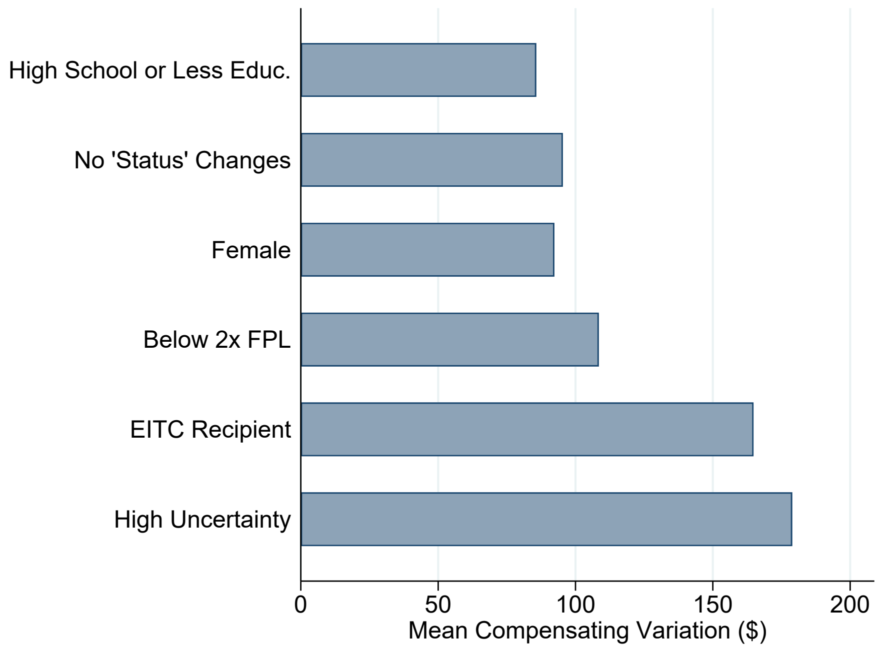
Note: This figure shows a binned scatterplot of the size of each filer's prediction error (actual refund - mean expectation) against the expected size of prediction error given their elicited beliefs (equal to $\sigma_i\sqrt{2/\pi}$ for a filer with subjective standard deviation σ_i).

Figure 3: Belief Updating



Note: This figure plots the distribution of $\frac{m_1 - r_0}{r_1 - r_0} \times 100$, the amount an individual updates relative to his/her past year refund, as a percentage of the actual change 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, reflecting partial updating. 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 4: Compensating Variation from Refund Uncertainty



Note: This figure shows the mean compensating variation (CV^{nu}) for filers with different demographic, belief, and tax characteristics. CV^{nu} measures an individual's willingness-to-pay to eliminate refund uncertainty when choosing debt and consumption levels. These numbers are computed assuming a CRRA utility function with $\gamma = 3$. High Uncertainty is defined as having above-median subjective standard deviation. FPL abbreviates federal poverty level. No 'Status' Changes refers to having the same filing status and number of dependents as in the preceding tax year. More information on how we compute CV is provided in Section 4.2. Results under alternative modeling assumptions are presented in Table 5.

Table 1: Characteristics of Filers

	Tax Data & Expectations Data (1)	Tax Data, Expectations Data, & Demographics (2)	Current and Prior Tax Data & Expectations Data (3)	Tax Data, Expectations Data, & Credit Data (4)
Demographic Characteristics				
Female	0.62	0.62	0.65	0.67
	(0.49)	(0.49)	(0.48)	(0.47)
Age	40.21	40.15	42.85	41.66
	(15.92)	(15.82)	(15.70)	(15.87)
BA Degree	0.15	0.15	0.18	0.20
	(0.36)	(0.36)	(0.38)	(0.40)
Economic and Tax Characteristics				
Adjusted Gross Income ($)	20,636.93	20,704.68	23,474.88	24,081.49
	(15930.39)	(15751.66)	(16228.46)	(16355.96)
Has Dependents	0.32	0.32	0.36	0.34
	(0.47)	(0.47)	(0.48)	(0.47)
Married	0.08	0.07	0.07	0.08
	(0.27)	(0.26)	(0.25)	(0.28)
Lost Job	0.08	0.07	0.07	0.06
	(0.27)	(0.26)	(0.25)	(0.24)
Tax Refund				
Refund Amount ($)	1,542.33	1,552.27	1,845.97	1,745.95
	(2207.11)	(2194.48)	(2384.90)	(2311.50)
Received EITC	0.35	0.35	0.35	0.31
	(0.48)	(0.48)	(0.48)	(0.46)
EITC Credit (If >0)	1,654.16	1,622.52	1,985.20	1,891.45
	(1661.35)	(1664.33)	(1795.86)	(1713.43)
EITC share	0.50	0.49	0.53	0.46
	(0.43)	(0.38)	(0.43)	(0.40)
Savings and Credit				
Estimated Savings Balance	523.36	523.36	545.97	633.82
	(576.15)	(576.15)	(583.24)	(606.28)
FICO Score	666	666	675	684
	(87)	(88)	(89)	(80)
Credit Card Balances ($)	1,686	1,780	2,005	2,630
	(4,985)	(5,228)	(5,925)	(6,026)
Observations	618	548	337	359
with Demographics	548	548	303	319

Note: The first column describes tax filers who completed the expectations survey. The remaining columns restrict to individuals for whom we have additional information from the demographic survey (column 2), prior year tax returns (column 3), or credit reports (column 4). All columns exclude individuals with subjective uncertainty (as measured by standard deviation of beliefs) in the top or bottom 1% of expectations survey respondents; with internally inconsistent probabilistic eliciations; with tax refund prediction errors in the top or bottom 1%; or with adjusted gross incomes below 0. These sample restrictions are discussed in section 2.4. Appendix Tables A1 and A2 present descriptive statistics for the full sample, including outlier observations.

Table 2: Elicited Beliefs by Filer Group

		Has Dependents		Marital Status		Any College		Relative to 2x Federal Poverty Line	
	Core Sample	Yes	No	Married	Not Married	Yes	No	Below	Above
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quantitative Responses									
Point Estimate	1682.1	3520.3	837.0	2468.6	1614.1	1656.4	1725.5	2799.5	1078.7
Features of Parametric Distribution									
Mean	1605.4	3364.6	794.3	2377.6	1538.8	1614.5	1618.1	2635.5	1043.9
Std. Dev	425.9	769.4	267.5	647.5	406.8	448.3	412.6	589.6	336.6
Adjusted Gross Income	21952.2	25669.9	19883.1	27489.8	21555.4	24370.6	20503.2	17864.6	24198.5
Savings	523.4	467.8	548.1	526.4	523.1	578.7	477.1	387.9	589.9
Refund	1542.3	3766.2	517.2	1998.9	1503.0	1589.0	1525.8	2959.3	770.1
Revolving Debt	2584.9	2948.1	2399.8	4424.2	2415.3	2537.4	2699.1	1965.9	2875.8
Observations	618	195	423	49	569	252	279	218	400

Notes: This table describes responses to the beliefs survey and financial characteristics of different tax filer groups. All statistics are means within each group. Any College refers to any college experience, regardless of degree attainment. Sample sizes for columns 6 and 7 reflect response rates to the Demographics survey (see Table 1), minus 17 respondents who did not provide education information. The second panel contains statistics based on the parametric distributions fit to the probabilistic survey question described in Section 3.

Table 3: Impact of Uncertainty on Borrowing

	Baseline Model (OLS)				2SLS Estimates		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable: 2-Month Reduction in Debt						
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 tax refund uncertainty affects filers' borrowing behavior. The regressions include all core-sample filers for whom we have expectations data and credit report data. The dependent variable is a 2-month reduction in non-installment debt balances, signed so that a repayment of debt is positive. Coefficients are scaled to be per-$1000 change in each regressor. Columns 1-4 present results from OLS regressions of the dependent variable on the expected refund amount and other covariates as listed. Columns 5-7 present 2SLS estimates, where we use the qualitative uncertainty measures as instruments for subjective uncertainty. The demographic controls include whether a filer is female, over 50, a college graduate, married, or has dependents. The tax determinants include controls for the absolute 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 in the current tax year. Robust standard errors are in parentheses. * $p < .1$ ** $p < 0.05$ *** $p < 0.01$

Table 4: Robustness of Borrowing Results

		Alternate Samples				Additional Specifications			
	Baseline	No Direct Deposit	No Savings	Can't Change Income	No Dependents	Refund Controls	Income Controls	Refund & Income	Winsorize at 1%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Expected Refund Amount	40.38	6.266	35.28	0.487	70.50	-17.86	41.14	-5.019	9.558
	(38.07)	(47.30)	(79.27)	(41.61)	(68.33)	(39.15)	(38.11)	(36.01)	(76.60)
Subjective Standard Deviation	-259.3**	-196.4	-486.0**	-370.7**	-576.4**	-283.3**	-253.0*	-252.4*	-552.4**
	(131.5)	(143.1)	(203.5)	(144.6)	(250.1)	(132.1)	(131.7)	(133.8)	(256.5)
Controls									
Demographics	X	X	X	X	X	X	X	X	X
Tax Determinants	X	X	X	X	X	X	X	X	X
Refund						Linear		Cubic	
Income							Linear	Cubic	
Observations	359	234	91	211	237	359	359	359	359
R-squared	0.096	0.103	0.273	0.130	0.107	0.112	0.097	0.120	0.073

Note: This table investigates the robustness of the borrowing results in Table 3. Column 1 repeats our preferred specification from Column 4 of Table 3. Columns 2-5 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 labor income. Columns 6-8 present results from regressions that include additional controls for the size of refund received and for AGI. Column 9 repeats the main specification using a dependent variable that is winsorized at the 1% level (rather than 5%). The demographic controls include indicators for whether a filer is female, over 50, a college graduate, married, and has dependents. The tax determinants include the absolute 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 in the current tax year. Robust standard errors are in parentheses. * $p < .1$ ** $p < 0.05$ *** $p < 0.01$

Table 5: Compensating Variation Under Alternative Modeling Assumptions

	Percent of Sample	Compensating Variation for No Uncertainty						
		Baseline Specification	Beta/Triangle Beliefs	Qualitative Uncertainty	CRRA, Gamma=1	CRRA, Gamma=5	CRRA, Heterogeneity	Allowing Savings
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
All Taxfilers	100%	92.51	95.26	88.55	23.63	125.21	83.27	90.41
		[11.75]	[21.74]	[9.96]	[3.82]	[20.05]	[11.84]	[10.89]
		(272.56)	(180.80)	(294.63)	(60.09)	(309.14)	(228.82)	(271.84)
High School or Less	45%	85.71	96.95	81.12	24.31	119.49	77.26	83.88
		[12.48]	[21.60]	[9.88]	[4.02]	[21.26]	[11.90]	[11.69]
		(240.53)	(186.75)	(273.76)	(64.52)	(287.61)	(204.22)	(241.49)
No Status Changes	47%	95.40	101.95	91.43	21.88	129.60	85.25	93.09
		[10.90]	[18.30]	[8.49]	[3.54]	[18.36]	[10.64]	[9.78]
		(326.91)	(211.54)	(366.04)	(58.02)	(356.94)	(267.69)	(324.58)
Female	52%	92.31	101.22	86.21	26.26	126.14	90.26	90.22
		[15.27]	[25.45]	[12.30]	[4.95]	[26.16]	[14.80]	[13.82]
		(248.74)	(173.53)	(268.93)	(65.78)	(296.86)	(247.75)	(246.83)
Below 200% Federal Poverty Line	64%	108.48	88.89	105.53	27.12	130.44	93.77	105.95
		[12.62]	[23.40]	[10.92]	[4.04]	[21.93]	[13.38]	[11.19]
		(308.52)	(175.67)	(339.31)	(68.09)	(295.59)	(238.36)	(308.42)
EITC Filer	35%	164.83	184.51	150.48	42.31	216.72	143.77	162.18
		[33.18]	[59.05]	[25.02]	[10.43]	[57.79]	[32.24]	[33.08]
		(368.15)	(256.67)	(391.21)	(85.00)	(417.49)	(294.08)	(367.69)
High Uncertainty Filer	50%	178.89	176.22	171.48	45.27	239.30	160.47	175.19
		[46.49]	[82.82]	[38.39]	[14.25]	[72.49]	[44.92]	[42.12]
		(365.73)	(228.04)	(400.00)	(79.26)	(406.16)	(304.69)	(365.43)

Note: This table shows the mean, median, and standard deviation of compensating variation from eliminating refund uncertainty for different tax filer groups. Column 2 presents results from our baseline model in which beliefs are normally distributed and all filers have a coefficient of relative risk aversion of $\gamma = 3$. Columns 3-8 consider alternative assumptions. Column 3 assumes beliefs follow a beta/triangle distribution rather than a normal distribution. Column 4 assumes that filers who say they are "very sure" about their refund amount, and who place positive probability mass on only one bin, have no uncertainty. Columns 5 and 6 assume a different coefficient of relative risk aversion ($\gamma = 1$ or $\gamma = 5$, respectively). Column 7 assumes filers' coefficients of relative risk aversion are distributed $U[1, 5]$ and have a 50 percent rank correlation with subjective uncertainty. Column 8 allows filers to consume any savings reported on their intake survey. High Uncertainty filers have an above-median subjective standard deviation, and No Status Changes refers to having the same filing status and number of dependents as in the preceding tax year. For each subgroup and column, medians are in square brackets, and standard deviations are in parentheses.