The Pass-Through of Uncertainty Shocks to Households*

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February 25, 2022

Abstract

Using new employer-employee matched data, this paper investigates the impact of uncertainty, as measured by idiosyncratic stock market volatility, on individual outcomes. We find that firms provide at best partial insurance to their workers. Increased firm-level uncertainty reduces total compensation, especially variable pay, and workers reduce their durable goods consumption in response. Such shocks also lead to greater financial fragility among lower-income earners. Constructing a new county-level uncertainty shock, we find that local uncertainty shocks reduce county-level durable consumption. Taken together, these findings show that uncertainty shocks can significantly affect local economic activity through households' consumption and savings decisions.

Keywords: Employment risk, Consumption, Insurance

JEL Classification: D14, D80, E52, G21

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*This paper supersedes an earlier paper titled "Household Credit and Local Economic Uncertainty." We want to thank Equifax Inc. for access to anonymized credit bureau data on borrowers including loan and payment amounts, plus anonymized employment and income information for a sample of borrowers. The views in this paper are those of the authors and do not necessarily reflect those of Equifax Inc., the Federal Reserve Bank of Philadelphia, or the Federal Reserve System. We thank Luigi Pistaferri, Jonathan Berk, Darrell Duffie, Scott Baker, Indraneel Chakraborty, Steve Davis, Harry DeAngelo, Matt Kahn, Jose Fillat, Justin Murfin, Pascal Noel, Anna Orlik, and Luke Stein as well as numerous seminar participants.

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1. Introduction

Common narratives identify uncertainty as a powerful driver of economic fluctuations. Uncertainty can, for instance, by increasing the real option value of delaying difficult-to-reverse investment and hiring decisions, shape employment and investment dynamics (Bernanke, 1983; Bloom, 2009). It can also increase demand for precautionary saving and liquidity, affecting economic activity and credit usage (Gourinchas and Parker, 2002; Bertola, Guiso and Pistaferri, 2005). The effects of uncertainty can operate directly through credit markets: Greater uncertainty or risk can lower collateral values and increase credit spreads in the presence of financial frictions, limiting the supply of credit to entrepreneurs and consumers, and slowing economic activity (Christiano, Motto and Rostagno, 2014).

Whereas the existing literature has mainly focused on the relationship between uncertainty shocks and firms' investment, the pass-through of uncertainty shocks from firms to their employees has been mostly overlooked. Estimates of how firms might transmit shocks to workers by affecting wages and employment could inform policy makers responsible for providing public insurance against such shocks. Furthermore, a better understanding of this relationship can also contribute to bridging the gap between the firm-level literature on uncertainty that investigates the impact of uncertainty on firms and the more recent macroeconomic literature studying the relationship between aggregate fluctuations and the distribution of income and income growth across households (e.g. McKay, 2017 and Busch et al., forthcoming). However, a key challenge in identifying the transmission mechanism to households is a lack of data to support a clear mapping between firm-level fluctuations and household behavior together with detailed information about households' choices over time.

This paper investigates the impact of stock market volatility on consumer outcomes using a unique employee-employer dataset collected by one of the major credit bureaus and updated monthly. The dataset provides a representative sample of the existing labor force in the United States. A large sample of U.S. firms employs the credit bureau for administrative and accounting purposes, ensuring the correctness of the data. Having detailed firm-level employment data, including wages, enables us to study the impact of firm-specific uncertainty on workers. We are also able to observe key credit outcomes sourced from credit reports for workers at these firms, enabling us to investigate the pass-through of firms' uncertainty shocks to workers' income and consumption decisions over time for the same worker-firm match. We also exploit the variation in credit attributes and other worker observables to identify heterogeneous responses across workers operating within the same firm, while controlling for the first moment shocks that simultaneously affect these firms.

Intuitively, we focus on the time variation in idiosyncratic firm-level risk rather than market-wide dislocations by building on the recent literature that uses stock returns residuals after taking into account the three Fama-French factors (Gilchrist et al., 2014; Alfaro, Bloom and Lin, 2018). We lag this residual-based measure and control for the first moment shock as captured by stock returns in order to disentangle the effect of uncertainty from these other relevant shocks. Using the idiosyncratic firm-level risk can help us isolate the causal effect of uncertainty, as the use of idiosyncratic risk means that the effect we find is not likely caused by economy-wide movement in uncertainty. More generally, because all specifications include time, firm, and individual fixed effects, the estimated effects of uncertainty are not likely to be due to aggregate shocks or differences in time-invariant firm or worker characteristics. The use of firm fixed effects enables us to exploit within-firm variation, assuring the robustness of our findings. We also include county by time fixed effects in the most conservative specifications to non-parametrically absorb time-varying local economic shocks. This enables us to compare outcomes for two individuals living in the same area at the same time earning similar wages in the previous year, but exposed to different uncertainty shocks. In light of this conservatism in our regression specification, we can more easily interpret our results as causal even in the absence of an instrumental variable or experimental data.

Our analysis first validates this residuals-based uncertainty measure at the firm level, demonstrating that firms reduce capital expenditures in response to increased uncertainty. These results are not an artifact of the sample of firms in our dataset; the same tests are performed for the universe of public firms available in Compustat, and estimated coefficients are indistinguishable across the two samples. Consistent with the hypothesis that periods of high uncertainty result in higher employment risk, employment declines significantly. A one standard deviation increase in uncertainty reduces employment by 8.9 percent. Uncertainty shocks also increase tail events. A one standard deviation increase in uncertainty leads to a 13 percent higher probability that the firm experiences a more than 10 percent decline in its total employment. We show these effects to be driven by a combination of a reduction in new hires and an increase in termination rates.

A key way uncertainty shocks transmit to workers is through wage reductions. In contrast to previous studies that argue that firms are best able to offer insurance to workers by absorbing these shocks, which would result in a small or insignificant elasticity of wages to uncertainty (i.e., wages are sticky), we find that wages decline significantly in response to uncertainty shocks. The main margin of adjustment is variable pay (i.e., bonuses and commissions) rather than base pay. In keeping with the variable pay margin of adjustment, we find the standard deviation of wages within firms to decrease as well, consistent with an overall compression of salaries. Note that our results, because they exploit only within-firm variation, are unlikely to be explained by self-selection of workers into riskier firms.

These effects are economically meaningful. A one standard deviation increase in uncertainty leads to a reduction in wages of about 2.3 percent. The probability of experiencing a reduction in income of at least 10 percent is significantly higher when uncertainty is high, stemming from a reduction in workers' variable pay. The impact of uncertainty shocks on job losses is also significant. We find that a one standard deviation increase in uncertainty leads to a 1 percentage point increase in involuntary job losses, equivalent to an 18 percent increase in probability of job loss from the baseline of 5.5 percent.

The existing literature examining the role of uncertainty on firms' outcomes finds large countercyclical second-moment fluctuations in productivity and returns, while the existing macroeconomic literature documents that idiosyncratic labor income risk becomes more left-skewed during recessions (Busch et al. forthcoming). We can provide an explanation for these two sets of findings that have existed independently until now. We perform quantile regressions on the relation between income growth and uncertainty shocks and find that uncertainty shocks lead to a negatively skewed increase in the dispersion of income growth. In other words, this result suggests that the partial insurance provided by the firms can be one of the channels that connects the rise of firm uncertainty to negatively skewed increases in the distribution of income growth during economic downturns (which are usually associated with the rise in uncertainty as well).

Having established the impact of uncertainty shocks on worker income, we turn to the effects on consumption. Absent a comprehensive measure of consumption, we are able to capture two key dimensions of durable consumption, which should be, in principle, the ones most affected: automobile and home purchases. We find that higher uncertainty reduces the propensity to purchase a car by about 0.8 percent and the likelihood of becoming a first-time homebuyer by 0.12 percent. By way of comparison, consider the elasticities reported by Di Maggio et al. (2017), who find that in response to an increase in monthly disposable income of $930 (annual increase of $11,200), the probability of purchasing a car increases by 0.3 percent per month (about 1 percent per quarter). Using the same elasticity, the $2,000 decline in income we find should correspond with a 0.2 percent decline in the probability of purchasing a car through this income channel. Our finding of a significantly larger effect suggests that a precautionary savings motive resulting from the uncertainty shock is likely to play an important role. These point estimates hint that a significant fraction of the reduction in economic activity during periods of turmoil can be attributed to higher uncertainty.

Individuals facing higher employment risk might alter their saving and borrowing decisions, which could ultimately increase their financial fragility. We find this to indeed be the case. Individuals become significantly more likely to slow mortgage repayments in an attempt to possibly build a buffer of liquid assets. A further indicator of the toll that can be exacted by uncertainty spikes is a higher likelihood of default and concomitant decline in credit scores.

Our empirical tests point to significant adjustment heterogeneity across consumers. Standard models observe that high income workers are likely to have larger buffer stocks of wealth or easier access to external sources of finance that limit the pass-through of uncertainty shocks to consumption. But because of their greater exposure to incentive compensation, high earners might also be more strongly tied to business fluctuations, and so could be more affected during periods of distress. We find reductions in income and car purchases to be significantly higher among top earners, but greater financial fragility, captured by likelihood of default and reduced credit scores, to be more widespread among lower income individuals. This is consistent with higher income earners having more discretionary consumption that they can contract in response to higher uncertainty, whereas individuals in the left tail of the income distribution, with fewer resources with which to cope with uncertainty, are more likely to be put in jeopardy.

We also exploit the heterogeneity among firms to test whether the pass-through of first and second-moment shocks to households is stronger for firms that appear more financially constrained based on their balance sheets. As a measure of firms' financial constraints, we follow Ottonello and Winberry (2020) and construct the firm's distance to default. We find that the transmission of uncertainty shocks is stronger when the firms' default risk is higher.

As a robustness check, we construct an additional measure of uncertainty using IBES data on analyst forecasts. Intuitively, higher analyst disagreement is likely to capture periods of higher uncertainty about firms. We confirm the main results of the paper by showing that an increase in analyst forecasts disagreement corresponds to a significant decline in income and consumption, corroborating the interpretation that our results are driven by increased uncertainty.

Our final set of tests complements the foregoing analysis by focusing on the economic consequences of uncertainty in the local area level. We first construct a new measure of local uncertainty: uncertainty specific to counties. This measure, similar to the earlier firm-level results, is derived from the excess returns of public firms and constructed to filter out aggregate first moment shocks through a factor model. Sectoral uncertainty at the 4-digit NAICS level can be computed using these adjusted stock returns. The industry uncertainty measures are mapped to the county level by weighting a county's relative exposure to each industry. Intuitively, this local uncertainty measure captures spatial and temporal variation in uncertainty due to local labor market risk emanating from idiosyncratic sectoral demand and technological shocks (Leduc and Liu, 2016).

We demonstrate its validity by providing evidence that this measure can in fact predict employment growth at both the sector and county level. We further show the measure to exhibit significant variation across counties, and its correlation, on average, with the VIX to vary significantly across counties. Using this new measure of local uncertainty to investigate whether and how uncertainty affects county-level durable consumption measured using data from the NY Fed/Equifax's Consumer Credit Panel (CCP), we find a one standard deviation increase in county-level uncertainty results in a 10 percent reduction in car purchases and an 11 percent reduction in first home purchases.

Results both at the firm-consumer level and at the county level show volatility in financial markets to have real adverse consequences even among populations that do not directly own financial assets. Furthermore, the results on the pass-through of firms' uncertainty shocks to workers suggest that government social insurance programs could be effective in reducing the consequences of heightened uncertainty on economic activities by insuring workers against income shocks.

The rest of the paper is organized as follows. In Section 2, we discuss the related literature, in Section 3 the data used in this study. Our main results and the heterogeneity analysis are presented in Section 4. Section 5 concludes.

2. Related Literature

This paper is related to multiple existing literatures in macroeconomics and finance. In macroeconomics, Bernanke (1983), Titman (1985), and Abel and Eberly (1994) developed the idea that the real-option value of waiting to enter into difficult-to-abrogate contracts is higher during periods of increased economic uncertainty. Building on this idea, more elaborate models have investigated the role of uncertainty in economic fluctuations. In a seminal paper, Bloom (2009) shows higher uncertainty to cause firms to temporarily pause investment and hiring, resulting in lower productivity consequent to lower reallocation across firms. Bloom, Bond and Van Reenen (2007) show higher uncertainty to reduce the responsiveness of investment to demand shocks as the increase in real options makes firms more cautious. Berger, Dew-Becker and Giglio (2020) show that, although innovations in realized stock market volatility are followed by economic contractions, shocks to forward-looking uncertainty do not exert a similar adverse impact on the aggregate economy. Gilchrist et al. (2014) and Alfaro, Bloom and Lin (2018) show this to be even more true in the presence of financial frictions, as ex-ante investment is reduced to a greater degree by financially constrained than by financially unconstrained firms.[1] Finally, Bloom et al. (2018) estimate that uncertainty shocks can generate declines in gross domestic product of around 2.5 percent. We complement this literature by using microeconometric evidence to show how household reactions to uncertainty shocks might explain, in part, the drop in aggregate demand[2].

Our measure of uncertainty is based on the realized volatility of abnormal returns of individual firms (i.e., a firm's return after removing the loading on the Fama-French factors), which is similar to the measure used in Gilchrist et al. (2014). Equity market based-measures are a useful proxy for uncertainty, and a key advantage of our empirical setting is the linking of an employer-specific equity market-based uncertainty measure to the financial and consumption decisions of individual employees.[3] We confirm the robustness of our results to a different measure based on equity analysts' disagreements.

Labor market risk is posited to be a key channel through which employer specific uncertainty might affect the financial decisions of employees. The underlying logic behind this channel is that in the presence of financial frictions an increase in idiosyncratic uncertainty — the variance of productivity shocks to firm capital — increases credit spreads for firms

[1]Using the residual returns helps to reduce the endogenous co-movement of uncertainty with first moment shocks (Benhabib, Liu and Wang (2016).

[2]Our county-level results provide evidence of the effects of uncertainty at the local level, although these county-level effects can be different from the aggregate impact of uncertainty due to spillovers or general equilibrium effects. We leave the study of these aggregate channels for future research.

[3]Dew-Becker and Giglio (2020) provide a measure of cross-sectional uncertainty using stock options on individual firms dating back to 1980; as do we, they consider heterogeneity among firms to be an important dimension to explore.

(Christiano, Motto, and Rostagno, 2014). Increased credit spreads can reduce investment and employment, exposing workers to greater employment and wage risk and leading them to engage in precautionary behavior, such as reducing spending and increasing credit lines in order to increase their financial flexibility (Hahm and Steigerwald, 1999; Gourinchas and Parker, 2002; Aydin, 2018). Ben-David et al. (2018) document the heterogeneity in uncertainty perception across households, finding higher individual-level uncertainty to be associated with greater precautionary behavior. Our empirical setting, with its matched firm-employee data, provides direct tests of this labor market risk channel on consumer decisions.[4]

Recent studies focused on the role of firms in insuring workers against risk include Guiso, Pistaferri and Schivardi (2005), who show that firms absorb temporary fluctuations fully, but insure workers against permanent shocks only partially. More recently, Low, Meghir and Pistaferri (2010) have shown increased employment risk to have significant effects on output and welfare. Friedrich et al. (2019), using Swedish data, show firm-specific permanent productivity shocks to affect the wages of high-skilled, and firm-specific temporary shocks to affect the wages of low-skilled, workers. Using patent-induced shocks to firm productivity, Kline et al. (2019) find that, on average, 30 percent of the increase in surplus due to new patents is passed to workers. Alfaro and Park (2019) use debit and credit card transaction data to analyze workers' consumption behavior, and Fagereng, Guiso and Pistaferri (2018) use Norwegian data to study the importance of uninsurable wage risk for individuals' portfolio allocations. Berk and Walden (2013) investigate the interaction between firms' access to capital markets and the insurance they provide workers, whereas Ellul, Pagano and Schivardi (2018) analyze the substitutability of unemployment insurance offered by government and family firms.[5]

[4] There is, of course, a large literature on individuals' precautionary responses to income risk; see, among others, Zeldes (1989), Deaton (1991), Carroll (1997), Carroll and Samwick (1997), Attanasio, Banks, Meghir, and Weber (1999), Banks, Blundell, and Brugiavini (2001), and Gourinchas and Parker (2002). In this tradition, Eberly (1994) focuses on car purchases and Bertola, Guiso and Pistaferri (2005) use Italian data to understand how consumers adjust durable goods consumption in response to microeconomic uncertainty; microeconomic studies focused on investment include Guiso and Parigi (1999) and recent work by Stein and Stone (2013).

[5] See Guiso and Pistaferri (2020) and Pagano (2019) for a review of this recent literature.

We contribute to this literature by showing the consequences of the at best partial insurance provided by firms for workers' decisions and financial health. We exploit credit report data augmented with detailed data on wages to trace the direct impact of firms' uncertainty shocks on household debt repayment, default probabilities, and wage composition. We also investigate the distributional impact of uncertainty shocks among workers within firms. Our evidence on the heterogeneous effects of uncertainty shocks also informs the debate on consumption inequality and housing wealth accumulation across households, and how these trends might be more pronounced after major uncertainty shocks.

3. Data

Lack of employee-employer linked data poses a major challenge to studying the pass-through of uncertainty shocks from firms to households. We use proprietary data provided by one of the main credit bureaus to construct key outcome variables. This data provides information on household balance sheets, specifically, monthly history of all borrower loans including auto, mortgage, and credit card (revolving). The data has granular information about the main features of these loans including date opened, account type, credit limit, monthly scheduled payment, balance, and performance history.

Our proprietary version is unique because our data include household balance sheet information as well as employment information about borrowers. More than ten thousand U.S. employers use the credit bureau's services for employment and income verification services. Our study uses anonymous employment and income information provided by employers.[6] We believe that our data provide a unique opportunity to shed light on whether households' consumption pass-through is directly affected by uncertainty shocks. Our measure of uncertainty shocks being based on the volatility of stock prices, we consider only public firms. Our data covers 323 firms from the third quarter of 2010 to the third quarter of 2018 and 374,283 individuals representing a 10 percent random sample of employees who worked at these firms

[6] See Kalda (2019) for a detailed discussion of the representativeness of the employment and income data.

during this period.

To measure firm-level uncertainty for each public firm, we first collect daily stock returns and risk-free rates from the Center for Research in Security Prices (CRSP) database. Then, for each firm, we remove the systematic component in daily excess returns by regressing the daily excess stock returns with a three factor model. We use the standard factors such as the returns of the S&P 500 index, the book to market ratio, and the relative market capitalization using data from 1990 to 2015. Through these procedures, the residuals from these regressions are unlikely to include aggregate first moment shocks, such as time-varying shocks to financing constraints. These residuals instead contain firm-level idiosyncratic demand or technological shocks, which constitute the main source of variation for our analysis. We compute firm-level uncertainty as the realized volatility of these residuals over a quarter for each firm. Similarly, we compute the quarterly average residual returns for each firm as a control variable for the first moment shock. Panels A and B of Table 1 report the key summary statistics for firms and individuals, respectively. Panel A shows the median firm to have 690 employees, with significant heterogeneity, the standard deviation being 3,119. Turnover is relatively high, on average, about one-fourth of employees being hired by, and 16 percent separating from, the firm within the year. On average, total employment decreases by 3 percent in a year. About 6 percent of firms experience a decline of greater than 10 percent in total employment in a year, while approximately 1.5 percent of firms experience an increase in total employment greater than 10 percent in a year. There is also significant heterogeneity in wage distribution across firms, with average income at the firm level being $85,403 with a standard deviation of $54,325 and the median being approximately $77,378.

[Insert Table 1 Here.]

Panel B shows average individual income for our sample to be approximately $81,000 and median income to be about $54,500, confirming the skewness of wages documented in previous studies. We further find that, on average, 94 percent of total compensation is in the form of base pay and 6 percent in the form of variable pay (e.g., commission, overtime, and bonus). The average growth rate of the income from a previous year is about 7.8 percent for our sample, with 18.8 percent of individuals experiencing an income decline greater than 10 percent. The probability of voluntary job loss within a quarter is about 2 percent, the probability of involuntary job loss 5.5 percent. In terms of durable purchases within a quarter, the probability of an automobile purchase is about 7 percent and that of a first-time home purchase about 2 percent. About 15 percent of individuals in the sample are delinquent on liabilities and average credit score is 705; these figures, being close to U.S. averages, confirm the representativeness of the sample.[7] Although individuals in our sample were employed by large public firms during the sample period, whereas other individuals in the credit population might have been employed by smaller firms or even unemployed, credit scores and probability of delinquency are quite similar.

4. Results

4.1. Firm-Level Evidence

We validate our empirical methodology by beginning our analysis with an investigation of the effect of uncertainty at the firm level. We estimate the following specification:

$$y_{it} = \beta \cdot Uncertainty_{i\,t_{1-4}} + \delta \cdot Avg\,Returns_{i\,t_{1-4}} + X_{it}'\alpha + \gamma_i + \eta_t + \varepsilon_{it} \tag{1}$$

where y_{it} are outcome variables, such as capital expenditures, employment, and wages, measured at the firm-month level. The coefficient of interest β measures the effect of changes in uncertainty, computed as an average over the previous four quarters. To ensure that we are controlling for the first moment shock, we include average returns over the previous four quarters. Depending on the specification, we also control for additional firm time-varying

[7] Table A.1 compares the characteristics of firms in our merged sample with all other public firms; firms in our sample are larger in terms of sales and total assets and have slightly higher book leverage, but lower debt to EBITDA and stock market volatility. Table A.2, which compares the main credit attributes and income as of July 2015 for our sample and all individuals in credit report data (about 234 million), shows individuals in our sample to have higher income, mortgages, revolving balances, and auto loan balances.

characteristics X_{it}. As all specifications control for firm and time fixed effects (e.g., γ_i and η_t), we can interpret β as measuring the effect of changes in uncertainty on the dependent variables. To facilitate interpretation of the results, we standardize the uncertainty and average return measures. One can thus think of the estimated coefficients as the impact of a one standard deviation change in the uncertainty measure.

Table 2 explores the effect of variables recorded in Compustat on capital expenditures. This table has the dual objectives of showing that uncertainty alters firm behavior and that our sample of firms is representative of other public firms. We also compare the effect of uncertainty shocks on capital expenditure for firms in Compustat and the sub-sample of firms covered by our data. Columns (1) and (3) are based on the entire sample of public firms, Columns (2) and (4) only on firms in the employer-employee dataset (TheWorkNumber). Columns (1) and (2) include firm and year fixed effects, Columns (3) and (4) firm and industry by year fixed effects. In this way, we absorb any shock that might affect a particular industry more than others (e.g., commodity shocks). We also control for other firm characteristics including size, measured as firm total sales, leverage, cash holding, and EBITDA. We find the effects of uncertainty to be statistically and economically significant, and a one standard deviation increase in uncertainty reduces capital expenditure by about 0.7-0.8 percent. These effects are consistent across sub-samples, and similar results are reported in the literature (see, for instance, Alfaro, Bloom and Lin, 2018). Similar estimates between all public firms and the subset of firms in WorkNumber data provide further evidence that our employer-employee sample is representative of all public firms.

[Insert Table 2 Here.]

Having confirmed our sample of firms to be reacting to uncertainty shocks in a manner similar to other public firms, we take advantage of our dataset to explore the effect of uncertainty shocks on a number of other dimensions at the firm level. Panel A of Table 3 considers employment. Column (3) shows a one standard deviation increase in uncertainty to reduce employment by 9 percent. When we decompose this result between new hires (Column 1) and termination of existing workers (Column 2), we find that the reduction in new hires and increase in terminations contribute almost equally to the decline in employment by 4.8 and 4.3 percent, respectively. Being interested as well in understanding whether the uncertainty shocks we capture are causing mainly small fluctuations or could be responsible for larger changes in hiring, we investigate, in Column (4), whether changes in uncertainty decrease the probability of an increase in employment and, in Column (5), increase the probability of a decline in employment greater than 10 percent. We find that a one standard deviation increase in uncertainty decreases the probability of a large increase in employment by 1.7 percent and increases the probability of large decline in employment by 13 percent.

[Insert Table 3 Here.]

Panel B complements the previous evidence by investigating whether uncertainty directly affects wages. Column (1) shows that uncertainty shocks lead to a reduction in the average wage. The effect is economically significant, with a one standard deviation increase in uncertainty precipitating a decline of 6.4 percent in wages. To understand the main margin of adjustment, we investigate this effect by decomposing it into base and variable pay. Bonuses and commissions are likely to be easier to adjust in response to changes in economic conditions. Column (2) provides evidence consistent with this hypothesis. We find that uncertainty shocks result in a significant increase in the fraction of wages classified as base pay over total pay (e.g., there is a reduction in bonuses). Column (3) also shows uncertainty to lead to a reduction in the dispersion of wages within a firm as measured by the standard deviation of wages. Columns (4)-(6), which show the impact of uncertainty shocks on different percentiles of wages within firms, suggest that wages in the top decile of the income distribution suffer the steepest reduction as a result of uncertainty shocks. Intuitively, because the mechanism for reduction in wages works through cuts in bonuses and commissions, these changes are more likely to affect high-earners than minimum wage workers, compressing the wage distribution within a firm. Collectively, this evidence showing firms to be highly sensitive to changes in uncertainty serves to validate our approach. We next examine the pass-through of these shocks to individual employees.

4.2. Effects on Individual Income

In principle, were firms to at least partially insure their workers, adverse effects of uncertainty on individuals' consumption and savings decisions might be mitigated. In addition, workers can self-select into occupations with different levels of uncertainty. This self-selection would predict that workers subject to the most uncertainty shocks are the ones who are best able to cope with the shocks. We take advantage of our individual-level data to investigate whether these suppositions hold.

Figure 1 provides an overview of the relationship between individual income and firm-level uncertainty. In the figure, we first define deciles of annual individual income growth based on the unconditional distribution of this variable. We then measure the relative frequency of individuals' income growth in each decile for individuals with employers in the bottom versus top quartile of uncertainty shocks. As Figure 1 shows, individuals who work in firms that experience higher uncertainty shocks are more likely to experience extreme movements in their income and therefore face higher individual income uncertainty.

[Insert Figure 1 Here.]

Table 4 estimates a specification similar to the previous one, but at the individual-quarter level. To capture potential heterogeneity we control for lagged income in the previous year. We include in all regressions firm, county-quarter, and, importantly, individual fixed effects. To the extent that latent risk preferences are time invariant, individual-level fixed effects help to address the self-selection issue. Potential adverse effects on individuals' income, however, result from broader negative economic shocks that increase the general level of uncertainty as well as affect individuals' income. To control for this possibility, we also include county by quarter fixed effects. In other words, we compare the effect of changes in uncertainty on individuals residing in the same areas at the same time, holding fixed the same level of past income and taking into account the time-invariant characteristics at the individual level.

[Insert Table 4 Here.]

We begin by analyzing the impact of uncertainty shocks on the probability of job loss. Table 4 shows a one standard deviation increase in our measure of uncertainty to increase the probability of voluntary job loss by about 0.6 percent and probability of involuntary job loss by 1 percent. The involuntary job loss result is consistent with the previous finding that firms reduce employment in response to uncertainty shocks, and the increase in voluntary job loss consistent with the idea that firms that face greater uncertainty are less appealing to workers.

Columns (3)-(6) of Table 4 restrict the sample to those who stayed with the firm. Column (3) shows that a one standard deviation increase in uncertainty leads to a reduction in log wages of 2.3 percent. Column (4) complements this finding by showing that uncertainty shocks also lead to a 1.4 percent higher probability of an individual experiencing a decline in income of at least 10 percent. That is, even after controlling for first moment shocks, higher uncertainty appears to have a large independent negative effect on worker outcomes. Columns (5) and (6) decompose this effect to show that although we do not find a reduction in base pay, the fraction of base pay over total compensation increases significantly, with bonuses and commissions being the principal adjustment margin. These effects do not seem to be affected by local heterogeneity—likely a consequence of constructing our uncertainty measure as a residual after taking into account systematic risk.

We complement the previous findings by presenting the results of quantile regressions on the relation between income growth and uncertainty shocks in Table 5. We find that the effects of uncertainty are negative and significant until the 75th percentile, with the magnitude declining significantly as we move from the left side of the distribution to the right. In other words, we find that uncertainty shocks lead to a negatively skewed increase in the dispersion of income growth because the ones to suffer the most are the ones earning the lowest salaries. Intuitively, the partial insurance provided by the firms can be one of the channels that connect the rise of firm uncertainty to negatively skewed increases in the distribution of income growth during economic downturns (e.g. McKay, 2017 and Busch et al., forthcoming). In sum, uncertainty shocks appear to affect individuals' income. The following section examines how households respond to uncertainty-induced income shocks.

[Insert Table 5 Here.]

4.3. Consumption and Financial Health

An increase in workplace uncertainty can affect households' consumption and financial decision making through a direct impact on income, with higher firm-level uncertainty affecting a worker's unemployment and income risk. An increase in firms' uncertainty can thus have a first order effect on aggregate demand. Evidence on the effects of uncertainty on consumer demand is thus key to both evaluating theories that emphasize the importance of uncertainty in aggregate fluctuations and developing policies to contain the aggregate consequence of uncertainty. The effects of stock market volatility occasioned by uncertainty shocks not only are felt by the relatively small fraction of the population directly exposed through portfolio holdings, but can trickle down to individuals through their employers, amplifying the potential aggregate effects of firm-level uncertainty by, for example, prompting individuals to postpone important decisions and large purchases, such as buying a car or becoming a homeowner.

Table 6 investigates this hypothesis. Expecting durables consumption to be most affected by changes in uncertainty, we use two measures computed using the credit report data, namely, the probability of purchasing a car and becoming a first-time homeowner. Column (1) shows a one standard deviation increase in firm uncertainty to reduce the probability of buying a car by 0.9 percent, which holds after controlling for local heterogeneity and is conditional on an individual having a car already or not. Column (2) shows that a one standard deviation increase in uncertainty leads to a reduction of about 0.12 percent in the probability of becoming a first-time home buyer.

[Insert Table 6 Here.]

We can assess these magnitudes by comparing them to the elasticities uncovered by Di Maggio et al. (2017), who find an increase in monthly disposable income of $930 (annual increase of $11,200) to increase the probability of purchasing a car by 0.3 percent per month (almost 1 percent per quarter) and a $2,000 decline in income to be associated with a 0.2 percent decline in the probability of purchasing a car through this income channel. Our finding of a significantly larger effect in this paper suggests that in addition to the direct income channel, a precautionary savings motive resulting from the uncertainty shock is also likely to play an important role.[8]

An increase in uncertainty and the resulting loss of income can also worsen individuals' financial health. Households subject to sudden and sharp reductions in income, for example, are likely to have more difficulty repaying liabilities. Consistent with this prediction, Column (3) of Table 6 shows that a one standard deviation increase in uncertainty results in a 0.24 percent increase in the probability that an individual becomes delinquent. In additon, Column (4) shows that the credit scores of such individuals are likely to be adversely affected. Negative loan performance and diminished creditworthiness are not the only dimensions where an effect is seen. Column (5) provides evidence that individuals subject to uncertainty shocks are less likely to pay down their mortgages and Column (6) shows that revolving utilization captured by total credit card balance over credit limits significantly increases, suggesting that individuals tend to rely more heavily on lines of credit during periods of uncertainty. Taken together, this evidence shows that individuals reduce consumption and experience increased financial fragility when uncertainty spikes.

4.4. Alternative Measure of Uncertainty

We followed the literature in constructing our main measure of uncertainty. We test the robustness of our findings by constructing an additional measure of uncertainty using IBES data on analyst forecasts. We consider the standard deviation of earnings per share predictions over the most recent four quarters relative to firms' historical average. Intuitively, higher analyst disagreement is likely to capture periods of higher uncertainty about a firm. For ease

[8] Note that although elasticity to positive and negative shocks can differ, the income shock analyzed by Di Maggio et al. (2017) is likely to be significantly more persistent than the uncertainty shocks considered here.

of interpretation, we normalize this, as we did the main measure.

Table 7 reports the same specifications as described above using the alternative uncertainty measure. Panel A considers results on income. We find that a one standard deviation increase in uncertainty leads to a significant decline in income, in particular, the variable pay component, and an increase of 0.4 percent in the probability of experiencing a large decline in income. The effects are significant and consistent irrespective of specification.

[Insert Table 7 Here.]

Panel B reports results for the consumption and credit regressions. We find that an increase in the alternative uncertainty measure reduces credit scores and the likelihood of a first-time home purchase and increases the probability of default and revolving utilization. The only result that becomes insignificant with this different uncertainty measure is the car purchase proxy of durable consumption. Overall, these results confirm the paper's main findings by showing an increase in uncertainty to lead to significant declines in income and consumption. This corroborates the interpretation that our results are driven by increased uncertainty. Consistent with the view that analyst disagreement captures only one dimension of uncertainty, we find smaller effects for our main outcome variables.

4.5. Heterogeneity

Consumers' risk-bearing capacities differ. We do not observe savings, but higher-income individuals are likely to have a greater buffer stock of resources to smooth uncertainty induced fluctuations in income. These agents also generally have access to cheaper sources of external financing. Income and credit scores could thus affect how consumers respond to uncertainty shocks. The results of Tables 3 and 4 suggest that such shocks disproportionately affect individuals with higher income or a higher fraction of variable pay. Table 8 thus estimates our baseline regression, but interacts the uncertainty shock with a dummy identifying individuals whose income in the past year is above the median income for our sample.

[Insert Table 8 Here.]

The results in Columns (1) to (4) show that high-income individuals indeed have higher exposure to uncertainty shocks. For example, the result in Column (1) shows that a one standard deviation increase in uncertainty reduces the income of people in the bottom half of the income distribution by 1 percent, but the income of people above the median wage in our sample by close to 4 percent. Columns (5) to (10) analyze the impact of uncertainty shocks on households' durables purchases and financial decisions. The results show uncertainty shocks to affect high-income and low-income individuals' durables purchases and financial decisions differently. For example, Column (5) shows that a one standard deviation increase in firm uncertainty reduces the probability of buying a car by almost 1 percent for high-income earners, while the effect is smaller lower-income earners at 0.7 percent. Columns (6), (7), (9) and (10) report no statistical differences in responses between high- and low-income individuals regarding the probability of becoming a homeowner, difficulty repaying liabilities, paying down mortgages, and revolving utilization. Column (8) shows uncertainty to positively affect the credit scores of high-income relative to low-income individuals. These results suggest that although high-income individuals have more financial resources to buffer against income shocks, even in the face of an uncertainty induced income shock more than twice as large, they adjust consumption, except for auto purchases, similarly to the lower-income sample.

At this point we can ask whether firms that are more financially constrained based on their balance sheet data have a higher pass-through of second-moment shocks to workers. Intuitively, firms that are more likely to be in distress will have a lower ability to insure their workers against these shocks and so we may observe their workers' outcomes respond more prominently. As a measure of firms' financial constraints, we follow Ottonello and Winberry (2020) and construct the firm's distance to default.

In Table 9 we report the estimated effects of first and second moment shocks for our main outcomes interacting our main independent variables with the distance to default measure. Similar to before, the measure of distance to default is standardized. Overall, the results in this table suggest that firms further away from default are significantly better at insulating their employees from the first moment and second moment shocks. For example, the estimates in Column (1) show that a one standard deviation increase in the distance to default measure (i.e. decrease in probability of default) reduces the effect of uncertainty on workers' income by about 11%. The reduction in the probability of default also reduces the pass-through of first moment shocks to workers' income by about 8%. Column (2) shows that a firm's low default risk also dampens the effect of the uncertainty shock on the probability of a large income decline. A one standard deviation increase in the firm's distance to default decreases the main effect by 44%. Finally, the results on car purchases, mortgage repayment, and revolving utilization further confirm that the pass-through of both first moment shocks and uncertainty shocks to households is larger for firms that are closer to default. For example, a one standard deviation increase in firm's distance to default measure reduces the uncertainty effect from 1.9 percent to 1.6 percent, a 16% reduction. Similarly, the effect of uncertainty shocks on the probability of paying down a mortgage is reduced by about 9% for firms that are further away from defaults. Overall, the results show that firms that are less financially constrained reduce the pass-through of uncertainty shocks to workers.

[Insert Table 9 Here.]

4.6. County-Level Consumption

The previous sections show that firm-level uncertainty affects individual consumption. In this section we use county-level data to explore the possibility that these individual-level effects of uncertainty on consumption might vanish at a more aggregated level.

As mentioned previously, macro indexes of uncertainty like the VIX are unlikely to provide sufficient variation for individual empirical tests of uncertainty. These indexes are also likely to endogenously co-vary with aggregate first-moment shocks that also drive credit decisions. To identify how uncertainty might influence consumption decisions, we develop an analog of our firm-level measure, a time-varying county-level measure of economic uncertainty constructed to be free of aggregate credit market and other first moment shocks, henceforth referred to as local uncertainty. Put simply, the measure captures the local labor market's exposure to industry-level idiosyncratic demand or technological uncertainty shocks, employing county-level exposure to fluctuations in firms' stock prices.

To construct the local uncertainty measure, we first remove for each public firm the systematic component by regressing the daily excess stock returns on a three factor model, constructed as in the previous sections using standard factors like the returns of the S&P 500 index, book to market ratio, and relative market capitalization with data from 1990 and 2015. The residuals from these regressions, being unlikely to include aggregate first moment shocks, such as time-varying shocks to financing constraints, instead include the firm-level idiosyncratic demand or technological shocks that constitute the main source of variation in our analysis.

We next compute the daily industry portfolio residual returns by weighting a firm's daily residual returns by its relative size among firms in the same 4-digit sectoral industrial classification (NAICS) code—the firm's relative market capitalization. We then calculate the quarterly sector-specific standard deviation of these daily idiosyncratic returns (see Gilchrist, Sim, and Zakrajšek, 2014 for a similar procedure) to produce a sector-specific index of volatility. Note that the firm-level idiosyncratic uncertainty index used in the previous sections does not simply reflect industry-wide uncertainty. A regression of firm-level idiosyncratic uncertainty on industry-level uncertainty produces an R-squared of 0.13. The information overlap across the two measures is thus relatively small.

Lastly, drawing on the quarterly sectoral employment data from the Quarterly Census of Employment and Wages (QCEW), which lists employment in each county by 4-digit NAICS code, we create an employment weighted index of economic volatility by county. The 4-digit NAICS sector-specific index of volatility is weighted by a county's employment share in that sector with a one-year lag. The use of employment shares captures the relative exposure of a county to different industry-level uncertainty shocks in the spirit of a Bartik instrument. The use of a one-year lag in employment share mitigates the potential contemporaneous endogenous response of employment to uncertainty.

Together with this second moment index, we construct the first moment analog as a control variable. The weighted mean idiosyncratic stock returns at the county level, henceforth referred to as local returns. For each sector, we weight each firm's residual returns by its relative market capitalization within the sector on a daily frequency, and take the average of the sectoral returns over a quarter to obtain the quarterly mean residual returns for the sector. As before, we standardize both the uncertainty and first moment measures.

Figure 2 illustrates the temporal variation in the aggregate VIX (orange solid line) and local uncertainty index. To show that there exists significant spatial heterogeneity in local uncertainty, Figure 2 plots the local uncertainty index at different points in its distribution—the 10^{th}, 50^{th}, and 90^{th} percentiles in each quarter—along with the VIX. In 2005 Q4, even with aggregate volatility at its lowest point in the sample period, some counties, mainly agricultural, such as Edwards County in Kansas (the 90^{th} percentile), experienced large spikes in local uncertainty on account of volatility in commodity prices. The 2008-2009 crisis is associated with a significant increase in the VIX, but county-quarter observations at the 10^{th} percentile of the local index experienced a far smaller increase (e.g., Flagler County, Florida). The 90^{th}-10^{th} percentile spread in the local index also increased by a factor of three, suggesting that because of differences in employment patterns and other factors, some counties were far more exposed to the crisis and fluctuations in economic uncertainty than others. For example, compared to the overall U.S. economy, Flagler County's economy—the 10^{th} percentile in 2008 Q4—is tilted more towards health care, which was less affected by the 2008-2009 financial crisis.

[Insert Figure 2 Here.]

[Insert Figure 3 Here.]

To illustrate what local uncertainty captures, Figure 3 shows the de-trended local uncertainty measures for San Francisco County, California and Upton County, Texas along with oil price volatility. Upton County has a large share of employment, and hence greater exposure to uncertainty shocks, in the oil and gas industry. San Francisco County, having a more diverse industry composition, has less exposure to oil price volatility. From Figure 3, the correlation between oil price volatility and the local uncertainty measure in Upton County is 0.4, in San

Francisco County 0.07. These differences indicate that the local uncertainty variable measures the variation in uncertainty shocks stemming from differences in local patterns of production.

This anecdotal evidence is confirmed by the simple correlations in Table 10, which plots the distributional heterogeneity across space. Movements in the VIX are correlated positively with all three series, especially during the crisis period. But when the sample is restricted to the post-2009 period, movements in the local uncertainty index at the 10^{th} percentile are negatively correlated with the VIX and the times series indicator of policy uncertainty developed by Baker, Bloom and Davis (2016) (BBD index henceforth). That is, for some counties, the local uncertainty index does not mechanically mirror aggregate uncertainty; rather it is likely to contain information about economic uncertainty relevant to the local area.

[Insert Table 10 Here.]

Before documenting the impact of local uncertainty on county-level consumption outcomes, we validate the local uncertainty measure in Table A.3 by taking into account the local labor market. In Column (1), the dependent variable is the quarterly log number of employees in each sector in each quarter, from the first quarter of 2000 through the last quarter of 2015, for both public and private firms, as provided by the QCEW. There are 313 sectors at the NAICS 4-digit level of disaggregation. The coefficient of interest is the one on the sector-specific uncertainty series, the standard deviation of the weighted daily residuals for public firms operating in the same 4-digit NAICS sector, where the weighting factor is a firm's relative market capitalization within the sector. Other controls include weighted mean returns within the quarter, sector fixed effects, year fixed effects, and year-quarter fixed effects. Because firms' employment decisions might respond with some lag to changes in uncertainty, Column (1) reports a specification in which both sectoral volatility and weighted mean returns enter with lags up to four quarters.

Although subject to measurement error because the sector uncertainty series uses only public firms and is derived from possibly excessively volatile equity market returns, the sector uncertainty point estimates are consistently negative and statistically significant at the third- and fourth-quarter lags. These coefficients suggest that a one standard deviation increase in sectoral volatility is associated with a 0.8 percent decrease in level of employment three quarters later, and as much as a 0.9 percent decline one year later. Column (2), which examines this relationship on an annual frequency, finds a one standard deviation increase in sectoral uncertainty to be associated with a 2.3 percent decline in sectoral employment one year later. Considered together with our earlier firm-level results, this suggests that an equity market derived measure of uncertainty is related to broader labor market outcomes.

We provide further evidence to validate our local uncertainty measure by investigating employment outcomes at the county level in Table 11. The dependent variable in Column (1) is quarterly growth in total QCEW employment in the county, the regressor of interest is the county-level local uncertainty variable, along with the first moment analog based on weighted local returns. Year and quarter fixed effects and county fixed effects are also included, and standard errors conservatively clustered at the state level. At the county level, increased uncertainty is associated with an immediate and sizeable decline in employment growth, as firms are likely to suspend hiring decisions. This is followed by a rebound in employment growth beginning three quarters after the initial increase in local uncertainty. The cumulative effect is, however, negative. Over the four quarters, a one standard deviation increase in the index is associated with a 0.8 percentage point decline in employment growth. The mean employment growth rate for the sample is 0.6 percent.

[Insert Table 11 Here.]

Increased uncertainty within a county might also be associated with increased labor market flux, such as greater labor re-allocation and dispersion in employment across sectors within a county. To proxy for re-allocation, we use the weighted standard deviation in employment growth across sectors within a county-quarter observation. Let g_{ijt} denote the growth rate in employment within sector i in county j between period t and $t-1$, and s_{ijt} equal sector i's employment share in county j in period t. The variable $\overline{g_{jt}} = \sum_i s_{ijt} g_{ijt}$ is the weighted average growth rate in employment within the county, computed over all sectors i; the dispersion measure in employment growth across sectors within a county is $d_{jt} = [\sum_i s_{ijt}(g_{ijt} - \overline{g_{jt}})^2]^{0.5}$.

The evidence in Column (2) suggests that increased uncertainty is associated with greater dispersion in employment growth rates across sectors within a county. This positive effect is most noticeable in the second and third quarters after an increase in local uncertainty. Over the four quarters, a one standard deviation increase in local uncertainty is associated with a 3.6 percent increase in dispersion in employment growth within a county. The basic correlations in this section suggest that the local uncertainty measure might be related to labor market fluctuations, a key source of risk that can influence the credit decisions of individuals and financial intermediaries.

Turning to indicators of consumption, we used for the county-level consumption measures a 20 percent sample from the Equifax/NY Fed CCP data, a proprietary consumer credit dataset similar to the credit report data used in previous sections, but not linked to employers. The sample results in a balanced panel of approximately 450,000 individuals and includes comprehensive quarterly information on key dimensions of debt usage for 2002-2015. We aggregate the data to the county level and, similar to the individual-level analysis in previous sections, look at variables like number of car and first home purchases.

Table 12 shows the regression results. To address concerns of local demand as confounding factors, all regressions control for first moment shocks, log local house price, local unemployment rate, and county and state-time fixed effects. The results are similar to those for the individual-level analysis. For example, a one standard deviation increase in county-level uncertainty is associated with a 10 percent reduction in car purchases (Column 1) and an 11 percent reduction in first home purchases (Column 2). The results in Columns (1)-(4), being consistent with those of the individual-level analysis, suggest that uncertainty shocks also matter at an aggregate level. Following the approach in Guren et al. (2021), Column (5) uses log local retail employment as a proxy for local consumption. It shows that a one standard deviation increase in county-level uncertainty is associated with a 1.6 percent reduction in local retail employment, suggesting that local uncertainty shocks negatively impact local consumption.

[Insert Table 12 Here.]

5. Conclusion

This paper sheds new light on the economic effects of uncertainty, and, more generally, how asset price movements, whether driven by fundamentals or sentiment, might affect the real economy. Contrary to the narrative that only richer households with significant exposure to the stock market are likely to be affected during periods of high volatility, we find that uncertainty is likely to have wider adverse effects. When uncertainty increases, firms contract their activities by reducing investment and laying off workers. We find these contractions to significantly affect households' consumption and savings decisions, as individuals tend to cut durables consumption, such as car and home purchases, and increase indebtedness. Higher debt balances coupled with lower wages result in lowered creditworthiness and a higher likelihood of default. We find similar results at the county level, where greater uncertainty is associated with reductions in employment and durable goods purchases.

Taken together, these findings highlight the importance of interventions that could limit labor risk and prevent uncertainty shocks from passing through from firms to workers. In the event of adverse short term shocks, for example, government aid conditional on firms continuing to pay workers and limit retrenchments could be effective in supporting consumption and aggregate economic activity. We leave it to future research to explore how heterogeneity across individuals and firms might shape the effects of government aid. For example, our research is ambiguous as to whether anti-retrenchment programs and pay guarantees should be aimed at less well-paid workers or those most subject to variable pay contracts.

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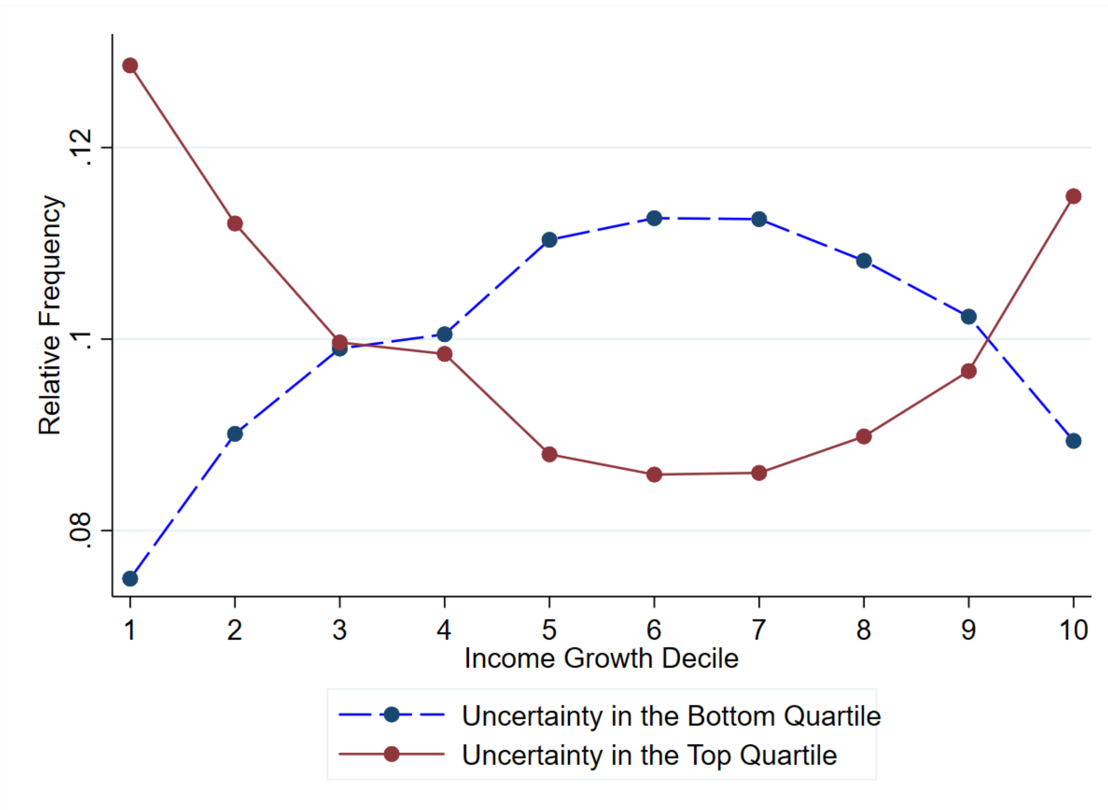
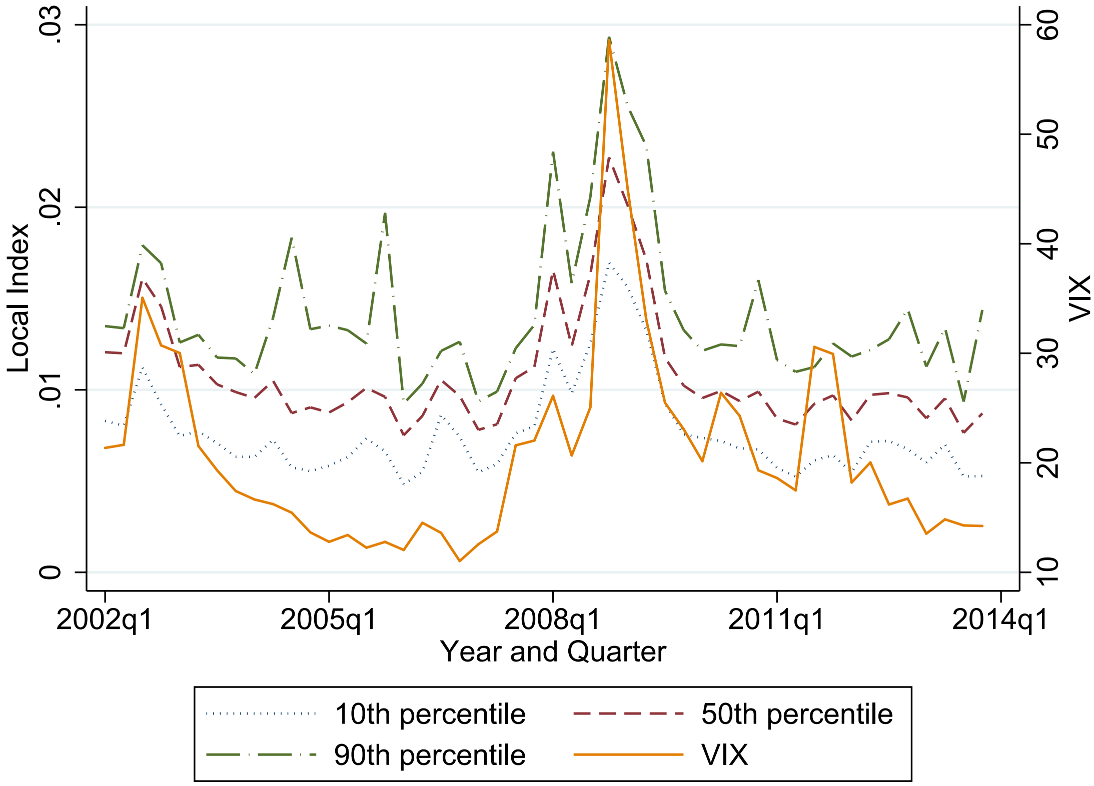
Figure 1. Change in Income by Uncertainty Quartiles



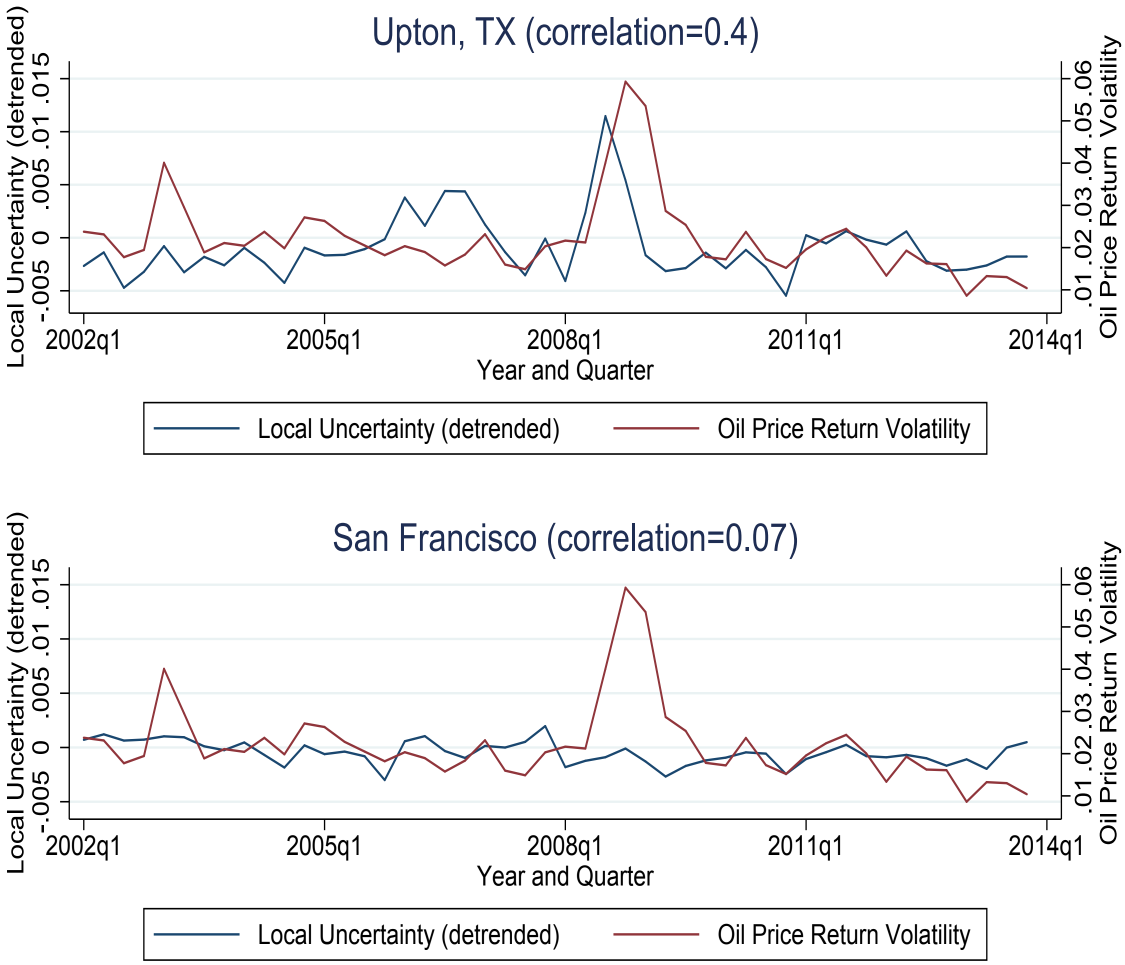
Note: This figure plots the relative frequency of change in income over the past year between the top and bottom quartiles of economic uncertainty. The X-axis is the decile of annual growth in individual income based on unconditional distribution of this variable. The Y-axis shows the relative frequency of individuals' income growth in each decile for individuals with employers in the bottom versus top quartile of uncertainty shocks.

Figure 2. Local Uncertainty and the VIX



Note: This figure plots the local uncertainty index in each quarter for values at the 10^{th}, 50th and 90th percentiles in the cross-section of counties in each quarter between 2002 and 2013. It also plots the VIX (solid line) over the same time period.

Figure 3. Correlation between Local Uncertainty and Oil Prices - An Illustrative Example



Note: This figure plots the local uncertainty series detrended by time fixed effects for two counties between 2002 and 2013. Oil price return volatility is computed as the quarterly realized volatility of daily WTI oil price returns.

Table 1: Summary Statistics

Panel A: Firms

Statistic	N	Mean	S.D.	Pctl(25)	Median	Pctl(75)
Employment	8,730	1,413.59	3,119.37	347	689.5	1,435
% New Hire	5,076	24.742	12	14.938	23.077	33.708
% Termination	5,076	15.842	8.001	10.189	13.612	20.423
Ch in Employment × 100	5,076	-3.011	9.3	-6.259	-2.298	1.302
I(Empl Ch $\geq$ 10%) × 100	5,076	1.497	12.145	0	0	0
I(Empl Ch ≤ -10%) × 100	5,076	6.206	24.128	0	0	0
Mean Income	8,730	85,403	54,325	52,733	77,378	102,358
Mean (% Base Pay)	8,730	93.297	9.93	89.755	96.68	99.974
SD Income	8,730	111,449	141,612	48,093	70,532	119,139
50^{th} Income	8,730	63,577	34,974	38,802	57,908	78,271
75^{th} Income	8,730	96,433	63,716	60,207	85,878	116,742
90^{th} Income	8,730	146,225	101,848	91,844	128,247	171,026
Distance to Default	6,091	10.093	6.481	5.673	9.063	13.096

Panel B: Individuals

Statistic	N	Mean	S.D.	Pctl(25)	Median	Pctl(75)
Uncertainty	12,346,323	0.014	0.028	0.009	0.011	0.016
Avg return	12,346,323	0.00005	0.01	-0.001	-0.0001	0.001
Income	12,346,323	80,611	169,015	31,634	54,452	95,530
Base Pay	12,351,339	73,765	164,713	30,167	50,485	88,288
% Base Pay	12,351,339	94	13	95	100	100
% Variable Pay	12,346,323	6	13	0	0	0
SD Income	12,351,339	11,239	75,789	1,150	3,678	9,425
Ch in Income	12,351,339	0.078	0.756	-0.043	0.029	0.102
I(Income Ch $\leq$ -10%) × 100	12,346,323	18.76	39.039	0	0	0
I(Voluntary Job Loss) × 100	13,310,011	1.926	13.745	0	0	0
I(Involuntary Job Loss) × 100	13,310,011	5.528	22.853	0	0	0
I(Buying Car) × 100	12,346,323	6.968	25.461	0	0	0
I(Home Purchase) × 100	12,346,323	2.298	14.983	0	0	0
I(FT Homebuyer) × 100	12,346,323	0.781	8.803	0	0	0
I(DLQ) × 100	12,346,323	15.577	36.264	0	0	0
Credit Score	12,346,323	704.845	104.656	635	729	794
Rev Utilization × 100	12,344,352	31.429	33.093	1.958	17.656	57.21
I(Paydown Mortgage) × 100	12,346,323	2.499	15.608	0	0	0
Firm Leverage	10,100,785	0.29	0.18	0.179	0.27	0.363
Firm EBITDA	10,067,762	0.15	0.09	0.11	0.15	0.184
FHFA HP Change	12,346,323	0.01	0.014	0.004	0.013	0.019
Unemployment Rate	12,346,323	6.273	2.383	4.5	5.8	7.7

Notes: Panels A and B report count, average, standard deviation, and distribution sample statistics for wage, job status, and consumer characteristics for individuals employed at the firms in our data at the firm level as well as at the individual level. *Ch in Income* reports the year-to-year growth in income. *I(Buying Car)* is an indicator for a car purchase in the previous quarter. *I(DLQ)* is an indicator of whether the individual is delinquent on any loan in the quarter. *I(Income Ch $\leq$ -10%)* is an indicator for a decrease in income greater than 10% in the year. *I(Voluntary Job Loss), I(Involuntary Job Loss), I(Buying Car), I(Home Purchase), I(FT Homebuyer), I(DLQ) and I(Paydown Mortgage)* indicate the respective event or status in a given quarter. *% New Hire* reports the percentage of employees hired in the previous year. *% Termination* reports the percentage of terminations in the previous year.

Table 2: Uncertainty and Capital Expenditure

	(1)	(2)	(3)	(4)
Dep Var	$CapitalExpenditure_t$ / $TotalAssets_{t-1}$			
Uncertainty qtrs 1-4	-0.788***	-0.852***	-0.743***	-0.711***
	(0.137)	(0.233)	(0.091)	(0.135)
Avg. return qtrs 1-4	0.429***	0.0315	0.467***	-0.0233
	(0.0772)	(0.132)	(0.0677)	(0.140)
Q_{t-1}	0.0097***	0.0095***	0.0091***	0.0093**
	(0.0009)	(0.0023)	(0.0009)	(0.0030)
$Leverage_{t-1}$	-0.0258***	-0.0120	-0.0247***	-0.0078
	(0.0046)	(0.0099)	(0.0048)	(0.0146)
$Cash_{t-1}$	0.0558***	0.0830**	0.0589***	0.0649**
	(0.0065)	(0.0336)	(0.0062)	(0.0193)
$EBITDA_{t-1}$	0.0323*	0.0065	0.0228	0.0062
	(0.0155)	(0.0709)	(0.0155)	(0.0832)
$Size_{t-1}$	0.0081***	0.0010	0.0083***	-0.0043
	(0.0022)	(0.0036)	(0.0022)	(0.0047)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Sample	All	WorkNumber	All	WorkNumber
N	104,916	7,405	104,789	7,032
Adjusted R^2	0.371	0.514	0.386	0.614

Notes: This table reports firm-level year-quarter OLS regressions where the outcome variable is capital expenditure as a percentage of the previous quarter's assets. The uncertainty measure is a standardized average of firm uncertainty over the previous four quarters. Returns is a standardized average of the previous four quarters. Q is market value of assets, defined as book value of assets minus book value of equity plus market value of equity. Leverage is defined as total debt over total assets. EBITDA is normalized by lagged total assets, cash holdings by total assets. Size is equal to the log of a firm's sales. Year fixed effects are included. Firm financial controls and year fixed effects are from the previous quarter. Standard errors are double-clustered by firm and year and reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%). The sample period is 2008 to 2016.

Table 3: Firm-level Outcomes

Panel A: Employment

	(1)	(2)	(3)	(4)	(5)
Dep Var	% New Hire	% Termi nation	Empl Change	I(Empl Ch $\geq 10\%$)	I(Empl Ch $\leq -10\%$)
Uncertainty qtrs 1-4	-4.828***	4.330***	-8.896***	-1.715**	13.100***
	(0.860)	(1.112)	(1.442)	(0.748)	(2.508)
Avg. return qtrs 1-4	-1.561*	-0.12	-2.377*	0.093	0.417
	(0.781)	(0.901)	(1.289)	(0.196)	(1.038)
Log(Income$_{t-4}$)	-0.665	5.854***	-16.617***	-0.273	-0.66
	(1.115)	(1.323)	(1.954)	(0.264)	(0.435)
Firm FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N	5,076	5,076	5,076	5,076	5,076
Adjusted R^2	0.744	0.758	0.375	0.174	0.364

Panel B: Wages

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Log(Mean Income)	Mean (% Base Pay)	SD (Income)	Log(50th Income)	Log(75th Income)	Log(90th Income)
Uncertainty qtrs 1-4	-0.064***	0.873***	-0.283***	0.014	-0.025*	-0.053***
	(0.015)	(0.248)	(0.023)	(0.017)	(0.014)	(0.011)
Avg. return qtrs 1-4	0.001***	0.054**	0.0001	0.0002	0.0001	-0.0004
	(0.000)	(0.024)	(0.001)	(0.000)	(0.000)	(0.000)
Lagged dep. var	0.051*			-0.016	0.012	0.081***
	(0.029)			(0.025)	(0.025)	(0.027)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	8,730	8,730	8,730	8,730	8,730	8,730
Adjusted R^2	0.929	0.894	0.785	0.944	0.933	0.939

Notes: This table reports firm-level year-quarter OLS regressions. In Panel A, Column (1) reports the outcome variable as the percent of employees who are new hires from the past year, Column (2) the percent of employees terminated since the past year, Column (3) percentage change in employment since last year, Column (4) and Column (5) an indicator for the annual change in number of employees being less than -10% or more than 10%. The uncertainty measure is a standardized average of firm uncertainty over the previous four quarters. Returns is a standardized average of the previous four quarters. Log of number of employees from four quarters prior is included as a control with firm and year fixed effects. Standard errors are clustered by year-quarter and reported in parentheses. In Panel B, Column (1) reports the outcome variable as the log of mean income, Column (2) the mean percent of employees' income made up by base pay, Column (3) the standard deviation of employees' income, Column (4) is the log of median income, Column (5) the log of 75th percentile of income, and Column (6) the log of 90th percentile of income. The log of mean income, log of median income, log of the 75th percentile of income, and log of the 90th percentile of income for each of the four quarters prior are included as controls in Columns (1), (4), (5), and (6), respectively. Firm and year fixed effects are included. Standard errors are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 4: Individual-Level Income

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Voluntary Job Loss	Involuntary Job Loss	Log (Income)	I($\Delta Income \leq -10\%$)	Log(Base Pay)	% Base Pay
Uncertainty qtrs 1-4	0.587***	1.000***	-0.023***	1.441***	-0.001	1.299***
	(0.063)	(0.079)	(0.0020)	(0.1830)	(0.002)	(0.081)
Avg. return qtrs 1-4	-0.011***	-0.019***	0.001***	-0.103***	0.002***	0.016***
	(0.001)	(0.002)	(0.0003)	(0.0180)	(0.001)	(0.005)
Log(Income$_{t-4}$)	-1.792***	-2.966***	0.057***	38.771***	0.048***	-0.388***
	(0.022)	(0.030)	(0.001)	(0.149)	(0.001)	(0.028)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No
County × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,590,173	12,590,173	12,351,339	12,351,339	12,351,057	12,351,339
Adjusted R^2	0.106	0.116	0.947	0.608	0.926	0.826

Notes: This table reports employee-level year-quarter OLS regressions. In column (1) the outcome variable is an indicator on whether the individual lost her job voluntarily in that quarter whereas column (2) reports the result for involuntary job loss in that quarter. In column (3) the outcome variable is the log of total income, in column (4) the outcome variable is an indicator for a decrease in income greater than 10% in the year, in column (5) the outcome variable is the log of base pay, and in column (6) the outcome variable is the percent of total income made up by base pay. The uncertainty measure is a standardized average of firm uncertainty over the previous four quarters. Returns is a standardized average of the previous four quarters. All regressions control for the log of income from the previous four quarters. Individual, firm, and county-time fixed effects are included in all regressions. Standard errors are double-clustered by firm and county and reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%). The sample period is 2010–2018.

Table 5: Quantile Regressions of Change in Income on Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Change in Income from Last Year					
	Quantile Regressions					OLS
	10^{th} Pctl	25^{th} Pctl	50^{th} Pctl	75^{th} Pctl	90^{th} Pctl	All
Uncertainty qtrs 1-4	-26.131***	-6.143***	-1.311***	-0.320***	7.688***	-3.446***
	(0.124)	(0.039)	(0.010)	(0.025)	(0.121)	(0.045)
Avg. return qtrs 1-4	0.145***	0.126***	0.061***	0.062***	-0.082	0.011
	(0.020)	(0.010)	(0.004)	(0.003)	(0.050)	(0.014)
Unemployment Rate	-6.025***	-1.086***	-0.218***	-0.234***	0.854***	-0.640***
	(0.016)	(0.003)	(0.001)	(0.003)	(0.014)	(0.006)
Constant	-2.715***	1.481***	4.199***	12.189***	25.483***	9.039***
	(0.114)	(0.017)	(0.008)	(0.019)	(0.083)	(0.040)
N	12351339	12351339	12351339	12351339	12351339	12351339

Notes: This table reports employee-level year-quarter quantile and OLS regressions. The dependent variable is percentage change of income from 4 quarters ago multiplied by 100. Main explanatory variable is the uncertainty measure, defined as a standardized average of firm uncertainty over the previous four quarters. Returns is a standardized average of the previous four quarters and unemployment rate is at county by year-quarter level. Quartile regressions are done using qr function in R. Standard errors are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 6: Individual-Level Consumption and Credit

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Buying Car	FT Home	Prob DLQ	Risk Score	Paydown Mortgage	Rev Utilization
Uncertainty qtrs 1-4	-0.847***	-0.124***	0.243***	-0.353**	-0.471***	0.252***
	(0.103)	(0.023)	(0.087)	(0.151)	(0.089)	(0.077)
Avg. return qtrs 1-4	-0.014	0.001	-0.024	0.026	0.009	-0.007
	(0.010)	(0.002)	(0.017)	(0.025)	(0.017)	(0.011)
log(Income$_{t-1}$)	-0.028	0.234***	-0.177***	1.865***	0.131	-0.669***
	(0.033)	(0.022)	(0.036)	(0.063)	(0.084)	(0.032)
Having car	-13.218***					
	(0.060)					
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No
County × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12,351,339	4,487,075	12,351,339	12,351,339	5,260,253	12,349,365
Adjusted R^2	0.081	0.03	0.559	0.88	0.072	0.652

Notes: This table reports employee-level year-quarter OLS regressions where the outcome variable is an indicator for buying a car in column (1), for becoming a first time home buyer in column (2), for having any delinquent debt in column (3), for credit score in column (4), for having paid down a mortgage by at least $10,000 in the quarter in column (5), and for revolving utilization (%) in column (6). The uncertainty measure is a standardized average of firm uncertainty over the previous four quarters. Returns is a standardized average of the previous four quarters. Controls include log of income from the previous four quarters, and an indicator for having a car in column (1). Individual, firm fixed, and county-time fixed effects are included in all regressions. Standard errors are double-clustered by firm and county and reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%). The sample period is 2010–2018.

Table 7: Alternative Uncertainty Measure Based on Analysts Forecasts

Panel A: Income

	(1)	(2)	(3)	(4)
Dep Var	Log (Income)	I($\Delta Income \leq -10\%$)	Log(Base Pay)	% Base Pay
Uncertainty qtrs 1-4	-0.004***	0.434***	-0.003***	0.128***
	(0.001)	(0.050)	(0.001)	(0.033)
Avg. return qtrs 1-4	-0.002*	-1.011***	0.008***	0.028
	(0.001)	(0.126)	(0.002)	(0.050)
Log(Income$_{t-4}$)	0.056***	38.941***	0.047***	-0.364***
	(0.001)	(0.173)	(0.001)	(0.031)
Individual FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	No	No	No	No
County $\times$ Time FE	Yes	Yes	Yes	Yes
N	10,162,747	10,162,747	10,162,747	10,162,747
Adjusted R^2	0.956	0.642	0.947	0.848

Notes: This table reports employee-level year-quarter OLS regressions where the outcome variable is the log of total income in column (1), an indicator for a decrease in income greater than 10% in the year in column (2), the log of base pay in column (3), and the percent of total income made up by base pay in column (4). The alternative uncertainty measure is based on the standard deviation of earnings per share predictions over the most recent four quarters relative to firms' historical average. We then use a standardized average of this measure for each firm over the previous four quarters. Returns is a standardized average of the previous four quarters. All regressions control for the log of income from the previous four quarters. Individual, firm, and county-time fixed effects are included in all regressions. Standard errors are double-clustered by firm and county and reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%). The sample period is 2010–2018.

Panel B: Consumption and credit

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	Buying Car	FT Home	Prob DLQ	Risk Score	Paydown Mortgage	Rev Utilization
Uncertainty qtrs 1-4	0.005	-0.032***	0.064**	-0.085*	-0.001	0.147***
	(0.021)	(0.005)	(0.028)	(0.051)	(0.020)	(0.025)
Avg. return qtrs 1-4	0.542***	0.024	-0.024	0.155	0.173*	-0.124**
	(0.081)	(0.027)	(0.066)	(0.103)	(0.092)	(0.055)
log(Income$_{t-1}$)	-0.006	0.240***	-0.170***	1.847***	0.056	-0.675***
	(0.037)	(0.025)	(0.040)	(0.072)	(0.093)	(0.037)
Having car	-13.253***					
	(0.068)					
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No
County × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N	10,162,747	3,735,969	10,162,747	10,162,747	4,388,832	10,161,210
Adjusted R^2	0.081	0.03	0.559	0.88	0.072	0.652

Notes: This table reports employee-level year-quarter OLS regressions where the outcome variable is an indicator for buying a car in column (1), for becoming a first time home buyer in column (2), for probability of delinquency in column (3), for credit score in column (4), for having paid down a mortgage by at least $10,000 in the quarter in column (5), and for revolving utilization (%) in column (6). The uncertainty measure is a standardized average of firm uncertainty over the previous four quarters and is based on the standard deviation of earnings per share predictions over the most recent four quarters relative to firms' historical average. Returns is a standardized average of the previous four quarters. All regressions control for the log of income from the previous four quarters. Column (1) also includes an indicator for having a car. Individual, firm, and county-time fixed effects are included in all regressions. Standard errors are double-clustered by firm and county and reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%). The sample period is 2010–2018.

Table 8: Heterogeneous Response Across Individuals' Income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep Var	Log (Income)	I($\Delta Income$ $\leq -10\%$)	Log(Base Pay)	% Base Pay	Buying Car	FT Home	Prob DLQ	Risk Score	Paydown Mortgage	Rev Utilization
Uncertainty qtrs 1-4	-0.010***	0.338*	0.009***	1.183***	-0.746***	-0.123***	0.316***	-0.599***	-0.475***	0.274**
	(0.002)	(0.203)	(0.002)	(0.074)	(0.109)	(0.024)	(0.109)	(0.183)	(0.105)	(0.127)
× High income	-0.026***	1.816***	-0.018***	0.231***	-0.223***	-0.005	-0.13	0.443**	0.008	-0.028
	(0.002)	(0.195)	(0.002)	(0.051)	(0.080)	(0.033)	(0.114)	(0.202)	(0.118)	(0.140)
Avg. return qtrs 1-4	0.001**	-0.060***	0.001***	0.011*	-0.030**	0.001	-0.007	0.024	-0.002	-0.027
	(0.000)	(0.021)	(0.001)	(0.006)	(0.013)	(0.003)	(0.024)	(0.033)	(0.016)	(0.020)
× High income	0.001	-0.085**	0.001	0.011	0.031*	-0.002	-0.034	0.005	0.02	0.024
	(0.000)	(0.033)	(0.001)	(0.009)	(0.018)	(0.003)	(0.027)	(0.039)	(0.026)	(0.027)
Log(Income$_{t-4}$)	0.062***	36.069***	0.052***	-0.345***	-0.273***	0.233***	-0.049	1.514***	0.183*	-0.644***
	(0.001)	(0.164)	(0.002)	(0.037)	(0.041)	(0.024)	(0.046)	(0.085)	(0.094)	(0.058)
High Income × car					0.760***					
					(0.054)					
Having car					-13.606***					
					(0.065)					
Individual Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,351,339	12,351,339	12,351,057	12,351,339	12,351,339	4,487,075	12,351,339	12,351,339	5,260,253	6,862,625
Adjusted R^2	0.947	0.609	0.926	0.826	0.081	0.03	0.559	0.88	0.072	0.683

Notes: This table reports employee-level year-quarter OLS regressions where the outcome variable is the log of total income in column (1), an indicator for a decrease in income greater than 10% in the year in column (2), log of base pay in column (3), percent of total income made up by base pay in column (4), an indicator for buying a car in column (5), for purchasing a home in column (6), probability of delinquency in column (7), credit score in column (8), an indicator for having paid down a mortgage by at least $10,000 in the quarter in column (9), and revolving utilization (%) in column (10). The uncertainty measure is a standardized average of firm uncertainty over the previous four quarters interacted with an indicator for the employee having income$_{t-4}$ above the median. Returns is a standardized average of the previous four quarters interacted with an indicator for the employee having a high income. Controls include log of income from the previous four quarters, county-level house price growth, unemployment rate for the previous quarter, and, in column (5) an indicator for having a car and its interaction with having a high income. Individual, firm, and county-time fixed effects are included in all regressions. Standard errors are double-clustered by firm and county and reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%). The sample period is 2010–2018.

Table 9: Heterogeneous Response Across Firms' Distance to Default

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep Var	Log (Income)	I($\Delta Income$ $\leq -10\%$)	Log(Base Pay)	% Base Pay	Buying Car	FT Home	Prob DLQ	Risk Score	Paydown Mortgage	Rev Utilization
Uncertainty qtrs 1-4	−0.019***	−0.598**	0.008***	1.497***	−1.889***	−0.150***	0.023	−0.230	−0.989***	0.282**
	(0.002)	(0.255)	(0.003)	(0.094)	(0.172)	(0.033)	(0.122)	(0.205)	(0.146)	(0.141)
× DD	0.002***	0.266***	0.001***	−0.006	0.230***	0.006	0.017	0.004	0.091***	−0.024
	(0.0002)	(0.025)	(0.0003)	(0.010)	(0.017)	(0.004)	(0.014)	(0.024)	(0.016)	(0.016)
Avg. return qtrs 1-4	−0.012***	1.026***	−0.026***	−0.844***	0.206	0.034	−0.131	0.174	0.637***	−0.315**
	(0.002)	(0.232)	(0.003)	(0.073)	(0.135)	(0.041)	(0.109)	(0.168)	(0.134)	(0.123)
× DD	0.001***	−0.306***	0.003***	0.135***	−0.015	−0.002	0.018	0.007	−0.060***	0.029**
	(0.0002)	(0.023)	(0.0002)	(0.007)	(0.013)	(0.004)	(0.011)	(0.018)	(0.014)	(0.013)
$Log(income_{t-4})$	0.057***	40.093***	0.049***	−0.424***	0.046	0.245***	−0.176***	1.894***	0.140	−0.629***
	(0.001)	(0.163)	(0.001)	(0.030)	(0.036)	(0.025)	(0.041)	(0.072)	(0.093)	(0.050)
DD	0.001***	−0.039***	0.001***	−0.008	−0.004	0.004**	−0.013*	0.023*	0.020***	−0.020**
	(0.0002)	(0.013)	(0.0002)	(0.007)	(0.007)	(0.002)	(0.007)	(0.012)	(0.007)	(0.008)
Having car × DD					0.138***					
					(0.008)					
Having car					−14.557***					
					(0.116)					
Individual Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10,365,719	10,365,719	10,365,448	10,365,719	10,365,719	3,810,928	10,365,719	10,365,719	4,466,969	5,807,594
Adjusted R^2	0.950	0.607	0.931	0.816	0.079	0.032	0.559	0.880	0.073	0.684

Notes: This table reports employee-level year-quarter OLS regressions where the outcome variable is the log of total income in column (1), an indicator for a decrease in income greater than 10% in the year in column (2), log of base pay in column (3), percent of total income made up by base pay in column (4), an indicator for buying a car in column (5), for purchasing a home in column (6), probability of delinquency in column (7), credit score in column (8), an indicator for having paid down a mortgage by at least $10,000 in the quarter in column (9), and revolving utilization (%) in column (10). The uncertainty measure is a standardized average of firm uncertainty over the previous four quarters interacted with the firm's distance to default defined, as in Ottonello and Winberry (2020), as $\frac{\log(V/D)+(\mu_v-0.5\sigma_v^2)}{\sigma_v}$. Here, V is the firm's value, D is the firm's debt, μ_v is the annual expected return on V, and σ_v is the annual volatility of the firm's value. Returns is a standardized average of the previous four quarters interacted with the firm's distance to default. Controls include log of income from the previous four quarters and, in column (5) an indicator for having a car and its interaction with distance to default. Individual, firm, and county-time fixed effects are included in all regressions. Standard errors are double-clustered by firm and county and reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%). The sample period is 2010–2018.

Table 10: County-Level Uncertainty Measures

Panel A: Summary Statistics

	Mean	SD	Pctl(25)	Median	Pctl(75)
Local Uncertainty	0.011	0.006	0.005	0.010	0.020
Local Mean Residuals	0.000007	0.00076	-0.00091	-0.00002	0.00100

Panel B: Correlation, 2002-2013

	Local Uncertainty			VIX	BBD Index
	Pctl(10)	Median	Pctl(90)		
Pctl(10)	1	0.96	0.76	0.71	0.08
Median	0.96	1	0.84	0.75	0.17
Pctl(90)	0.76	0.84	1	0.61	0.14
VIX	0.71	0.75	0.61	1	0.54
BBD Index	0.08	0.17	0.14	0.54	1

Panel C: Correlation, 2009-2013

	Local Uncertainty			VIX	BBD Index
	Pctl(10)	Median	Pctl(90)		
Pctl(10)	1	0.37	0.24	-0.15	-0.42
Median	0.37	1	0.92	0.42	0.44
Pctl(90)	0.24	0.92	1	0.23	0.42
VIX	-0.15	0.42	0.23	1	0.71
BBD Index	-0.42	0.44	0.42	0.71	1

Notes: This table reports summary statistics for the local uncertainty measure and local mean residuals, and the correlation between different uncertainty measures. Local uncertainty shock is measured as the employment weighted average of sectoral-level uncertainty shocks, which are constructed as the standard deviation of public firm abnormal stock returns. The local mean residuals are similarly constructed using the average of public firm abnormal stock returns. All correlations in the table are significant at the 5 percent level or better. The VIX is the implied volatility of the S&P 500 index options. The BBD index is the policy uncertainty index developed by Baker, Bloom and Davis (2016) (policyuncertainty.com).

Table 11: Local Uncertainty Measure and Employment Growth

	(1)	(2)
Dep Var	Employment Growth	Within-County Employment Dispersion
Local uncertainty$_{t-1}$	-1.720***	1.097
	(0.0868)	(0.814)
Local uncertainty$_{t-2}$	-0.507***	2.773***
	(0.0949)	(0.854)
Local uncertainty$_{t-3}$	0.264***	2.434***
	(0.0840)	(0.469)
Local uncertainty$_{t-4}$	1.186***	-2.746***
	(0.0914)	(0.738)
Local returns$_{t-1}$	6.879***	-8.911***
	(0.385)	(2.880)
Local returns$_{t-2}$	-3.135***	-8.862***
	(0.451)	(2.626)
Local returns$_{t-3}$	-4.960***	-13.02***
	(0.391)	(2.081)
Local returns$_{t-4}$	-4.917***	-16.04***
	(0.426)	(2.957)
County FE	Yes	Yes
Year Quarter FE	Yes	Yes
N	209,021	208,360
Adjusted R^2	0.075	0.138

Notes: The dependent variable in column (1) is employment quarterly growth in a county from the Quarterly Census of Employment and Wages. Column (2) uses the log dispersion in employment growth across sectors within a county-quarter unit as the dependent variable. The dispersion measure is defined as $d_{jt} = [\sum_i s_{ijt}(g_{ijt} - \overline{g_{jt}})^2]^{0.5}$, where $\overline{g_{jt}} = \sum_i s_{ijt}g_{ijt}$ is the weighted average growth rate in employment within the county. The independent variables are the lagged local uncertainty shocks and local residual returns. Local uncertainty shock is measured as the employment weighted average of sectoral-level uncertainty shocks, which are constructed as the standard deviation of public firm abnormal stock returns. The local mean residuals are similarly constructed using the average of public firm abnormal stock returns. The data are observed at the county-quarter frequency, and all regressions include county, year, and quarter fixed effects. The sample period is 2000-2015. Standard errors are clustered at the state level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table 12: Local Uncertainty and Consumption

	(1)	(2)	(3)	(4)	(5)
Dep Var	Buying Car	FT Home	HELOC Increase	Paydown Mortgage	Log Retail Employment
Uncertainty qtrs 1-4	-0.100***	-0.11***	-0.15***	-0.18***	-0.016***
	(0.014)	(0.025)	(0.017)	(0.019)	(0.0027)
Avg. return qtrs 1-4	0.022**	-0.052***	-0.0013	0.097***	-0.0043***
	(0.0098)	(0.015)	(0.012)	(0.013)	(0.0016)
Log house price	0.17***	0.40***	0.92***	0.27***	0.10***
	(0.051)	(0.066)	(0.050)	(0.063)	(0.0057)
Unemployment rates	-0.0072**	0.018***	0.0010	-0.024***	-0.0030***
	(0.0033)	(0.0049)	(0.0036)	(0.0039)	(0.00049)
County FE	Yes	Yes	Yes	Yes	Yes
State Time FE	Yes	Yes	Yes	Yes	Yes
N	62326	62326	62326	62326	62267
R-sq	0.966	0.836	0.951	0.953	0.999

Notes: This table reports county-level year-quarter OLS regressions where the outcome variable is the log number of car purchases in column (1), log number of first home purchases in column (2), log number of individuals with HELOC increasing more than $3,000 in column (3), log number of individuals who paid down a mortgage by at least $10,000 in the quarter in column (4), and log retail employment in a county in column (5). The uncertainty measure is the standardized industry weighted uncertainty over the previous four quarters. Returns is the standardized industry weighted average returns of the previous four quarters. Both industry uncertainty and returns are computed using residuals from a three factor model to filter out the systematic component of the stock returns. Controls include county-level log house price and unemployment rate for the previous quarter. County and state-time fixed effects are included in all regressions. Regressions are weighted by county population in 2002. Standard errors are reported in parentheses and asterisks denote significance levels (***=1%, **=5%, *=10%). The sample period is 2002–2015.

Appendix

Table A.1: Firm Characteristics Sample Comparison

Sample	Public Firms in WorkNumber			Other Public Firms		
	No of Firms	Mean	SD	No of Firms	Mean	SD
Log(Sale)	5,889	7.368	1.735	77,215	4.331	2.217
Log(Total Assets)	5,890	8.935	1.928	77,312	6.536	2.030
Leverage	5,890	0.262	0.205	77,312	0.204	0.207
Tobin's Q	5,877	1.761	0.913	75,617	1.767	1.280
Debt to EBITDA	5,506	10.84	15.27	61,086	12.84	19.01
Uncertainty qtrs 1-4	5,890	0.0152	0.00861	77,312	0.0250	0.0162
Average Returns qtrs 1-4	5,890	0.00	0.00128	77,312	0.00	0.00185

Notes: This table compares quarterly values of the main characteristics for public firms in our sample with all other public firms for the period 2010-2018.

Table A.2: Household Characteristics Sample Comparison

Sample	Our Sample			All Individuals in Credit Report Data		
	No of Individuals	Mean	SD	No of Individuals	Mean	SD
Total Debt	379,074	122,178	166,972	233,645,500	86,031	194,069
Auto Debt	379,074	9,651	14,242	233,645,500	6,900	13,502
Rev Debt	379,074	10,109	28,755	233,645,500	8,242	33,680
Mortgage Debt	379,074	96,406	159,883	233,645,500	63,304	149,104
Prob of DLQ $\times$ 100	379,074	14.947	35.655	233,645,500	12.958	33.584
Credit Score	379,074	706.201	103.504	233,645,500	700.868	104.098
Income	379,074	83,444.19	175,865.60	15,533,012	67,035.50	164,445.65

Notes: This table compares the main variables for individuals in our sample with all individuals in credit report data. We take a snapshot of credit attributes and income as of July 2015, midpoint of the sample period for both samples.

Table A.3: Uncertainty and Sectoral Employment

	(1)	(2)
Dep Var	Log(Employment in Sector)	
Sample	Quarterly	Annual
Sectoral uncertainty$_{t-1}$	-0.743	
	(0.618)	
Sectoral uncertainty$_{t-2}$	-0.610	
	(0.471)	
Sectoral uncertainty$_{t-3}$	-0.796**	
	(0.331)	
Sectoral uncertainty$_{t-4}$	-0.885**	
	(0.444)	
Sectoral returns$_{t-1}$	-0.586	
	(0.855)	
Sectoral returns$_{t-2}$	-1.448	
	(1.039)	
Sectoral returns$_{t-3}$	-0.519	
	(1.052)	
Sectoral returns$_{t-4}$	-0.705	
	(0.995)	
Sectoral uncertainty$_{t-1}$		-2.281*
		(1.371)
Sectoral returns$_{t-1}$		-1.681
		(3.357)
Sector FE	Yes	Yes
Year Quarter FE	Yes	No
Year FE	No	Yes
N	17,412	4,481
Adjusted R^2	0.972	0.975

Notes: The dependent variable is the log number of employees within a sector from the Quarterly Census of Employment and Wages. The data are observed at the sector-quarter level (2000 Q1: 2015 Q4) in column (1) and sector-year level in column (2). The independent variables are the lagged sectoral uncertainty shocks and sectoral residual returns. A sector is defined at the 4-digit NAICS level; there are 312 sectors. Sectoral uncertainty shocks are constructed as the standard deviation of public firm abnormal stock returns, weighted by the capitalization of those firms within each sector. The sectoral residual returns are similarly constructed using the average of public firm abnormal stock returns. All regressions include sector and time fixed effects. Standard errors are clustered at the sector level.