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HOUSEHOLD CREDIT AND LOCAL ECONOMIC UNCERTAINTY

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Household Credit and Local Economic Uncertainty[1]

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Abstract

This paper investigates the impact of uncertainty on consumer credit outcomes. We develop a local measure of economic uncertainty capturing county-level labor market shocks. We then exploit microeconomic data on mortgages and credit-card balances together with the cross-sectional variation provided by our uncertainty measure to show strong borrower-specific heterogeneity in response to changes in uncertainty. Among high risk borrowers or areas with more high risk borrowers, increased uncertainty is associated with housing market illiquidity and a reduction in leverage. For low risk borrowers, these effects are absent and the cost of mortgage credit declines, suggesting that lenders reallocate credit towards safer borrowers when uncertainty spikes. A similar pattern is observed in the unsecured credit market. Taken together, local uncertainty might independently affect aggregate economic activity through consumer credit markets and could engender greater inequality in consumption and housing wealth accumulation across households.

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1. Introduction

This paper investigates the impact of uncertainty on consumer credit markets. Influential economic arguments observe that increased uncertainty can shape economic activity and credit usage. Greater uncertainty can, for instance, increase the real option value of delaying difficult-to-reverse investment and hiring decisions, shaping employment and investment dynamics (Bernanke (1983), Bloom (2009)). Uncertainty can also increase the demand for precautionary saving and liquidity, affecting economic activity and credit usage (Bertola, Guiso and Pistaferri (2005), Gourinchas and Parker (2002)). It can also operate directly through credit markets: Higher 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, again slowing economic activity (Christiano, Motto and Rostagno (2014)).

Common narratives centered on these arguments also identify uncertainty as a powerful driver of economic fluctuations. The effects of uncertainty are also posited to be especially large around economic crises—events that produce dramatic changes in financial regulation and other economic policies.[2] To wit, the Federal Reserve's policy experimentation that began with the 2008-2009 financial crisis ignited a debate about the potentially damaging effects of policy uncertainty on the post-crisis recovery path. And heighted uncertainty post-2009 might also explain that period's anemic consumption and growth (Pistaferri (2016)).[3] However, as with narratives, the aggregate evidence is difficult to interpret causally, and the underlying mechanisms remain poorly understood, especially in the case of consumer credit markets. Yet consumer credit decisions are of enormous economic importance: the stock of mortgage and

[2] Criticisms of the New Deal activism during the Great Depression also mainly centered around the harmful effects of policy uncertainty on business investment (Shales (2008)). The head of DuPont observed in 1938: "…there is uncertainty about the future burden of taxation, the cost of labor, the spending policies of the Government, the legal restrictions applicable to industry—all matters affecting computations of profit and loss. It is this uncertainty rather than any deep-seated antagonism to governmental policies that explains the momentary paralysis of industry. It is that which causes some people to question whether the recuperative powers of industry will work as effectively to bring recovery from the current depression as they have heretofore." –excerpted from Akerlof and Shiller (2009), pg. 72.

[3] The aggregate VAR evidence in Bloom (2009) and Caldera et. al (2016) show for example that volatility shocks might be associated with significant declines in output and employment. Knotek and Khan (2011) find that uncertainty has only modest effects on aggregate household consumption, and the results depend on the specification of the VAR model.

unsecured consumer credit in the US economy was around 12 trillion dollars as of 2013. The consumer credit market was also at the epicenter of the 2008-2009 financial crisis, and remains central to understanding economic activity.

There are at least two principal challenges to identifying the effects of uncertainty on individuals' credit decisions. First, uncertainty is usually measured in the aggregate. Indexes such as the VIX, which are useful when characterizing economy-wide response to turbulence, do not provide sufficient local variation to identify an individual's response to uncertainty. Second, uncertainty might endogenously co-move with "first moment" shocks (Benhabib, Lu and Wang (2016)). For instance, policy-related uncertainty usually increases after a period of weak economic activity, as governments experiment with new policies.[4] This makes it especially difficult to disentangle credibly the effects of uncertainty on credit decisions from the first moment negative shocks that drive these decisions.

To help overcome the intrinsic identification challenges associated with aggregate data, this paper investigates the impact of uncertainty on consumer credit outcomes using detailed county-level and individual-level data spanning both the mortgage market and the unsecured credit market. In particular, we use two proprietary datasets that span from 2002 up through 2013—periods of remarkable quiescence and unprecedented economic uncertainty. These datasets contain information on major credit card decisions and a rich set of observables such as credit scores, age and zip code of residence. For a subset of individuals, one of these datasets also links information on liabilities to detailed information on mortgage contracts. With multiple detailed datasets across different credit markets, we can assess the impact of uncertainty using a variety of empirical specifications and detailed individual-level controls. Given the magnitude of the measurement and identification challenge, this approach helps to both limit the scope for biased estimates due to unobserved heterogeneity, and to gauge the external validity of our estimates.

The first main contribution of this paper is to construct a new measure of *local uncertainty*—uncertainty specific to counties, to exploit the spatial granularity available in the consumer credit data. This measure is derived from the excess returns of public firms and is 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

4 A number of other mechanisms can also generate endogenous countercyclical fluctuations in uncertainty over the business cycle (see Van Nieuwerburgh and Veldkamp (2006), Fajgelbaum, Schaal, Taschereau-Dumouchel (forthcoming); Ludvigson, Ma and Ng (2016), Yu (2017); and the discussion in Kozeniauskas, Orlik and Veldkamp (2016)).

measures are then mapped into the county level by weighting the county's relative exposure to each industry. Intuitively, this local uncertainty series captures the spatial and temporal variation in uncertainty due to local labor market risk emanating from idiosyncratic sectoral demand and technological shocks (Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2016), and Leduc and Liu (2016)). To show the validity of this measure, we start our analysis by providing evidence that our measure can in fact predict employment growth both at the sector level as well as at the county level. Furthermore, we also show that this measure exhibits significant variation across counties, and that although it is on average correlated with the VIX, this correlation varies significantly across counties. This result highlights that aggregate uncertainty might not capture the significant underlying spatial variation in uncertainty.

We use this new measure to investigate whether and how uncertainty affects consumer credit outcomes. In the case of the mortgage market, quarterly data from 2000-2013 suggests that increased uncertainty is associated with greater illiquidity in housing markets. A one standard deviation increase in local uncertainty is associated with about a 9 percent drop in new mortgage originations over two quarters in a county. We find similar results when analyzing the number of mortgage originations. To ensure that these results are driven by our local uncertainty measure, all specifications include controls capturing local market conditions, such as the unemployment rate, house price growth and the first moment of our measure as controls, in addition to county and time fixed effects.

We use the heterogeneity in risk profiles across borrowers to better understand the underlying mechanism. This approach builds on the fact that borrowers with different risk profiles face different pecuniary costs of default—the damage to their credit history and the relative cost of future credit access, as well as the amount of assets included in default settlements. High-credit-score borrowers generally face higher pecuniary default costs and are unlikely to engage in risk-shifting behavior or strategic mortgage defaults when uncertainty increases.[5] Instead, to protect their credit reputation and future credit access, these borrowers are likely to demand greater liquidity and financial flexibility in response to increased uncertainty, reducing their demand for mortgage credit. In contrast, given their lower default costs, the demand for mortgage debt among low-credit-score borrowers is likely to be less sensitive to

[5] See Corbae et. al (2007) and the survey evidence on strategic defaults by Guiso et. al (2013).

uncertainty. These borrowers in turn are more likely to face a contraction in the supply of mortgage credit when uncertainty increases, as lenders anticipate greater risk shifting incentives and higher default risk among the pool of low-credit-score borrowers.

The evidence strongly suggests a "flight to safety" in response to increased uncertainty. In counties where the median credit score is below the national median—less creditworthy borrowers—the negative impact of uncertainty on transaction volumes is about three times higher than in counties populated by safer borrowers. Moreover, not only does uncertainty decrease liquidity in counties with less credit worthy borrowers, but there is also a concomitant collapse in the use of leverage in these areas. A one standard deviation increase in uncertainty is associated with a 1 percentage point decrease in the weighted mean loan to value ratio of mortgages originated in equilibrium; the impact of uncertainty on leverage is insignificant in the sample of high-credit-score counties. Greater uncertainty is also associated with more selective credit access in counties with riskier borrowers, as the average FICO score of originated mortgages rises sharply in response to uncertainty. There is again no significant impact on average FICO scores in counties with safer borrowers.

There is also suggestive evidence that these results might emanate from the supply channel. Specifically, while increased uncertainty is associated with decreased credit volumes and less leverage in areas with riskier borrowers, there is no significant impact on equilibrium interest rates. If anything, consistent with the "flight to safety" channel, the average mortgage interest rate actually declines in counties populated by safer borrowers. This suggests that lenders, concerned about strategic defaults and risk-shifting behavior among borrowers with low default costs, might reallocate mortgage credit toward safer borrowers when uncertainty increases.

The unsecured consumer credit market operates differently from the mortgage market, and the available individual-level data offer a potentially richer set of controls, but the basic results are nearly identical. Among less credit-worthy borrowers, increased local uncertainty is associated with a significant increase in credit card balances and a contraction in credit limits: Their credit utilization increases. But as with the mortgage market, more credit-worthy borrowers appear to respond to increased uncertainty by targeting greater financial flexibility. Credit card balances decrease while their access to credit actually improves, when measured in terms of the size of credit card borrowing limits.

To explore further the link between uncertainty and households' decisions, we build on Di

Maggio et. al (forthcoming). Our research design exploits the plausibly exogenous timing of exposure to interest rate risk in adjustable rate mortgages (ARMs) to identify the impact of local uncertainty on consumer behavior. In these ARMs, the mortgage interest rate is fixed for the first 5 years, but then adjusts to the prevailing market mortgage. Thus, after the reset date, borrowers' monthly payments are determined by the prevailing short-term interest rate, thereby exposing them to greater uncertainty in future mortgage payments and disposable income. We exploit this variation in the timing of exposure to interest rate risk across individuals, which is predetermined five years in advance, and compare the credit card balances of individuals with the same type of contract and similar characteristics, who experience the rate reset at different point in time. Even within this very specific research design, we find evidence of amplification: Around the reset, when future mortgage payments become subject to greater variability, increased local uncertainty is associated with smaller credit balances among higher-credit-score borrowers. And as before, low-credit-score borrowers evince far less sensitivity to uncertainty. Also, the point estimates match closely the more general results. We also show that these results are not artifacts of the local uncertainty measure and corroborate the main findings using the Baker, Bloom and Davis (forthcoming) monthly newspaper-based monetary policy uncertainty index (MPU).

This paper builds on an important tradition of empirical research that has sought to measure the impact of uncertainty using microeconomic data. Some notable antecedents in the case of consumption include Bertola, Guiso and Pistaferri (2005), which uses Italian data to understand how consumers adjust durable goods consumption in response to microeconomic uncertainty, and Eberly (1994), which focuses on car purchases, while microeconomic studies focused on investment include Guiso and Parigi (1999) and recent work by Stein and Stone (2014), Bloom, Baker and Davis (2016), and the survey in Bloom (2014).

This paper is however the first to develop a spatially disaggregated time varying measure of uncertainty in the United States, and to document that economic uncertainty might have economically large effects on consumer credit decisions and financial constraints. In particular, the evidence of increased illiquidity and reduced debt capacity in these markets in response to greater uncertainty is new. [6] Also new is the finding that the effects of uncertainty can differ sharply across credit-risk types. This suggests that uncertainty might not only shape economic

[6] These results are related to the recent microeconomic literature on the demand and supply forces that might shape consumption. See for example Mian, Rao, and Sufi (2013), Ramcharan, Verani, and van den Heuvel (2016), Benmelech, Meisenzahl and Ramcharan (forthcoming).

outcomes through consumer credit markets, but that increased uncertainty might be associated with greater inequality in consumption and housing wealth accumulation across households, especially after major credit-related uncertainty shocks. In Section 2 of the paper we discuss some of the underlying theories and data; Sections 3 and 4 present the main results for the different credit market and empirical strategies and Section 5 concludes.

2. Hypothesis and Data

2.A Hypothesis

There are several well-known channels through which uncertainty might affect consumer credit decisions. In the presence of financial frictions, an increase in idiosyncratic uncertainty — the variance of productivity shocks to firm capital—increases credit spreads for firms (Christiano, Motto, and Rostagno, 2014).[7] Increased credit spreads can in turn reduce investment and employment. Precautionary behavior in response to greater labor market uncertainty might then induce some individuals to reduce spending and increase credit lines in order to target greater financial flexibility (Aydin (2015), Gourinchas and Parker (2002), Hahm and Steigerwald (1999)). Then, labor market risk is a key channel through which uncertainty might affect consumer credit decisions. Furthermore, mortgages are long-term obligations that are difficult to abrogate. And the real-option value of waiting to enter into difficult-to-abrogate debt contracts might be higher during periods of increased economic uncertainty (Bernanke (1983), Bloom (2009) and Titman (1985)).

These arguments all suggest that economic uncertainty can have a sizeable impact on credit decisions, but its impact might also vary across individuals (Corbae et. al (2007)). One reason for heterogeneous responses is that there is substantial heterogeneity in the option value of default across individuals. Borrowers with low credit scores have substantially more expensive and limited access to credit, making the default option cheaper for these borrowers (Guiso et. al (2013), Morse (2011)). Greater uncertainty can then increase their incentives to engage in risk shifting, increasing low-credit-score borrowers' demand for mortgage and other consumer debt when risk increases.

[7] Models of frictional unemployment also note that an increase in the variance of idiosyncratic shocks--demand or technological--can increase job destruction, reallocation and the unemployment rate, and consequently the demand for some kinds of credit (Mortensen and Pissarides (1994)).

In contrast, because of their ready access to cheap and plentiful sources of finance, default is significantly more expensive for borrowers with high credit scores, and risk shifting incentives are less likely to feature in their credit decisions. If anything, to avoid costly default and retain financial flexibility, the credit decisions of high credit score borrowers might evince the most sensitivity to uncertainty. Lender decisions might also reinforce the heterogeneity in equilibrium credit outcomes across individuals. In anticipation of risk shifting incentives or greater employment risk, lenders might be unwilling to enter into longer term debt contracts with low-credit-score borrowers during periods of increased uncertainty. Instead, in a "flight to safety," lenders might reallocate credit to those perceived to be more able to repay when risk increases.[8] Our empirical strategy allows us to study the relationship between local uncertainty and credit decisions in both the mortgage market and the unsecured consumer credit market, and to provide novel evidence on the heterogeneous response to uncertainty shocks.

2.B Data

Measuring Local Uncertainty

Aggregate indexes of uncertainty are unlikely to provide sufficient variation for individual and lender-level empirical tests of uncertainty. These indexes are also likely to endogenously co-vary with aggregate first-moment shocks that also drive credit decisions. Therefore, to help identify how uncertainty might influence individual and lender credit decisions, we develop a new time-varying county-level measure of economic uncertainty that is 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 through the county's exposure to fluctuations in firms' stock prices.

To construct the local uncertainty measure, for each public firm we first remove the systematic component in daily excess returns by regressing the daily excess stock returns on an augmented three factor model: we first use the standard factors such as the returns of the S&P

[8] There is some evidence of this "flight to safety" or increased lending standards when lenders face first moment shocks—see (Ramcharan, Verani, and van den Heuvel (2016)).

500 index, the book to market ratio, and the relative market capitalization (Fama and French, 1992). However, because we are especially concerned about mis-measurement due to “first moment” aggregate credit shocks, which might influence individual credit outcomes, we also include the TED spread and the market-wide spread between BBB and AAA corporate bonds. The TED spread—the difference between the interbank rate and the 3-month Treasury bill— is a common measure of aggregate banking sector distress, while the corporate bond spread proxies for distress in bond markets as a whole. As during the 2008 financial crisis, sudden increases in the TED spread and the BBB-AAA spread coincided with a market-wide shock and a general contraction in credit supply.

Thus, by construction, 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. The second step computes the daily *industry portfolio* residual returns by weighting the daily residual returns of firms by the firm’s relative size among firms in the same 4-digit sectoral industrial classification code (NAIC) code—the firm’s relative market capitalization. The third step calculates the quarterly sector-specific standard deviation of these daily idiosyncratic returns (see Gilchrist, Sim, and Zakrajšek, 2014 for a similar procedure). This produces a sector-specific index of volatility.

The final step draws upon the quarterly sectoral employment data from the Quarterly Census of Employment and Wages (QCEW), which lists employment in each county by the 4-digit NAIC code. In this final step, we use the QCEW data to create an employment weighted index of economic volatility by county: the 4-digit NAIC sector specific index of volatility is weighted by the 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, sharing the spirit of a Bartik instrument. The use of a one-year lag in the employment share mitigates the potential contemporaneous endogenous response of employment to uncertainty.

Along with this second moment index, we also construct the first moment analog: The weighted mean idiosyncratic stock returns at the county level—henceforth referred to as local returns. For each sector, we compute the sectoral daily weighted residual returns by weighting each firm’s residual returns by its relative market capitalization within the sector at a daily frequency. We then take the average of the sectoral returns over a quarter to obtain the quarterly mean residual returns for the sector. As before, we map these sector level weighted idiosyncratic returns into the local economy by weighting the sectoral returns by the lagged employment shares at the county level.

Figure 1. illustrates the temporal variation in both the aggregate VIX (solid orange line) and the local uncertainty index. To show that there exists a significant spatial heterogeneity in local uncertainty, Figure 1 plots the local uncertainty index at different points in its distribution—the 10th, 50th and 90th 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 90th 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 10th percentile of the local index experienced a far smaller increase in the index (e.g. Flagler County, Florida). The 90th-10th 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 US economy, Flagler County's economy—the 10th percentile in 2008 Q4--is more tilted towards health care, which was less affected by the 2008-2009 financial crisis.

As an illustrative example of what the local uncertainty might capture, Figure 2 shows the de-trended local uncertainty measures for San Francisco County and Upton County in Texas along with oil price volatility. Upton County has a very large share of employment in the oil and gas industry and hence a larger exposure to uncertainty shocks in the oil and gas industry. San Francisco County has a more diverse industry composition and hence has less exposure to oil price volatility. From Figure 2, the correlation between oil price volatility and the local uncertainty measure in Upton County is 0.4; in San Francisco the correlation is 0.07. These differences indicate that the local uncertainty variable measures the variation in uncertainty shocks stemming from differences in the local pattern of production.

This anecdotal evidence is confirmed by the simple correlations in Table 1, which are revealing of this distributional heterogeneity across space. Movements in the VIX are correlated positively with all three series, especially during the crisis period. But restricting the sample to the post 2009 period, movements in the local uncertainty index at the 10th percentile are actually 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 likely contains information about economic uncertainty relevant for the local area.

Validating the Local Uncertainty Measure

There is already significant evidence in the literature that local economic activity responds to aggregate shocks differently across localities based on the types of industries that dominate in the locality. [9] However, measurement error remains a key concern for at least three reasons, and this subsection provides correlations suggestive of a robust link between our equity market based local-uncertainty measure and county and sector level employment outcomes. The first possible source of measurement error stem from the fact that sectoral idiosyncratic volatility is derived solely from public firms, but mapped into the county-quarter dimension using QCEW employment data, which is derived from both public and private firms. If private and public firms differ in the idiosyncratic shocks that they face, the local uncertainty index may poorly measure sectoral and county-level economic uncertainty. Second, if the local uncertainty series is driven by firm-specific rather than sector-specific shocks, the series may also mis-measure sectoral uncertainty across space. And third, this equity market based approach is also subject to the more general criticism that because financial markets can be excessively volatile, the local uncertainty measure might contain little relevant information.

To address these concerns, first we note that the establishment-level evidence in Bloom *et. al* (2014) connecting equity market volatility to establishment-level productivity shocks does suggest that equity market derived measures of uncertainty might contain relevant economic information. Furthermore, in Table IA.1 in the Internet Appendix, we compare our measure of local uncertainty with the measures of TFP and sales volatility constructed by Bloom et al. (2014) based on US Manufacturing Census data. The evidence in Table IA.1 shows that at the sectoral level, our uncertainty measure is associated with both the uncertainty measure based on the TFP estimates and based on sales.

Since the Bloom et al. (2014) measure exists only for the manufacturing sector annually, while our uncertainty measure spans more than 300 industries at the quarterly frequency, we also

[9] See for example the evidence in Tuzel and Zhang (2017) on the role of local firm "betas" in transmitting systematic shocks to local wages and real estate prices.

document the relationship between local uncertainty and employment outcomes at both the sectoral and county levels to more directly gauge the external validity of our uncertainty measure.[10] If our local uncertainty index captures uncertainty related to an increased likelihood of layoffs, we should observe a negative correlation between lagged uncertainty and sectoral employment.

We test this hypothesis in Table 2A. In Column (1) the dependent variable is the quarterly log number of employees in each sector, beginning in 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 NAIC four 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 NAIC sector, where the weighting factor is a firm's relative market capitalization within the sector. The other controls include the weighted mean returns within the quarter, sector fixed effects, along with quarter fixed effects. Since firms' employment decisions might respond with some lag to changes in uncertainty, Column (1) reports a specification where both the sectoral volatility and weighted mean returns enter with lags up to four quarters.

Although measurement error can arise 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 1.4 percent decrease in the level of employment three quarters later, and up to a 2.1 percent decline one year later. Column (2) examines this relationship at an annual frequency. In this case, a one standard deviation increase in sectoral uncertainty is associated with a 3 percent decline in sectoral employment one year later. All this further suggests that an equity market derived measure of uncertainty is related to broader labor market outcomes.

We can also provide further evidence validating our local uncertainty measure by investigating employment outcomes at the county level in Table 2B. The dependent variable in Column (1) of Table 2B is the quarterly growth in total QCEW employment in the county, and

[10] See more detailed evidence in Davis et al. (2010) linking business variability to direct measures of job creation, destruction and unemployment. Shoag and Veuger (2016) also provide evidence at the state level linking uncertainty and unemployment.

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 along with county fixed effects are also included, and standard errors are 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 likely 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 0.4 percentage point decline in employment growth; the mean employment growth rate in the sample is 0.6 percent.

Increased uncertainty within a county might also be associated with increased labor market flux: Greater labor re-allocation and dispersion in employment across sectors within a county. To help proxy for re-allocation, we create 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 let 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 $d_{jt} = \left(\sum_i s_{ijt}\left(g_{ijt} - \overline{g_{Jt}}\right)^2\right)^{0.5}$.

The evidence in column (2) suggests that increased uncertainty is associated with greater dispersion in employment growth rates across sectors inside a county. This positive effect is most noticeable in the second and third quarters after an increase in local uncertainty. And over the four quarters, a one standard deviation increase in local uncertainty is associated with a 1.25 percent increase in the 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. We next describe the data on credit decisions.

Credit Decisions

We now present our main dependent variables on mortgage and consumer credit decisions. According to the Federal Reserve's Flow of Funds data, these two sources of credit account for approximately 12 trillion dollars or about 90 percent of total consumer liabilities in 2015.[11] Our various data sources are representative of these two very different credit markets, and together comprehensively cover the US consumer credit market.

Mortgage and Consumer Credit Data

We employ several data sources. First, we employ data from CoreLogic, which contain records of housing transactions in the U.S. We also use data from LPS —a proprietary source of mortgage data derived from seven of the largest mortgage loan processers—to collect information on loan origination outcomes, such as information on LTV, FICO scores, and interest rates, which can help gauge the impact of uncertainty on credit outcomes. These data also include key borrower characteristics like income, race, county of the property and loan amount. We collected these data quarterly from 2002-2013. We use these data to construct the average interest rate, weighted by loan shares, for newly originated mortgages.

In addition, we draw a twenty percent sample from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (Equifax). This is a proprietary consumer credit dataset, and the sample results in a balanced panel of about 450,000 individuals. It includes comprehensive quarterly information on key dimensions of debt usage: credit card balances, as well as credit limits from 2002-2013. The panel also includes relevant individual-level information on age; zip code of the primary residence; and the Equifax risk score—an important credit scoring index commonly used in credit decisions; higher values suggest less credit risk. In what follows, we primarily use data on credit card balances and borrowing limits to measure consumer credit.

We supplement this Equifax sample with proprietary data from BlackBox Logic (BBL) panel. The BBL data links consumer credit usage with mortgage contract terms at the monthly frequency. The structure of the dataset allows us to make further progress in causally identifying the impact of uncertainty on consumer credit outcomes.

Table 3 reports basic summary statistics for some of the individual variables, observed in 2008 Q1 from Equifax and BBL. The Equifax panel is more representative of the general credit-

[11] The Flow of Funds data can be found here: https://www.federalreserve.gov/releases/z1/current/accessible/b101.htm

using population, and contains information on non-homeowners and homeowners alike. The average credit card limit in Equifax is around $16,500, while the average credit card balance is about $6,000. The average utilization rate, the ratio of balances to limits, is around 70 percent. The average age, around 48, is higher than the US average; and the typical risk score is just under 700—well above the traditional subprime cutoff of 660 for mortgage credit.

Unlike Equifax, BlackBox Logic contains a richer set of data but for homeowners with prime credit. Vantage scores—similar to but distinct from Equifax risk scores—are significantly higher, with the average around 740. The mean credit card limit and balance are also much higher than the more general population surveyed in Equifax, but utilization rates are much lower. Mortgage balances are also much higher among the BBL ARM sample. Unlike Equifax, BBL also contains mortgage contract loan terms. These loans were contracted during 2005-2007 and the mean interest rate is around 5.8 percent, with LTV ratios averaging 77 percent.

The panel in Figure 3 plots the median outcomes for these variables over the crisis and post crisis sample period (2002 Q1-2014Q4) among the set of individuals with positive balances for both the more general Equifax dataset and the BBL data. There are differences across the two samples, likely reflecting the different economic circumstances of the median individual across the two datasets ((Di Maggio et al. (forthcoming)). In both datasets for example, utilization rates decline sharply with the crisis, but this rate recovers after the recession in the Equifax data, but it continues to decline in the BBL dataset, potentially due to the mortgage debt overhang after the housing crisis.

3. Main Results

3.A Local Uncertainty and Mortgage Credit

This subsection studies the impact of local uncertainty on mortgage credit. Table 4 uses quarterly data from CoreLogic and LPS. The dependent variable in Column (1) is the log number of new housing transactions inside the county within the quarter from Corelogic. Column (1) reports the regression estimates from a simple regression of log number of housing transaction on the local uncertainty and the local mean returns. Column (2) adds as year-by-quarter fixed effects and county fixed effects, which non-parametrically absorb aggregate and time-invariant county-level characteristics. For the remaining columns, we also include the one quarter lagged unemployment rate and house price growth to help absorb relevant local "first moment" shocks. All regressions are weighted by population—averaged between 2006 through 2009—and standard errors are conservatively clustered at the state level.

There is significant evidence that increased local uncertainty is associated with greater illiquidity in the housing market. From Column (3), a one standard deviation increase in local uncertainty in a given quarter is associated with a 9.9 percent decline in the number of housing transactions inside a county. But this result masks substantial heterogeneity across borrower credit risk subsamples. Specifically, Column (4) restricts the sample to those counties where there was a higher fraction of low FICO score borrowers, while Column (5) considers counties with a lower fraction of low FICO score individuals.[12] Because credit scores can endogenously reflect economic conditions, we use the credit score in 2000 prior to the beginning of the sample period to mitigate this potential endogeneity.

The evidence suggests that differences in default costs and risk-shifting incentives across borrowers might help shape the impact of uncertainty on credit outcomes. Among individuals living in counties with more high risk borrowers, a one standard deviation increase in uncertainty leads to a 17.2 percentage point reduction in housing transactions. Column (5), instead, shows the local uncertainty coefficient is insignificant for counties where there are fewer high risk borrowers, with an implied economic effect 65 percent smaller than that observed in the high risk sample.

Columns (6)-(8) investigate further the effect of local uncertainty on the mortgage market by analyzing the effect on the log of the number of mortgage originations for residential home purchases. The pattern of evidence is similar to that obtained using the log number of transactions. Greater uncertainty is associated with a sharp decline in mortgage origination, and this effect is primarily concentrated in counties with riskier populations. We find for example that a one standard deviation increase in local uncertainty reduces the number of mortgage transactions by 0.75 percent (column (6)).[13] And the point estimate obtained using the low-

[12] A low-credit-score county is one in which fewer than 45% of residents in 2000 had FICO scores above 680. A high-credit-score county is one in which more than 45% of residents in 2000 had FICO scores above 680. This definition roughly splits the sample in half.

[13] This decline in liquidity is very consistent with anecdotal evidence relating the uncertainty surrounding Brexit with the slow down of the housing market in the UK. See for instance the analysis here https://www.bloomberg.com/news/articles/2017-04-23/london-house-prices-post-biggest-annual-decline-in-eight-years.

credit-score subsample (column (7)) is about 9 times larger than that obtained in the high-credit-score sample (column (8)).

To better understand how uncertainty might affect the mortgage market, Table 5 shows regression results of various mortgage characteristics on the local uncertainty index. Illiquidity is often associated with a decline in the debt capacity of the underlying collateral, and columns (1) and (2) use the log number of mortgages with loan to value (LTV) ratios higher than 81%--the standard LTV cutoff in most mortgage underwriting. From column (1)—the low-credit-score sample, there is a sizeable decline in the use of leverage when uncertainty increases. A one standard deviation increase in local uncertainty is associated with a 9.1 percent drop in the number of highly leveraged loans. And as before, the impact is small and not statistically significant in the high-credit-score sample (Column 2). In Columns (3) to (4), the dependent variable is the log value weighted mean of the LTV ratio of originated mortgages for each county and year-quarter. We find that also on this intensive margin there is a significant reduction in leverage in response to increased uncertainty in low-credit-score areas.

The negative relationship between uncertainty and the use of leverage suggests that lenders might reduce the supply of mortgage credit to riskier borrowers during periods of heightened uncertainty. The evidence in Columns (5) and (6) appears consistent with this “flight to safety” channel. The dependent variable is the log value weighted average of FICO score of originated mortgages for each county and year-quarter. There is a significant increase in the average FICO score, weighted by newly originated mortgages, when uncertainty increases in riskier areas (column (5)). The evidence on mortgage interest rates suggests further that these results likely reflect the supply response to uncertainty. In Columns (7) and (8), the dependent variable is the value weighted average of the initial interest rates of mortgages originated for each county and year-quarter. Only fixed interest rate mortgages are included for Columns (7) and (8). We show that the average interest rate drops in high-credit-score areas in response to increased uncertainty, suggesting a reallocation of credit towards safer borrowers when uncertainty increases.

In sum, the evidence in this subsection suggests that increased uncertainty is associated with a “flight to safety” in the mortgage market, as credit appears to shift away from riskier borrowers. In low-credit-score areas, increased uncertainty is associated with greater illiquidity in housing markets, and a decline in leverage. The average credit score on originated transactions also rises sharply, yet there is no decline in the cost of mortgage debt. But in high-credit-score areas, where pecuniary default costs are higher, the effects on illiquidity and leverage is economically and statistically small, and there is a sizeable decline in the cost of mortgage debt.

3.B Local Uncertainty and Consumer Credit

We next study the impact of local uncertainty on credit decisions made in the unsecured consumer credit market. This market operates very differently from the mortgage market, helping us to gauge the generalizability of these results. The data on unsecured consumer credit transactions also offer a richer set of individual-level controls, which can help us better isolate the underling mechanism.

Table 6 examines the impact of local uncertainty on unsecured consumer debt decisions using individual-level data from Equifax. The data are quarterly and the sample period extends from 2002Q1 through 2013Q4. All specifications control for local returns in the county, unemployment rate and house price growth, as well as individual-level observables such as age, the previous year's average Equifax risk score (since the current score can endogenously reflect current economic conditions). We also include individual fixed effects and year-by-quarter fixed effects; individual fixed effects absorb possibly time invariant individual level factors such as risk aversion, trust and other factors that might shape non-pecuniary default costs, while year-by-quarter effects captures aggregate first moment and other shocks.

As before, we also control for local returns at the county-level—the first moment analog to the 4-digit NAIC based local uncertainty index and standard errors are clustered at the state level. Equifax offers several measures of consumer credit usage, and in Column (1) of Table 6, the dependent variable is the log of the individual's credit card balance in the quarter. In that specification, we also control for the individual's debt capacity using the log of the credit limit in that quarter as a regressor. The coefficient on the local uncertainty variable is negative but not statistically different from zero. The coefficient itself suggests that a one standard deviation increase in uncertainty is association with a 1.1 percent drop in credit card balances.

Default costs and risk shifting incentives vary sharply by risk score. And we have already seen evidence that these incentives can shape the impact of uncertainty in mortgage markets. To measure heterogeneous responses to uncertainty within the unsecured consumer credit market, we create an indicator variable that equals one if a borrower's risk score (lagged by one year) is above the median in the Equifax sample (732) and zero otherwise. We interact this variable with both the local uncertainty measure, as well as the local returns series; all variables are linearly included in the specifications as well. This interaction term measures whether the impact of uncertainty differs across borrowers with “high” or above median risk scores. As before, we control linearly for the log of age and the previous year’s risk score and employ individual-level fixed effects and conservatively cluster standard errors at the state-level.

Even in unsecured credit markets, default costs and risk shifting incentives appear to shape consumer responses to uncertainty. In fact, Column (2) shows that for borrowers below the median risk score, a one standard deviation increase in local-uncertainty is associated with a 4.8 percent increase in credit card balances. However, a similar increase in uncertainty suggests a 4.4 percent drop in credit card balances for above median risk score borrowers. That is, while low risk borrowers respond to increased uncertainty by reducing their credit card balances, higher risk borrowers appear to do the opposite.

The heterogeneity in the supply response to uncertainty is equally stark. The dependent variable in column (3) is the log of the credit limit. In this case, for the below median Risk score borrower—high risk borrowers—increased uncertainty is associated with a considerable decline in the size of the credit limit: A one standard deviation increase in local uncertainty is associated with a 5.4 percent drop in credit lines. However, for low risk borrowers—those above the median risk score—such an increase in uncertainty is associated with a 1.4 percent increase in the size of credit lines.

Column (4) investigates the effect of uncertainty on the utilization ratio and confirms that safer borrowers tend to cut down on borrowing when uncertainty increases. Taken together, the evidence in both the mortgage and unsecured credit markets suggests that local uncertainty significantly impacts these consumer credit markets. The pattern of evidence across these two very different markets is also very similar. Low risk borrowers respond to increased uncertainty by reducing their use of credit, and increasing financial flexibility through larger credit lines. High risk borrowers appear less sensitive to increased uncertainty. However, in both markets, lenders tend to restrict credit to these borrowers when uncertainty increases.[14]

[14] We have controlled for a number of potential first moment shocks at the county level, but these results could still reflect the fact that the local uncertainty measure might be systematically related to aggregate first moment shocks or aggregate uncertainty itself. In Table IA3, we interact the “Low Risk Borrower” indicator variable with a veritable kitchen sink of aggregate variables: GDP growth, the 3 month and 10 year Treasury

4. Further Evidence through Mortgage Contract Design

Up to now, we have focused on a measure of local uncertainty mainly capturing employment risk, which allowed us to use the heterogeneity across counties as the main source of variation. However, there are other important forms of uncertainty that might impact households' behavior in credit markets. For instance, since mortgages constitute the most significant fraction of the households' liabilities, one could expect that any sudden shock to interest rates risk, which would result in fluctuations in monthly mortgage payments, might shape a household's consumption decision.

Thus, to provide further evidence that increased uncertainty significantly impacts individual spending decisions, we exploit the exogenous timing of the interest rate resets in a large panel of adjustable rate mortgages (ARMs) as in the setting presented in Di Maggio, Keys, Kermani, Piskorsi, Seru, Ramcharan and Yao (forthcoming). Specifically, we collect data consisting of borrowers with ARMs originated between 2005 and 2007. These contracts have a fixed interest rate for the first 5 years. After this initial 5 year period, borrowers become directly exposed to interest rate risk: The ARM adjusts to the prevailing short term interest rate index on the first month of the 6th year, and then continues to adjust either every 6 months or every 12 months thereafter.

The design of these ARMs can provide additional evidence identifying the role of uncertainty. In fact, after the reset, borrowers experience a sizeable decline in monthly mortgage payments, and this can boost current spending (Di Maggio et al., forthcoming). But borrowers also become exposed to increased uncertainty about their current and future mortgage payments: Future payments can now fluctuate with short-term interest rates after the reset. This future payment uncertainty can then amplify the impact of labor market uncertainty, as measured by our measure, on spending decisions.

In particular, we might expect that an increase in local uncertainty—greater employment or portfolio risk—might then moderate a borrower's spending response even more around the mortgage reset window. For example, in the quarters around the reset when future payments become uncertain, increased labor market risk, as measured by local uncertainty, might induce a borrower with high default cost— a high credit score—to spend less than otherwise in order to

rates; the VIX, the BBD and EPU indices, along with their various subcomponents. Throughout, our main results remain unchanged: Increased local-uncertainty is associated with increased credit utilization and relatively less credit access among riskier borrowers.

increase financial flexibility relative to other time periods and otherwise similar borrowers who are not exposed to payment uncertainty. Equivalently, the credit balances of high credit score individuals might become even more sensitive to local uncertainty when these borrowers also face increased uncertainty surrounding the size of their future mortgage payments, and thus, net disposable income.

Moreover, because the decision to obtain a mortgage in our sample precedes current spending and credit decisions by five years, it is unlikely that the home buying decision along with the choice of mortgage contract is systematically made in anticipation of the economic environment and prevailing levels of local uncertainty five years in the future. Put differently, borrowers in our sample do not systematically time or select their exposure to interest rate risk in anticipation of near-term uncertainty or other economic and policy shocks.

We can therefore exploit the plausibly exogenous variation in the timing of an individual's exposure to interest rate risk within a difference-in-difference framework in order to identify the impact of uncertainty on credit decisions. Let S_{jt} denote local uncertainty in quarter t in county j, and let y_{it} denote individual i's credit card balance in quarter t. The indicator R_{it+0} equals one if individual i's first interest rate reset--the beginning of the individual's exposure to interest rate risk--occurs on that specific date t; similarly, R_{it+1} equals one in the quarter after the first reset and zero otherwise and R_{it-1} is an indicator for the quarter just before the reset.

We then estimate the following difference-in-difference specification:

$$y_{it} = \sum_{k=-\tau}^{\tau} \alpha_k S_{jt} R_{it+k} + \beta_k R_{it+k} + X_{it}\Theta + \eta_t + \phi_i + \varepsilon_{it}$$

The vector X_{it} contains time-varying individual level observables such as the log of credit card limits—the individual’s maximum borrowing capacity. Individual-level time invariant characteristics are absorbed in the individual fixed effect ϕ_i and aggregate shocks are linearly captured in year by quarter fixed effects η_t. As with all the previous specifications, to absorb analogous first moment shocks, we also interact local returns with the reset indicators. The parameters α_k measure the response of the individual's credit card balances to local uncertainty in the period τ quarters before and after the interest rate reset.

The exact timing of these responses will depend on whether individuals anticipate the reset date, pay attention to uncertainty, and can easily adjust their consumption plans. Mortgage servicers are required to send notices to borrowers about the future reset of interest rates 2 to 8 months in advance. Thus, borrowers are likely to become aware of the uncertainty surrounding future mortgage payment changes as the reset date nears. But if individuals perceive local uncertainty shocks to dissipate rapidly with time, then they might still optimally ignore local uncertainty until very close to the reset date. Liquidity constraints or habit persistence could also delay any consumption response to the local uncertainty shocks until very close to the reset date.

In column (1) of Table 7, we use this difference-in-difference framework to estimate the impact of local uncertainty on bank card balances around the date of reset. Column (1) suggests that for the full sample, increased local uncertainty leads to larger balances two quarters after the reset, but these estimates are imprecise. And as before, the full sample masks remarkable heterogeneity in the response to risk across borrower credit grades.

Column (2) uses the subsample of borrowers with credit scores above the 720 median in the BlackBox Logic sample. Consistent with the precautionary motive, an increase in local uncertainty one quarter before the reset is associated with a significant contraction in credit balances: a one standard deviation increase in uncertainty suggests a 6.2 percent drop in credit card balances. This impact is about 2 percentage points higher than that obtained using the full Equifax sample over the same time period.

Also consistent with our previous results, borrowers with below median credit scores are far less sensitive to local uncertainty when exposed to increased payment risk (column (3)). The similarity between the results derived from the full population of borrowers in Equifax and that obtained from this very specific difference-in-difference framework based on mortgage resets suggests that local uncertainty is indeed important for consumer credit decisions.

We can further analyze the role of uncertainty by using the Baker, Bloom and Davis (2016) monthly monetary policy uncertainty index (MPU). This aggregate index varies at the monthly frequency and is derived from newspaper mentions of monetary policy topics—Federal Reserve; quantitative easing etc.—and words associated with uncertainty. It is also likely to affect credit decisions through a very different channel than the local uncertainty measure. An increase in monetary policy uncertainty in the months before the reset increases the variance of the distribution of possible interest rate resets, and thus the variance of future possible monthly payments and disposable income. Given this increase in the variability of future disposable income, we would expect that high credit score borrowers will target greater financial flexibility, and decrease their credit card balances relative to periods with less monetary policy uncertainty increases. The monthly frequency of the MPU series can also help us better understand the timing of an individual's response to uncertainty.

Table 8 presents the difference-in-difference results using the monthly MPU series for the full sample of borrowers; we again focus on the 6 months around the reset. Column (1) suggests that an increase in monetary policy uncertainty is associated with a significant decline in credit card balances beginning two months before the reset date, and continuing up to two months afterwards; the effects however peak in the month just before the reset, and the results are also economically significant. A one standard deviation increase in the MPU index is associated with a 1.1 percent drop in balances two months prior to the reset; a 2.3 percent decline one month prior; and a 1.3 percent drop one month after reset. Effects are also detectable up to two months afterwards, where a standard deviation increase in MPU suggests a 1.3 percent drop in credit card balances.

The heterogeneity in the consumption response to this monetary policy based uncertainty measure across borrower credit grades is strikingly similar to all the previous results. Column (2) estimates the baseline difference-in-difference specification for above median credit score borrowers; column (3) repeats the exercise for the below median subsample. Even though this monetary policy source of uncertainty is constructed very differently from the local uncertainty series, the credit card usage of borrowers with above median credit risk scores appears significantly more sensitive to monetary policy uncertainty than those with below median scores. The below median subsample continues to evince a positive response to uncertainty.

Tables IA.2 and 1A.3 in the Internet Appendix consider a number of robustness tests. Using the 5-year ARM contract design helps facilitate causal inference, as the identification strategy exploits the plausibly exogenous timing of the reset, and is arguably robust to the nonrandom selection into specific types of mortgage contracts. But the specific nature of the contract itself might make it difficult to generalize these results. Individuals that select into ARMs might for example also have a different consumption profile. To gauge how this might affect inference, we combine the 5 year ARM sample with borrowers holding 10 year ARMs. The latter borrowers also elected to use longer-term ARMs to finance their home purchases, and we can use this sample as a control group to help gauge the robustness of these results. From column (1) of Table IA.2, the impact of the MPU index remains unchanged.

Rather than reflecting the direct effects of monetary policy uncertainty, these results could be driven by actual movements in the interest rate that coincide with movements in the MPU index. In column (2), we include analogous interaction terms for the mean 3-month Treasury rate as controls. The MPU results are unchanged. As a further robustness check, column (3) includes interaction terms with the 10-year Treasury rate as control variables. If anything, the estimated impact of uncertainty appears somewhat larger after controlling for the 10-year rate. Mean interest rate movements do not appear to drive the MPU results and columns (4) and (5) control for realized interest rate volatility using the monthly standard deviation of the three-month Treasury (column (4)) and the 10 year Treasury (column (5)) computed daily. The evidence continues to strongly suggest that an increase in the MPU around the reset date, especially the month before the reset, tends to have a large negative impact on credit card balances.

As a further robustness check, we include other standard time series indicators of uncertainty within the difference-in-difference framework. Column (1) of Table IA.3 adds the VIX and the related reset-timing interaction terms as control variables to the baseline specification. The coefficient on the VIX is negative and statistically significant in the months immediately around the reset. In the month of reset for example, a one standard deviation increase in the VIX is associated with a 4 percent decline in credit card balances. The correlation between the VIX and the MPU is 0.43, but the impact of the MPU remains generally negative.

We next consider a range of categorical policy-related uncertainty measures. Column (2) uses the broad monthly fiscal uncertainty measure computed by Baker, Bloom and Davis (2016), while column (3) employs the financial regulation uncertainty index gleaned from newspapers. The general fiscal policy uncertainty index in column (2) enters with a small negative sign, while the financial regulation index (column (3)) has a positive sign. The MPU variable is however little changed. The remaining columns of Table IA.3 use a range of indices measuring different facets of policy uncertainty. As the source of uncertainty becomes less relevant for the distribution of near-term short-run interest rates—health policy for example—the estimates of α_j decline in economic and statistical significance. The impact of monetary policy uncertainty remains broadly stable across these various specifications.

5. Conclusion

This paper has used several comprehensive datasets of debt and credit decisions to understand the role of economic uncertainty in shaping these decisions. To better identify the role of uncertainty in individual-level credit decisions, we also created a new equity-based measure of local uncertainty at the county level which can potentially be used in future research. Across a range of specifications, the evidence indicates that local uncertainty can significantly influence both the mortgage market and the unsecured credit market.

Moreover, we uncover considerable heterogeneity in the impact of uncertainty across borrower credit grades, as increased uncertainty is associated with a "flight to safety" in the mortgage market. In areas populated by riskier borrowers, mortgage markets become more illiquid and leverage declines. These effects are absent among safer borrowers. Indeed, among safer borrowers, the cost of mortgage credit actually declines, suggesting an expansion in the supply of credit. These effects are replicated in the unsecured market. Higher uncertainty is associated with a decrease in balances and an increase in credit lines for safer borrowers; the exact opposite is obtained for riskier borrowers.

This evidence suggests that in part by affecting borrowing constraints for some households and credit demand for others, uncertainty might significantly influence economic fluctuations. Moreover, these effects are likely to be particularly strong after credit-related shocks. The variation across borrower risk types also suggests that increased uncertainty could also shape inequality in consumption and housing wealth accumulation across households, with effects again especially large after periods of credit disruptions and change. We leave it to future research to document these effects on inequality and their potential economic and political consequences.

Table 1. Uncertainty Measures

This table reports the summary statistics of the local uncertainty measure and the local mean residuals, and the correlation between different uncertainty measures. All correlations in the table are significant at the 5 percent 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).

Summary Statistics

	Mean	Std Deviation	5th Percentile	Median	95the Percentile
Local Uncertainty	0.011	0.0057	0.0052	0.010	0.020
Local Mean Residuals	7.12E-06	0.00076	-0.00091	-0.000021	0.001

Correlation, 2002-2013

	Local Uncertainty, 10^{th} percentile	Local Uncertainty, 50^{th} percentile	Local Uncertainty, 90^{th} percentile	VIX	BBD Index
Local Uncertainty, 10^{th} percentile	1.00	0.96	0.76	0.71	0.08
Local Uncertainty, 50^{th} percentile	0.96	1.00	0.84	0.75	0.17
Local Uncertainty, 90^{th} percentile	0.76	0.84	1.00	0.61	0.14
VIX	0.71	0.75	0.61	1.00	0.54
BBD Index	0.08	0.17	0.14	0.54	1.00

Correlation, post 2009

	Local Uncertainty, 10^{th} percentile	Local Uncertainty, 50^{th} percentile	Local Uncertainty, 90^{th} percentile	VIX	BBD Index
Local Uncertainty, 10^{th} percentile	1.00	0.37	0.24	-0.15	-0.42
Local Uncertainty, 50^{th} percentile	0.37	1.00	0.92	0.42	0.44
Local Uncertainty, 90^{th} percentile	0.24	0.92	1.00	0.23	0.42
VIX	-0.15	0.42	0.23	1.00	0.71
BBD Index	-0.42	0.44	0.42	0.71	1.00

Table 2A. Uncertainty and Sectoral Employment

The dependent variable is the log number of employees within a sector. The data are observed at the sector-quarter level (2000Q1:2015 Q4) in column (1) and the sector-year level in column (2). All regressions include sector-fixed effects, and year fixed effects; column (1) also includes quarter fixed effects. A sector is defined at the 4-digit NAIC level—there are 312 such sectors. Standard errors are clustered at the sector level.

	Log employment in sector	
	(1)	(2)
	Quarterly	Annual
Sectoral uncertainty, 1 quarter lag	-0.743	
	(0.618)	
Sectoral uncertainty, 2 quarter lag	-0.610	
	(0.471)	
Sectoral uncertainty, 3 quarter lag	-0.796**	
	(0.331)	
Sectoral uncertainty, 4 quarter lag	-0.885**	
	(0.444)	
Sectoral returns, 1 quarter lag	-0.586	
	(0.855)	
Sectoral returns, 2 quarter lag	-1.448	
	(1.039)	
Sectoral returns, 3 quarter lag	-0.519	
	(1.052)	
Sectoral returns, 4 quarter lag	-0.705	
	(0.995)	
Sectoral uncertainty, 1 year lag		-2.281*
		(1.371)
Sectoral returns, 1 year lag		-1.681
		(3.357)
Observations	17,412	4,481
R-Sq	0.972	0.975

Table 2B. Local Uncertainty Measure and Employment Growth

The dependent variable in column (1) is employment growth in a county. Column (2) uses the log dispersion in employment growth across sectors within a county-quarter unit as the dependent variable. The data are observed at the county-quarter frequency, and all regressions include county, and year and quarter fixed effects. The sample period extends from 2000-2015, and standard errors are clustered at the state level.

	Employment growth	Within-county employment dispersion
Local uncertainty, 1 quarter lag	-1.720***	1.097
	(0.0868)	(0.814)
Local uncertainty, 2 quarter lag	-0.507***	2.773***
	(0.0949)	(0.854)
Local uncertainty, 3 quarter lag	0.264***	2.434***
	(0.0840)	(0.469)
Local uncertainty, 4 quarter lag	1.186***	-2.746***
	(0.0914)	(0.738)
Local returns, 1 quarter lag	6.879***	-8.911***
	(0.385)	(2.880)
Local returns, 2 quarter lag	-3.135***	-8.862***
	(0.451)	(2.626)
Local returns, 3 quarter lag	-4.960***	-13.02***
	(0.391)	(2.081)
Local returns, 4 quarter lag	-4.917***	-16.04***
	(0.426)	(2.957)
Observations	209,021	208,360
R-Sq	0.075	0.138

Table 3. Summary Statistics of Credit Data

NY Federal Reserve Equifax Panel, 2007-2013.

	Age	Equifax Risk Score	First Mortgage Total Balance	Credit Card Limit	Credit Card Balance	Utilization Rate: Balance/Limit
Mean	48	697	187,654	16,738	6,195	0.71
Median	48	724	133,434	12,500	3,042	0.88
25^{th} percentile	35	620	75,867	5,000	1,016	0.45
75^{th} percentile	59	789	228,074	21,990	7,563	1.00
Min	18	284	55	1.0	3.0	0.00
Max	80	841	8,938,310	817,704	239,832	1.00
Std Deviation	16	109	217,629	20,653	10,700	0.34

Black Box Logic, 2005-2013

	Vantage Risk Score	Credit Card Balance	Credit Card Limit	Utilization Rate: Balance/Limit	Loan to Value Ratio, Origination	Interest Rate, Origination	Mortgage, Origination
Mean	737	11,280	34,027	0.35	77.1	5.9	362,292
Median	719	5,096	24,700	0.27	80.0	6.4	293,000
25^{th} percentile	690	799	10,080	0.07	75.0	5.8	186,918
75^{th} percentile	754	14,573	47,273	0.59	80.0	6.9	467,462
min	658	0.0	0.0	0.00	5.0	0.0	10,000
max	9,999	912,240	1,005,712	2.47	148.5	14.0	8,196,501
Std Deviation	357	18,054	34,743	0.32	10.1	2.1	271,928

Table 4. Local Uncertainty and Housing Transactions

This table shows regression results of various housing market outcomes on the local uncertainty index. In columns (1) to (5), the dependent variable is the log number of housing transactions for each county and year-quarter from CoreLogic. In columns (5) to (8), the dependent variable is the log number of mortgages originated for each county and year-quarter from LPS. Refinancing mortgages are excluded in these data. All regressions control for local mean residuals, and regressions in columns (3) to (8) control for county unemployment rate, county house price growth, county fixed effects and year-quarter fixed effects. Standard errors are clustered at the state level. A low-credit-score county is one in which fewer than 45% of residents in 2000 had FICO scores above 680. A high-credit-score county is one in which more than 45% of residents in 2000 had FICO scores above 680. This definition roughly splits the sample in half.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log Housing Transaction	Log Housing Transaction	Log Housing Transaction	Log Housing Transaction (Low Credit Score County)	Log Housing Transaction (High Credit Score County)	Log Number of Mortgage Originations	Log Number of Mortgage with FICO less than 680 Originated	Log Number of Mortgage with FICO Higher or equal to 680 Originated
Local Uncertainty	-22.7*	-18.1*	-17.3*	-30.2**	-10.6	-1.32*	-12.3**	-0.79
	(13.1)	(10.6)	(9.91)	(13.3)	(11.3)	(0.68)	(5.34)	(3.73)
Local Mean Residuals	64.9*	13.5	14.9	24.2	11.3	-3.95**	-28.3***	-20.2**
	(36.3)	(28.8)	(29.0)	(39.3)	(33.6)	(1.65)	(9.72)	(9.03)
Lagged Unemployment Rate			-0.028	-0.024	-0.026	-0.0023*	-0.026**	-0.047***
			(0.020)	(0.034)	(0.023)	(0.0012)	(0.012)	(0.012)
House Price Growth			2.19***	2.16*	2.52***	0.0039	2.30***	2.30***
			(0.73)	(1.16)	(0.42)	(0.026)	(0.31)	(0.35)
Observations	53267	53267	52264	27603	24661	57453	57265	58619
R-squared	0.001	0.799	0.803	0.754	0.846	0.999	0.967	0.981
Fixed Effects	No	County FE and Time FE	County FE and Time FE	County FE and Time FE	County FE and Time FE	County FE and Time FE	County FE and Time FE	County FE and Time FE

Table 5. Local Uncertainty and Mortgage Characteristics

This table shows regression results of various mortgage characteristics on the local uncertainty index. In columns (1) to (2), the dependent variable is the log number of mortgages originated with loan-to-value (LTV) ratio higher than 81%. In columns (3) to (4), the dependent variable is the log of the value weighted mean of LTV ratio of the originated mortgages for each county and year-quarter. In columns (5) and (6), the dependent variable is the log of the value weighted average of FICO score of originated mortgages for each county and year-quarter. In columns (7) and (8), the dependent variable is the value weighted average of the initial interest rates of mortgages originated for each county and year-quarter. Only fixed interest rate mortgages are included for columns (7) and (8). All regressions control for local mean residuals, county unemployment rate, county house price growth, county fixed effects and year-quarter fixed effects. Standard errors are clustered at the state level. A low-credit-score county is one in which fewer than 45% of residents in 2000 had FICO scores above 680. A high-credit-score county is one in which more than 45% of residents in 2000 had FICO scores above 680. This definition roughly splits the sample in half.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log Number of Mortgage with LTV Higher than 81%	Log Number of Mortgage with LTV Higher than 81%	Log Weighted Mean of LTV of Originated Mortgage	Log Weighted Mean of LTV of Originated Mortgage	Log Weighted Mean of FICO Score of Originated Mortgage	Log Weighted Mean of FICO Score of Originated Mortgage	Weighted Mean of Initial Interest Rate of Originated Fixed Rate Mortgage	Weighted Mean of Initial Interest Rate of Originated Fixed Rate Mortgage
	Low Credit Score County	High Credit Score County	Low Credit Score County	High Credit Score County	Low Credit Score County	High Credit Score County	Low Credit Score County	High Credit Score County
Local Uncertainty	-16.1**	-4.37	-1.69***	-0.34	0.35***	-0.0046	-2.47	-7.65**
	(7.21)	(7.43)	(0.53)	(0.83)	(0.12)	(0.18)	(2.28)	(3.16)
Local Mean Residuals	-26.0	5.77	-2.31	0.53	0.23	-0.49	3.22	-2.14
	(21.3)	(16.2)	(1.42)	(1.53)	(0.46)	(0.42)	(7.62)	(11.7)
Lagged Unemployment Rate	-0.016	-0.0093	0.0013	0.0034***	0.00013	-0.00079*	-0.014**	-0.028***
	(0.028)	(0.022)	(0.0013)	(0.0011)	(0.00027)	(0.00044)	(0.0056)	(0.0082)
House Price Growth	2.19***	1.89***	-0.022	-0.017	0.019	0.018	0.37**	0.72***
	(0.36)	(0.43)	(0.022)	(0.021)	(0.013)	(0.022)	(0.15)	(0.21)
Observations	30580	26851	30589	26862	30590	26863	30589	26862
R-squared	0.964	0.972	0.892	0.859	0.898	0.892	0.990	0.987
Fixed Effects	County FE and Time FE	County FE and Time FE	County FE and Time FE	County FE and Time FE	County FE and Time FE	County FE and Time FE	County FE and Time FE	County FE and Time FE

Table 6. Local Uncertainty and Credit Card Accounts

This table estimates the effect of local uncertainty on credit card borrowing, and by different risk profiles. The data are from the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (20% sample) over the sample period 2002 Q1-2013 Q4. The unit of observation is individual-year-quarter. All regressions include local returns in the county; the individual's average risk score the previous year; age (log); unemployment rate in the county; change in house prices at the zip code level; individual fixed effects and year-by-quarter fixed effects. Columns (2)-(5) also interact local uncertainty and local returns with an indicator variable that equals one if an individual lives in a zip code with above median income (income data from the IRS) and 0 otherwise. Columns (2)-(5) also interact local returns with the "Low Risk Borrower" indicator variable. "Low Risk Borrower" equals 0 for borrowers with below median risk scores and 1 otherwise. This variable also enters linearly. Standard errors are clustered at the state-level. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
	Credit card balances, log	Credit card balances, log	Credit card limit, log	Log Utilization Ratio of Credit Card
Local uncertainty	-1.97	8.38***	-9.54***	1.08***
	(2.37)	(2.98)	(2.64)	(0.32)
Local uncertainty * low risk borrower		-16.2***	12.0***	-1.81***
		(1.27)	(1.37)	(0.19)
Local uncertainty * high income county		-1.28	-4.21**	-0.23
		(1.43)	(1.91)	(0.19)
Local Mean Residuals	-15.4***	17.7	-124.9***	4.73***
	(4.39)	(14.1)	(18.7)	(1.46)
Local Mean Residuals * low risk borrower		-77.2***	195.4***	-7.96***
		(9.12)	(17.9)	(1.40)
Local mean residuals * high income county		12.8	22.0	-0.72
		(11.5)	(13.4)	(0.86)
Average individual risk score (previous year)	-4.12***	-3.86***	-2.01***	-0.19***
	(0.047)	(0.047)	(0.12)	(0.0077)
Age (log)	6.15***	6.35***	-0.99***	0.14***
	(0.19)	(0.19)	(0.18)	(0.014)
Lagged Unemployment rate	0.0012	0.0016	0.013***	0.00015
	(0.0026)	(0.0027)	(0.0044)	(0.00033)
House price growth	-0.36***	-0.36***	0.10	-0.039***
	(0.081)	(0.086)	(0.094)	(0.0088)
Credit card limit, log	0.079***	0.080***		
	(0.0035)	(0.0034)		
Low risk borrower		0.017	-0.10***	-0.064***
		(0.023)	(0.015)	(0.0024)
Observations	5490518	5474593	7115169	5447316
R-squared	0.594	0.594	0.443	0.561
Fixed Effects	County, Year-Quarter	County, Year-Quarter	County, Year-Quarter	County, Year-Quarter

Table 7. Interest Rate Reset and Local Uncertainty

This table estimates the impact of local uncertainty around the two quarters before and after the mortgage reset date—Equation 1. The dependent variable is the log of credit card balances. All regressions include the current interest rate on the mortgage; the monthly payment; and the credit card limit; dummies for the two quarters around the reset date; local returns are also interacted with these dummy reset variables. Local returns and local uncertainty are included linearly along with individual fixed effects and year-by-quarter fixed effects. The sample period extends from 2006 Q1: 2012Q2. Standard errors are clustered at the state-level. *** p<0.01, ** p<0.05, * p<0.1. The individual-level data are observed monthly and aggregated up to the quarterly level. The full sample includes all individuals. The "high credit score" sample (column (2)) includes those individuals with FICO scores at loan origination above 720—the median in the sample. Column (3) includes individuals with FICO scores at loan origination below the 720 median.

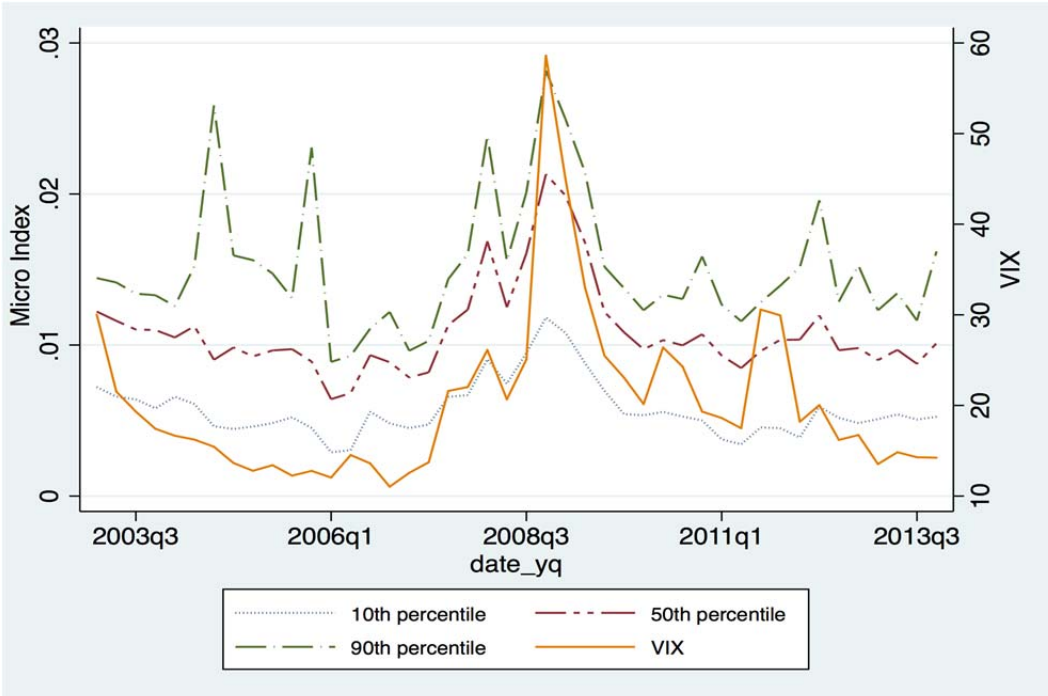
	(1)	(2)	(3)
	Full Sample	High Credit Score	Low Credit Score
Local uncertainty*2 quarters before reset	-2.271	-6.627	1.164
	(3.810)	(5.699)	(7.187)
Local uncertainty*1 quarter before reset	-3.351	-15.99**	8.435
	(5.706)	(7.766)	(8.963)
Local uncertainty* quarter of reset	1.901	-0.660	4.848
	(4.069)	(6.704)	(6.421)
Local uncertainty* 1 quarter after reset	1.297	-4.302	7.742
	(5.870)	(9.091)	(8.854)
Local uncertainty* 2 quarters after reset	11.31*	12.75	11.81*
	(6.422)	(10.04)	(7.124)
Observations	770,000	390,670	379,330
R-squared	0.707	0.700	0.713

Table 8. Interest Rate Reset and Monetary Policy Uncertainty

This table estimates the impact of the Baker Bloom and Davis (2016) monthly monetary policy index around the 6 months before and after the mortgage reset date—Equation 1. The independent variable is the log of credit card balances. All regressions include the current interest rate on the mortgage; the monthly payment; and the credit card limit; dummies for the 6 months around the reset date; individual fixed effects and year-by-quarter fixed effects. The sample period extends from 2006 Q1: 2012Q2. Standard errors are clustered at the state-level. *** p<0.01, ** p<0.05, * p<0.1. The individual-level data are observed monthly. The full sample includes all individuals. The "high credit score" sample (column (2)) includes those individuals with FICO scores at loan origination above 720—the median in the sample. Column (3) includes individuals with FICO scores at loan origination below the 720 median.

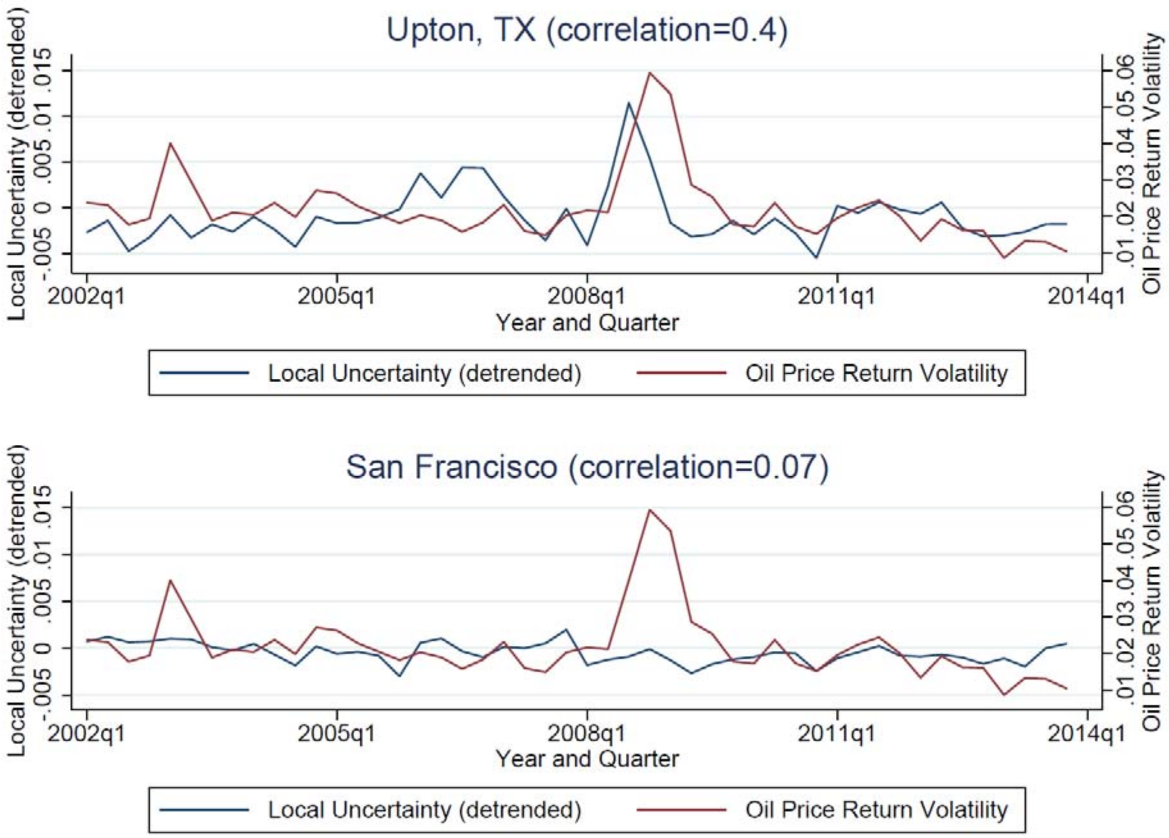
	(1)	(2)	(3)
VARIABLES	Full Sample	High Credit Score	Low Credit Score
Monetary policy uncertainty, 1 month before reset	-0.000484***	-0.000516**	-0.000431**
	(0.000148)	(0.000193)	(0.000192)
Monetary policy uncertainty, 2 months before reset	-0.000233*	-0.000114	-0.000390
	(0.000129)	(0.000208)	(0.000252)
Monetary policy uncertainty, 3 months before reset	-0.000112	-1.13e-05	-0.000220
	(8.15e-05)	(0.000146)	(0.000216)
Monetary policy uncertainty, 4 months before reset	0.000120	7.39e-05	0.000185
	(0.000135)	(0.000111)	(0.000222)
Monetary policy uncertainty, 5 months before reset	4.09e-05	0.000237	-0.000117
	(0.000102)	(0.000159)	(0.000163)
Monetary policy uncertainty, 6 months before reset	-3.15e-05	0.000121	-0.000166
	(0.000169)	(0.000256)	(0.000135)
Monetary policy uncertainty, month of reset	-0.000267*	-0.000357**	-0.000161
	(0.000143)	(0.000160)	(0.000197)
Monetary policy uncertainty, 1 months after reset	9.49e-05	-0.000197	0.000401**
	(0.000121)	(0.000153)	(0.000158)
Monetary policy uncertainty, 2 months after reset	-0.000279**	-0.000625***	5.61e-05
	(0.000127)	(0.000178)	(0.000223)
Monetary policy uncertainty, 3 months after reset	-0.000179	-0.000233	-0.000131
	(0.000133)	(0.000171)	(0.000191)
Monetary policy uncertainty, 4 months after reset	9.58e-07	0.000113	-4.82e-05
	(0.000127)	(0.000220)	(0.000206)
Monetary policy uncertainty, 5 months after reset	0.000219	0.000453	4.59e-05
	(0.000203)	(0.000328)	(0.000226)
Monetary policy uncertainty, 6 months after reset	0.000291	0.000102	0.000594*
	(0.000180)	(0.000137)	(0.000332)
Observations	2,329,821	1,181,033	1,128,771
R-squared	0.667	0.657	0.677

FIGURE 1. LOCAL UNCERTAINTY AND THE VIX



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

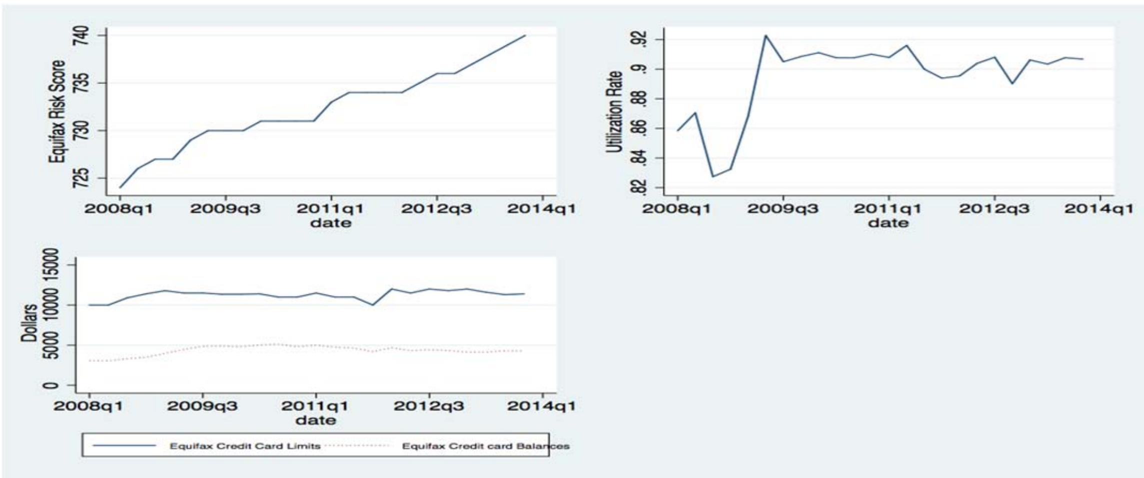
FIGURE 2. CORRELATION BETWEEN LOCAL UNCERTAINTY AND OIL PRICES – AN ILLUSTRATIVE EXAMPLE



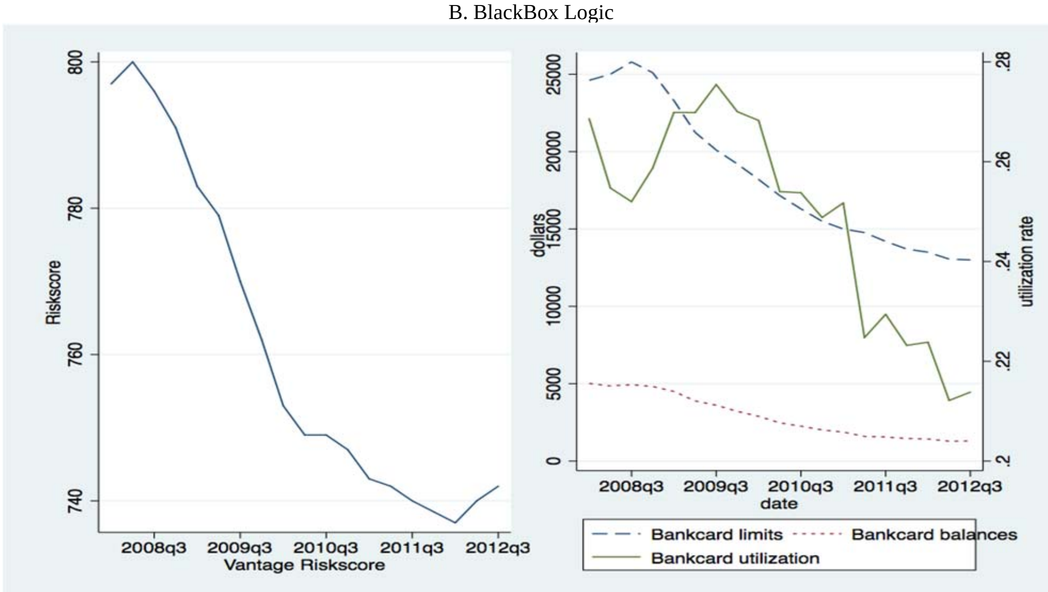
This figure plots the local uncertainty series detrended by time fixed effects for two counties as an illustrative example. The oil price return volatility is computed as the quarterly realized volatility of daily WTI oil price returns.

FIGURE 3. CONSUMER CREDIT USAGE OVER TIME

A. Equifax



B. BlackBox Logic



This figure reports the median (year-quarter) outcome of each variable for individuals in the Equifax panel (panel A) and BlackBox Logic Panel (panel B)

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Internet Appendix

Table IA.1 Local Uncertainty in the Manufacturing Sector

This table reports the correlation of the local uncertainty measure with uncertainty measures for the manufacturing sector in Bloom el al (2014). The unit of observation is 4-digit NAICS industry by year. The variable "Uncertainty (Aggregate Component)" is constructed using the systematic component returns of the factor regressions. Standard errors are clustered at the 4-digit NAICS level.

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP Uncertainty			Sales Uncertainty		
Uncertainty (Aggregate Component)	1.596*	2.851***	3.077**	1.746***	1.630***	1.556*
	(0.953)	(0.684)	(1.314)	(0.349)	(0.370)	(0.848)
Local Uncertainty	0.940	0.0623	0.926**	0.322	0.166	0.669***
	(1.082)	(0.571)	(0.382)	(0.238)	(0.231)	(0.218)
Constant	0.407***	0.406***	0.364***	0.211***	0.215***	0.192***
	(0.0162)	(0.00549)	(0.0121)	(0.00540)	(0.00339)	(0.00764)
Fixed Effects						
4 Digit NAICS	N	Y	Y	N	Y	Y
Year	N	N	Y	N	N	Y
Observations	939	939	939	939	939	939
R-squared	0.030	0.754	0.812	0.090	0.567	0.657

Table IA.2. Interest Rate Reset Extra Controls

The dependent variable is the log of monthly credit card balances. All specifications control for the current mortgage interest rate; the current monthly mortgage interest payment (logs) and the log of the individual's credit card limit; state fixed effects and year-by-month fixed effects. Column (2) interacts the mean three month Treasury rate with the reset indicators; column (3) interacts the mean 10 year Treasury rate with the reset indicators; columns (4) and (5) include respectively interaction terms with the standard deviation of the 3 month and 10 year Treasury rate (computed over the trading days in the month) and the reset indicators. Standard errors are clustered at the state level.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	5 and 10 Year ARMs	Monetary policy & short-term interest rates	Monetary policy & long-term interest rates	Monetary policy & interest rate volatility (3month)	Monetary policy & interest rate volatility (10 year)
Before Reset					
Monetary policy uncertainty, 1 month before reset	-0.000467***	-0.000475***	-0.000575***	-0.000470***	-0.000491***
	(0.000143)	(0.000155)	(0.000177)	(0.000149)	(0.000147)
Monetary policy uncertainty, 2 months before reset	-0.000208*	-0.000209	-0.000357**	-0.000193	-0.000237*
	(0.000117)	(0.000134)	(0.000143)	(0.000128)	(0.000138)
Monetary policy uncertainty, 3 months before reset	-7.41e-05	-0.000127	-0.000275***	-5.29e-05	-0.000135
	(8.63e-05)	(8.11e-05)	(8.47e-05)	(9.96e-05)	(0.000104)
Monetary policy uncertainty, 4 months before reset	0.000167	0.000117	-7.61e-05	0.000144	0.000239
	(0.000156)	(0.000112)	(0.000130)	(0.000138)	(0.000178)
Monetary policy uncertainty, 5 months before reset	8.68e-05	5.13e-05	-0.000137	3.41e-05	6.04e-05
	(0.000126)	(9.28e-05)	(8.74e-05)	(0.000137)	(0.000124)
Monetary policy uncertainty, 6 months before reset	1.03e-05	-6.84e-05	-0.000256*	3.46e-05	1.01e-05
	(0.000199)	(0.000137)	(0.000152)	(0.000193)	(0.000196)
Month of Reset					
Monetary policy uncertainty, month of reset	-0.000248*	-0.000258*	-0.000368**	-0.000331**	-0.000234*
	(0.000140)	(0.000144)	(0.000176)	(0.000134)	(0.000134)
After Reset					
Monetary policy uncertainty, 1 months after reset	0.000127	0.000118	1.78e-05	4.52e-05	0.000124
	(0.000119)	(0.000120)	(0.000150)	(0.000124)	(0.000121)
Monetary policy uncertainty, 2 months after reset	-0.000236*	-0.000247*	-0.000356**	-0.000272**	-0.000306**
	(0.000124)	(0.000136)	(0.000142)	(0.000134)	(0.000129)
Monetary policy uncertainty, 3 months after reset	-0.000140	-0.000178	-0.000272**	-0.000191	-0.000167
	(0.000127)	(0.000142)	(0.000123)	(0.000139)	(0.000125)
Monetary policy uncertainty, 4 months after reset	4.09e-05	1.07e-05	-6.39e-05	6.75e-06	-1.43e-05
	(0.000126)	(0.000132)	(0.000116)	(0.000119)	(0.000120)
Monetary policy uncertainty, 5 months after reset	0.000267	0.000234	0.000113	0.000283	0.000235
	(0.000198)	(0.000204)	(0.000176)	(0.000222)	(0.000203)
Monetary policy uncertainty, 6 months after reset	0.000347*	0.000293	0.000151	0.000321*	0.000262
	(0.000185)	(0.000184)	(0.000212)	(0.000169)	(0.000176)
Observations	3,809,141	2,329,821	2,329,821	2,329,821	2,329,821
R-squared	0.664	0.667	0.667	0.667	0.667

Table IA.3 Interest Rate Reset and Other Policy Uncertainty Measures

The dependent variable is the log of monthly credit card balances. All specifications control for the current mortgage interest rate; the current monthly mortgage interest payment (logs) and the log of the individual's credit card limit; state fixed effects and year-by-month fixed effects. The regressions also control for the interaction terms between the reset indicators with the following categorical uncertainty measures, one for each column: VIX, fiscal policy; financial regulation; sovereign crises; trade policy; entitlement policy and health care policy. The coefficient estimates of these interaction terms are reported on the following page due to the long table. The "Other uncertainty measure" in those rows refers to the corresponding control of the uncertainty measure indicated in the column header. Standard errors are clustered at the state level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Monetary policy & VIX	Monetary policy & Fiscal Policy	Monetary policy & Financial Regulation	Monetary policy & sovereign crises	Monetary policy & trade policy	Monetary policy & entitlement policy	Monetary policy & health care policy
Before Reset							
Monetary policy uncertainty, 1 month	-0.000351*	-0.00063***	-0.000401**	-0.000434*	-0.00047***	-0.000541***	-0.00065***
before reset	(0.000199)	(0.000180)	(0.000169)	(0.000220)	(0.000149)	(0.000175)	(0.000159)
Monetary policy uncertainty, 2 months	-0.000115	-0.000228	-0.000213*	-0.000356**	-0.000157	-0.000234	-0.000285*
before reset	(0.000149)	(0.000196)	(0.000123)	(0.000167)	(0.000134)	(0.000194)	(0.000163)
Monetary policy uncertainty, 3 months	-7.93e-05	-0.000323*	-7.14e-05	-0.000157	-0.000117	-0.000341**	-0.000280*
before reset	(9.37e-05)	(0.000163)	(9.16e-05)	(9.61e-05)	(9.25e-05)	(0.000156)	(0.000143)
Monetary policy uncertainty, 4 months	0.000131	-0.000122	0.000203	1.88e-05	0.000130	-5.48e-05	-2.59e-05
before reset	(0.000154)	(0.000216)	(0.000189)	(0.000139)	(0.000137)	(0.000197)	(0.000142)
Monetary policy uncertainty, 5 months	-1.41e-05	0.000269	6.38e-05	-0.000272**	6.56e-05	0.000150	0.000187
before reset	(0.000123)	(0.000206)	(0.000129)	(0.000103)	(0.000112)	(0.000211)	(0.000112)
Monetary policy uncertainty, 6 months	-4.60e-05	-0.000218	-4.82e-05	-0.000389**	-5.18e-05	-0.000284	-6.43e-05
before reset	(0.000196)	(0.000280)	(0.000149)	(0.000162)	(0.000186)	(0.000271)	(0.000294)
Month of Reset							
Monetary policy uncertainty, month of	-2.79e-05	-0.000278	-0.000250	-0.000372*	-0.000186	-0.000415**	-0.000363**
reset	(0.000158)	(0.000172)	(0.000152)	(0.000206)	(0.000131)	(0.000195)	(0.000175)
After Reset							
Monetary policy uncertainty, 1 months	0.000353***	0.000365	0.000202	-0.000434*	0.000198	0.000180	0.000256
after reset	(0.000132)	(0.000251)	(0.000133)	(0.000220)	(0.000119)	(0.000192)	(0.000192)
Monetary policy uncertainty, 2 months	-0.000261*	-4.65e-06	-0.000249**	-0.000356**	-0.000270*	8.90e-05	-0.000126
after reset	(0.000155)	(0.000202)	(0.000120)	(0.000167)	(0.000136)	(0.000195)	(0.000181)
Monetary policy uncertainty, 3 months	-0.000190	0.000107	-0.000242	-0.000157	-0.000160	0.000196	9.61e-06
after reset	(0.000198)	(0.000224)	(0.000152)	(9.61e-05)	(0.000155)	(0.000209)	(0.000177)
Monetary policy uncertainty, 4 months	-1.53e-05	0.000173	-7.88e-05	1.88e-05	4.56e-05	8.85e-05	0.000132
after reset	(0.000154)	(0.000187)	(0.000152)	(0.000139)	(0.000136)	(0.000182)	(0.000176)
Monetary policy uncertainty, 5 months	0.000241	0.000132	0.000259	-0.000272**	0.000196	0.000119	3.82e-05
after reset	(0.000209)	(0.000256)	(0.000207)	(0.000103)	(0.000235)	(0.000324)	(0.000199)
Monetary policy uncertainty, 6 months	0.000376	0.000360	0.000256	-0.000389**	0.000304	0.000396	0.000393
after reset	(0.000230)	(0.000393)	(0.000243)	(0.000162)	(0.000239)	(0.000290)	(0.000336)

(Table continues on the next page)

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VARIABLES	(1) Monetary policy & VIX	(2) Monetary policy & Fiscal Policy	(3) Monetary policy & Financial Regulation	(4) Monetary policy & sovereign crises	(5) Monetary policy & trade policy	(6) Monetary policy & entitlement policy	(7) Monetary policy & health care policy
Before Reset							
Other uncertainty measure, 1 month before reset	-0.00207	0.000117	-7.64e-05	-2.07e-05	-9.70e-05	2.92e-05	0.000107
	(0.00127)	(0.000128)	(4.95e-05)	(3.73e-05)	(0.000137)	(7.37e-05)	(7.23e-05)
Other uncertainty measure, 2 months before reset	-0.00197**	-6.38e-06	-1.96e-05	4.05e-05	-0.000346**	-3.13e-06	3.59e-05
	(0.000917)	(0.000140)	(4.76e-05)	(3.30e-05)	(0.000144)	(9.67e-05)	(8.85e-05)
Other uncertainty measure, 3 months before reset	-0.000673	0.000176	-4.66e-05	1.44e-05	1.19e-05	0.000136	0.000123**
	(0.000715)	(0.000108)	(4.49e-05)	(2.80e-05)	(0.000188)	(9.13e-05)	(6.11e-05)
Other uncertainty measure, 4 months before reset	-0.000304	0.000204	-0.000104	2.99e-05	-5.59e-05	0.000108	0.000113
	(0.000874)	(0.000191)	(9.29e-05)	(3.09e-05)	(0.000187)	(9.67e-05)	(0.000114)
Other uncertainty measure, 5 months before reset	0.000901	-0.000182	-2.24e-05	8.55e-05***	-0.000109	-5.92e-05	-0.000106
	(0.000714)	(0.000204)	(6.36e-05)	(2.16e-05)	(0.000183)	(0.000149)	(9.24e-05)
Other uncertainty measure, 6 months before reset	0.000318	0.000151	2.80e-05	9.60e-05***	9.14e-05	0.000145	2.50e-05
	(0.000944)	(0.000149)	(7.99e-05)	(2.83e-05)	(0.000153)	(8.63e-05)	(0.000116)
Month of Reset							
Other uncertainty measure , month of reset	-0.00367***	2.62e-06	-1.63e-05	3.54e-05	-0.000371*	8.34e-05	5.86e-05
	(0.000971)	(0.000120)	(4.71e-05)	(3.53e-05)	(0.000186)	(7.23e-05)	(6.85e-05)
After Reset							
Other uncertainty measure , 1 months after reset	-0.00421***	-0.000225	-9.06e-05	9.56e-06	-0.000495***	-5.10e-05	-0.000106
	(0.00117)	(0.000188)	(5.42e-05)	(3.65e-05)	(0.000164)	(0.000102)	(9.73e-05)
Other uncertainty measure , 2 months after reset	-0.000283	-0.000224**	-2.44e-05	-4.71e-06	-4.03e-05	-0.000217***	-0.000100*
	(0.00117)	(0.000109)	(4.65e-05)	(2.16e-05)	(0.000246)	(6.50e-05)	(5.64e-05)
Other uncertainty measure , 3 months after reset	0.000139	-0.000231*	5.37e-05	3.68e-05	-7.98e-05	-0.000215***	-0.000120*
	(0.00157)	(0.000127)	(4.35e-05)	(2.59e-05)	(0.000228)	(7.57e-05)	(6.12e-05)
Other uncertainty measure , 4 months after reset	0.000239	-0.000141	7.26e-05*	-6.97e-06	-0.000191	-4.97e-05	-8.23e-05
	(0.00105)	(0.000112)	(4.04e-05)	(2.59e-05)	(0.000177)	(7.36e-05)	(6.54e-05)
Other uncertainty measure , 5 months after reset	-0.000312	7.61e-05	-3.13e-05	-8.89e-06	9.27e-05	6.29e-05	0.000114
	(0.000665)	(0.000139)	(4.57e-05)	(2.11e-05)	(0.000315)	(0.000118)	(8.02e-05)
Other uncertainty measure , 6 months after reset	-0.00134	-5.11e-05	3.08e-05	4.10e-05	-5.93e-05	-5.55e-05	-5.82e-05
	(0.00174)	(0.000234)	(8.48e-05)	(3.92e-05)	(0.000405)	(0.000105)	(0.000148)
Observations	2,329,821	2,329,821	2,329,821	2,329,821	2,329,821	2,329,821	2,329,821
R-squared	0.667	0.667	0.667	0.667	0.667	0.667	0.667