Household Credit and Local Economic Uncertainty

BY MARCO DI MAGGIO, AMIR KERMANI, RODNEY RAMCHARAN AND EDISON YU[1]

Abstract

This paper investigates the impact of uncertainty on consumer credit outcomes. Individual-level data on credit-card balances and mortgages reveal strong borrower-specific heterogeneity in response to changes in an equity-based measure of county-level economic uncertainty. Low-risk borrowers reduce their credit-card balances and use of mortgage credit in response to increased localized uncertainty, while lenders expand the availability of credit to these borrowers. The opposite is obtained for high-risk borrowers. The economic magnitudes are especially large during the recent financial crisis. This evidence suggests that localized uncertainty about economic conditions might independently affect aggregate economic activity through consumer credit markets.

[1] Di Maggio: Harvard Business School and NBER (mdimaggio@hbs.edu); Kermani: University of California, Berkeley, Haas School of Business and NBER (kermani@berkeley.edu);Ramcharan: University of Southern of California, Price School of Public Policy (rodney.ramcharan@gmail.com); Yu: Federal Reserve Bank of Philadelphia (Edison.Yu@phil.frb.org). The views in this paper are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. We thank Steve Davis, Harry DeAngelo, Matt Kahn Jose Fillat, Justin Murfin as well as seminar participants at the Bank of Canada, Bank of Chile, Bank of International Settlements, BYU (Marriott School of Business), CEPR Household Finance Conference, Federal Reserve Bank of Atlanta, Federal Reserve Bank of Philadelphia, Northeastern, Santiago Finance Conference, Stanford and USC for helpful comments.

I. Introduction

Increased uncertainty usually coincides with a contraction in economic activity and credit usage. This relationship can emerge because greater uncertainty can 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)).

Narrative evidence also identify uncertainty as a powerful driver of economic fluctuations, notably around economic crises.[2] The Federal Reserve's policy experimentation that began with the 2008-2008 financial crisis ignited a debate about the potentially damaging effects of policy uncertainty on the post-crisis recovery path. The mostly aggregate statistical evidence also suggests that uncertainty might drive economic fluctuations, including during the 2008-2009 financial crisis (Jurado, Ludvigson and Ng (2015), Stock and Watson (2012)).[3] Heighted uncertainty post-crisis might also explain the observed anemic consumption and growth (Pistaferri (2016)). However, as with the narrative evidence, this aggregate evidence is difficult to interpret causally and the

[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 chemicals 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. Bloom, Baker and Davis (2015) provide further evidence, showing that firms most exposed to the public sector might be most sensitive to political uncertainty, while Kelly, Pastor and Veronesi (2015) show that political uncertainty also affects asset prices.

underlying mechanisms remain poorly understood, especially in the case of credit markets.

To help overcome the intrinsic identification challenges associated with aggregate data, this paper investigates the impact of uncertainty on consumer credit outcomes using detailed individual-level data. Consumer credit decisions are of enormous economic importance: the stock of mortgage and unsecured consumer credit in the US economy was around 13 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.[4]

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 turbulent times, do not provide sufficient local variation to identify an individual's response to uncertainty. Second, several arguments have observed that 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.[5] 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.

We use individual-level data to help overcome these inference challenges. In particular, we use two proprietary datasets that span the period before the crisis (2002-2006), the 2007-2009 financial crisis, and up through 2013—periods of remarkable quiescence and unprecedented economic uncertainty. These datasets contains 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,

[4] There is already substantial evidence that consumer credit outcomes, reflecting both supply and demand forces, shaped economic activity during and after the 2008-2009 financial crisis (Mian, Rao, and Sufi (2013), Ramcharan, Verani, and van den Heuvel (2016), Benmelech, Meisenzahl and Ramcharan (forthcoming)).

[5] 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 (2013); Ludvigson, Ma and Ng (2016); and the discussion in Kozeniauskas, Orlik and Veldkamp (2016)).

one of these datasets also link information on liabilities to detailed information on mortgage contracts. We also have separate data that comprehensively cover the mortgage market over a similar time period, including data on loan applications and the cost of mortgage credit. Together, these datasets span both the mortgage and unsecured consumer credit markets in the US.

We then exploit the spatial granularity available in the consumer credit data, constructing new measures of *localized* uncertainty—uncertainty specific to counties. These measures are derived from the excess returns of public firms and are constructed to be free of aggregate first moment shocks. They are then aggregated up to the 4-digit NAIC sector level and mapped into counties using quarterly sectoral employment data. Intuitively, this local uncertainty series captures in part the spatial and temporal variation in uncertainty due in part to local labor market risk emanating from idiosyncratic sectoral demand and technological shocks (Bloom, Floetotto, Jammovich, Saporta-Eksten and Terry (2016).

We uncover evidence that uncertainty can drive consumer credit outcomes. The economic magnitudes are most pronounced during the financial crisis and the period afterwards and there is stark heterogeneity in the impact of uncertainty across individuals depending on their credit risk. In the case of the mortgage market, increased local uncertainty is associated with a precautionary contraction in the demand for credit among high-credit-score borrowers. In contrast, for low-credit-score borrowers, the demand for mortgage credit is far less sensitive to uncertainty. This heterogeneity likely reflects the fact that high-credit-score borrowers generally face higher default costs and are less likely to engage in risk-shifting behavior when uncertainty increases (Corbae et. al (2007)).

The lender response to uncertainty mirror these results. Increased local uncertainty has no significant impact on loan denial rates for high-credit-score borrowers. As a result, the equilibrium drop in mortgage originations in these areas likely reflect the precautionary contraction in demand. But among low-credit-score borrowers, lenders respond to increased uncertainty by sharply increasing denial rates. The evidence on loan pricing comports with this differential rationing: Increased uncertainty has no significant impact on equilibrium mortgage rates in high-credit-score areas but is associated with higher rates in low-credit-score counties. A one standard deviation increase in local uncertainty in low-credit-score counties is associated with a 17 basis point increase in the average 30 year fixed rate on new loans one quarter later. Equivalently, increased uncertainty is associated with a contraction in loan demand in high-credit-score counties, but a drop in mortgage credit supply for riskier borrowers.

The unsecured consumer credit market operates differently from the mortgage market, 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 decline in the size of credit lines: 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 lines and the number of cards. While this pattern holds even in the 2002-2006 sample period, the effects of uncertainty are especially pronounced during the financial crisis and its aftermath (2007-2013).

Although these results are similar across very different credit markets, data collection methods and controls, they might still be driven by unobserved heterogeneity or be specific to the local uncertainty measure. Therefore, to facilitate better causal inference and gauge the generalizability of these results, we build on Di Maggio et. al (2015). In particular, we exploit the plausibly exogenous timing of exposure to interest rate risk in adjustable rate mortgages (ARMs) to identify the impact of uncertainty on consumer behavior.

In these ARMs, the mortgage interest rate is fixed for the first 5 years, but then adjusts to the prevailing LIBOR or Treasury rate after this period. Thus, after the reset date, borrowers' monthly payments are determined by the prevailing short-term interest rate. To wit, disposable income uncertainty increases. We exploit this variation in the timing of exposure to interest rate risk across individuals, which is predetermined five years in advance, to 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 institutional setting, we find that around the reset, when payments are subject to greater variablity, 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.

These results are not an artifact of the local uncertainty measure, nor do they reflect latent first moment shocks that are specific to the local uncertainty variable. We corroborate the main findings using the Baker, Bloom and Davis (2016) monthly newspaper-based monetary policy uncertainty index (MPU). Within the context of mortgage rate resets, the MPU index is especially apt. 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. In response to the increase in the variability of future disposable income associated with higher monetary policy uncertainty around the reset date, high-credit-score borrowers again disproportionately target a greater buffer-stock of resources by spending less than otherwise.

Taken together, the evidence in this paper suggests that economic uncertainty might significantly affect consumption and consumer credit decisions. These findings also suggest that the increase in economic and policy-related uncertainty commonly observed during and after a financial crises could independently impede the supply of credit, reducing consumption and economic activity over an extended period. The heterogeneity across credit-risk types also suggests uncertainty could drive financial constraints across the business cycle for some kinds of borrowers. These results In section 2 of the paper we discuss some of the underlying theories and data; Section 3 presents the main results and Section 4 concludes.

II. Hypothesis and Data

II.A Hypothesis

There are several channels through which uncertainty might affect consumer credit decisions. 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)). Labor market risk is also a key channel 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).[6] 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)).

Precautionary behavior can also affect credit decisions through uncertainty around asset prices and an individual's financial net-worth (Kelly, Pastor and Veronesi (2015), Pastor and Veronesi (2012). For example, during periods of high stock market volatility, households, especially those with a higher fraction of their wealth denominated in stocks, might face greater uncertainty about the value of their financial wealth. And rather than committing to a contract requiring a series of payments extending far into the future, these households might then find it

[6] 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)

optimal to target a buffer-stock of resources, postponing some credit commitments until uncertainty abates.

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)). 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 (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.

In contrast, because of their ready access to cheap and plentiful sources of external 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 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, lenders may increase credit access to those perceived to be more able to repay when risk increases (Ramcharan, Verani, and van den Heuvel (2016)).

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 the 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. This local-uncertainty measure reflects instead the idiosyncratic volatility or risk that likely affects local labor markets and individual portfolios. Direct evidence on the latter is difficult, but we provide correlations suggestive of a robust link between this equity market based local-uncertainty measure and county and sector level employment outcomes.

The empirical strategy then studies the relationship between local-uncertainty and credit decisions in both the mortgage market and the unsecured consumer credit market. These markets operate very differently and are subject to very different laws and regulations, allowing us to gauge the generalizability of the results. They also collectively represent about 90 percent of the overall US consumer credit market. In both markets, we also have access to comprehensive datasets that span the financial crisis as well as the periods before and after. Because of this level of detail, we can control for myriad aggregate and local economic conditions—first moment shocks—and establish associations between local uncertainty and credit decisions that are robust across very different data generating processes.

However, proprietary data from Black Box Logic merged with Equifax (BBL) offers powerful direct causal evidence of the impact of uncertainty on consumer behavior. The BBL dataset consists of borrowers with adjustable rate mortgages (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 uncertainty: The ARM resets 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.

We use this data generating process to study the response of the individual's monthly credit card balances to local-uncertainty in the period around the interest rate reset (Di Maggio et. al (2016)). Because the variation in the timing of exposure to interest rate uncertainty across individuals is predetermined some five years prior, these responses plausibly reflect the causal impact of uncertainty on credit decisions. This identification strategy—the focus on the change in interest rate exposure—also suggests very specific sources of uncertainty and it allows us to gauge further the generalizability of these findings to other measures of uncertainty. In particular, monetary policy uncertainty is likely to be most relevant for consumer decision making when interest rate exposure is imminent. We next describe the various datasets before turning to these specific tests.

II.B Data

Measuring Uncertainty

Because labor market risk and exposure to financial assets—the key channels through which economic uncertainty might affect credit decisions—varies substantially across space, this subsection develops a time varying county-level measure of economic uncertainty that is likely free of aggregate credit market and other first moment shocks—henceforth referred to as local uncertainty. The measure captures the variance in idiosyncratic demand or technological shocks within local labor markets.

For each public firm, we first remove the systematic component in daily excess returns by regressing excess stock returns on an augmented three factor model: returns of the S&P 500 index, the book to market ratio, and relative market capitalization (Fama and French (1992)); because we are especially concerned about mismeasurement due to "first moment" aggregate credit shocks, which might influence individual credit outcomes, we also include the TED spread and the 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. The residuals from these regressions are unlikely to include aggregate first moment shocks, such as time-varying shocks to financing constraints, but instead contain firm-level idiosyncratic demand or technological shocks.

The second step computes the daily industry portfolio residual returns by weighting the daily residual returns of firms by their 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 (Gilchrist, Sim, and Zakrajšek (2014)). 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. 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 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 variation in both the aggregate VIX and the local uncertainty index. It plots the time variation in the local uncertainty index at different points in its distribution—the 10^{th}, 50^{th} and 90^{th} percentiles in each quarter—along with the VIX. While the 2008-2009 crisis is associated with a significant increase in the VIX, county-quarter observations at the 10^{th} percentile of the local index experienced a far smaller increase in the index. The 90^{th}-10^{th} percentile spread in the local index also increased by a factor of three, suggesting that because of differences in employment patterns and other factors, some counties were far more exposed to the crisis and fluctuations in economic uncertainty than others.

The simple correlations in Table 1 also reveal more 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 BBD index. The latter is a times series indicator of policy uncertainty developed by Baker, Bloom and Davis (2016). That is, for some counties, the local-uncertainty index does not mirror mechanically aggregate uncertainty, but likely contains information about economic uncertainty relevant for the local area.

That said, the local uncertainty series is likely measured with error. Sectoral idiosyncratic volatility is derived solely from public firms, but mapped into the county-quarter dimension using QCEW employment data 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. Similarly, if the local uncertainty series is driven by firm-specific rather than sector specific shocks, the series may also mis-measure sectoral uncertainty. 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 for individual credit outcomes.

However, the establishment-level evidence in Bloom et. al (2014) connecting equity market volatility to establishment-level productivity shocks does suggests that equity market measures might contain relevant information about local uncertainty. We build on this evidence and before examining the impact of local uncertainty on consumer credit decisions, we first show that the empirical relationship between the local uncertainty measure and employment outcomes is broadly consistent with predictions from the theoretical literature. [7]

[7] 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.

In column 1 of Table 2A, the dependent variable is the log number of employees in each sector in each quarter, beginning 2000 Q1 through 2015 Q4, for both public and private firms—the data are from the QCEW. There are 313 sectors at the NAIC four digit level of disaggregation. The regressor of interest is the sector specific uncertainty series: The standard deviation of the weighted daily residuals for public firms operating in the same 4-digit NAIC sector; 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 year and quarter fixed effects. Firm employment decisions might respond with some lag to uncertainty, and in column 1, 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 decline in the level of employment three quarters later, and up to a 2.1 percent drop one year later. Column 2 examines this relationship at an annual frequency. A one standard deviation increase in sectoral uncertainty is associated with a 3 percent decline in sectoral employment one year later. All this suggests that notwithstanding measurement error at the sectoral level, an equity market derived measure of uncertainty might be related to broader labor market outcomes.

We next examine the relationship between the local uncertainty series and employment outcomes at the county level. The dependent variable in column 1 of Table 2B is the quarterly growth in total QCEW employment in the county, and 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 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 $d_{jt} = \sum_i s_{ijt}\left(g_{ijt} - \overline{g_{Jt}}\right)^{0.5}$.

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

The analyses focus on mortgage and consumer credit decisions. According to the Federal Reserve's Flow of Funds data, these two sources of credit account for approximately 13 trillion dollars or about 90 percent of total consumer liabilities in 2015.[8] Our various data sources are representative of these two very different credit markets, and together comprehensively cover the US consumer credit market.

Mortgage Credit: Loan Processing Service (LPS) and Home Mortgage Disclosure Act (HMDA)

Data from HMDA record the universe of mortgage credit applications and outcomes for non-rural Metropolitan Statistical Areas in the United States. Data on applications as well as loan origination outcomes can help gauge the impact of uncertainty both on the demand for mortgage credit as well as the supply response of lenders. These data include key borrower characteristics like income, race, census tract of the property and loan amount; the loan application is linked to the bank in many cases. We collected these data annually from 2004-2013, yielding some 72 million mortgage credit applications. Unfortunately, while HMDA provides information on quantities, it does not consistently record interest rates. We thus turn to county-level quarterly data from LPS—a proprietary source of mortgage data derived from seven of the largest mortgage loan processers. We use these data to construct the average interest rate, weighted by loan shares, for newly originated mortgages. The panel in Figure 2 presents denial rates and median applicant income over time (HMDA), and mortgage interest rate spreads (LPS) over 2004-2013.

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

Consumer Credit: NY Federal Reserve's Equifax Consumer Credit Panel and Black Box Logic

We draw a two percent sample from the New York Federal Reserve's Equifax Consumer Credit Panel (Equifax). This is a proprietary consumer credit dataset, and the sample results in a balanced panel of about 220,000 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; census tract 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 lines to measure consumer credit. We supplement Equifax with proprietary data from Black Box 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 the Equifax and BBL. The Equifax panel is more representative of the general credit-using population, and contains information on non-homeowners and homeowners alike. The average credit card limit in Equifax is around $13,500 while the average credit card balance is a little less than half that number. 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, Black Box 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 (2008 Q1-2013Q4) 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 (2016)). 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.

III. Main Results

IIIA. Local Uncertainty and Mortgage Credit

This subsection studies the impact of local uncertainty on the mortgage market. Table 4A uses the HMDA applications data over the period 2004-2013 to study the relationship between uncertainty and mortgage credit demand. To proxy for demand, the dependent variable in Table 4A is the total log volume of mortgage credit contained in mortgage applications within the county in a calendar year. Column 1 uses the full sample period: 2004-2013. Controls include standard demographic and income variables from the American Community Survey, including the log of population and area, all observed between 2007-2010, along with year and state fixed effects; standard errors are clustered at the state-level and all county-level regressions are weighted by population. For the full sample period, there is no evidence of a robust statistical relationship between local uncertainty and these proxies for mortgage credit demand.

The financial crisis and the period afterward saw unprecedented experimentation in monetary policy and large scale regulatory changes to the financial system, including regulations that govern consumer credit, e.g. establishment of the Credit Financial Protection Bureau (CFPB). It was thus a period of extraordinary uncertainty, and there is already evidence that this uncertainty might have affected mortgage markets (Gissler et. al (2016). Indeed, Figure 4 shows that the relationship between local uncertainty and the demand for mortgage credit changed sharply over the sample period. Therefore, we focus on this turbulent time period to provide further evidence on the role of uncertainty in shaping consumers' credit decisions.

In column 2, we focus on the 5 year panel that begins in 2009 through 2013. A one standard deviation increase in the local uncertainty index is associated with a 5.4 percent drop in the amount of mortgage credit demanded in loan applications. The estimates in column 2 are economically important. Using the local uncertainty index coefficient in column 2, we use the variation in the index to compute the predicted drop in the volume of mortgage credit demanded. Over the 2009-2013 sample period, this point estimate suggests a $141 billion decline or about a $28.4 billion per annum drop in the volume of mortgage credit sought by potential borrowers.

Mortgage loan applications are an imperfect proxy for loan demand, as these results could reflect borrowers' anticipation of a decrease in credit supply. We thus use the variation in borrower credit risk across counties in order to understand better the negative relationship between local uncertainty and the loan demand proxy. This approach builds on the fact that borrowers with high credit scores are less likely to face a decline in credit supply. And any negative relationship between the local uncertainty series and loan applications for this subsample is more likely to reflect precautionary behavior in response to uncertainty.

The incentives confronting low-credit-score borrowers are different from the high-credit-score subsample. Low-credit-score borrowers are more likely to face credit constraints when uncertainty increases. Anticipatory behavior then can lead to an bigger drop in applications from this sub-sample when local uncertainty increases. However, heightened risk-shifting incentives among this group can generate the opposite result. Given their lower default cost, riskier borrowers may be more inclined to increase their demand for mortgage debt when uncertainty increases, or evince significantly less sensitivity to increased risk compared with high-credit score borrowers. HMDA does not identify the applicant's credit score. But we use data from TransUnion to split the sample into counties where the median credit score is above or below 680—the national median credit score reported in TransUnion. Credit scores are endogenous to the business cycle, and we use TransUnion credit score data in 2006 to conduct the 2009-2013 sample splits.

Consistent with the demand interpretation, local uncertainty has a significantly larger negative impact on loan demand among the high credit score sample. A one standard deviation increase in local uncertainty is associated with about a 7 percent drop in loan volume demand among the high credit score sample (column 3). The effect is about 2 percentage points smaller in the low credit score sample (column 4). These differences persist even when using county fixed effects to absorb relevant time invariant county unobservables (columns 5 and 6).

The decline in house prices during this period was primarily concentrated in low-credit-score areas during this period. Because of this difference across the two samples in the price of houses, the volume of credit demanded as the dependent variable could mechanically understate the extent of the heterogeneous response to uncertainty across risk scores. Table 4B thus replicates the analysis using the log number of loan applications inside the county as the dependent variable. The differences across the two samples are now much larger. From columns 5 and 6, a one standard deviation increase in local uncertainty is associated with a 7.9 percent drop in the number of loan applications in the high credit score sample; the effect is about 4.3 percentage points smaller in the low credit score sample.

Table 5 uses the individual-level application data to study the supply response of lenders to local-uncertainty. We focus first on the extensive margin. The dependent variable in column 1 is the probability that a loan application is denied. We use the full sample of loans available over the 2009-2013 period, about 21 million loan applications. The individual-level application data allow us to control for important borrower characteristics such as the log of borrower income; the log of the requested loan amount; race and gender. We also use county and year fixed effects and cluster standard errors at the state-level.

From column 1, holding constant key borrower and county-level characteristics, local uncertainty is positively associated with a decline in mortgage loan supply. The point estimate suggests that a one standard deviation increase in local uncertainty is associated with a 0.2 percentage point increase in the probability that a loan is denied; the mean unconditional probability of denial is 11 percent in the sample period.

But lender responses to uncertainty at the extensive margin differ markedly across borrower credit risk, almost mirroring the demand results in Tables 4A and 4B. Column 2 of Table 5 restricts the sample to counties with median FICO scores above the 680 national median. In this sample, the local uncertainty point estimate drops by about 10 percent in magnitude and is no longer statistically significant. In contrast, this point estimate increases by about 10 percent when using the sample of individuals living in counties with median FICO scores below the 680 national median (column 3). These differences become even more dramatic when restricting the sample to individuals living in subprime counties: Counties where the median FICO score is less than 660. The local uncertainty point estimate doubles relative to the full sample (column 4).

When taken together, this evidence shows that while low-credit risk borrowers disproportionately reduce their demand for mortgage credit in response to increased local uncertainty, lenders disproportionately restrict credit at the extensive margin for borrowers likely to be perceived as high risk. These differential responses can affect both the quantity of loan origination and the cost of credit at the intensive margin. In equilibrium for example, this pattern of evidence implies that in low-credit risk counties, increased uncertainty might be associated with a drop in loan originations, while the cost of credit might be little affected.

Table 6 investigates the relationship between local uncertainty and equilibrium credit outcomes in the mortgage market. The dependent variable in column 1 is the log value of mortgages originated inside the county within the year. The sample period is 2009-2013 and we use county and year fixed effects, with standard errors clustered at the state level; all regressions are weighted by county population. Using the full sample of counties, the relationship between local uncertainty and the volume of originated credit is significant and negative. A one standard deviation increase in local uncertainty is associated with a 7 percent drop in originated volumes.

Moreover, the pattern of evidence remains the same. The impact of local uncertainty on loan volumes is considerably larger in high-credit-score counties. From column 2, a one standard deviation in uncertainty suggests a 10 percent drop in loan volumes. Given that lenders do not appear to significantly restrict credit in these counties in response to local uncertainty (Table 5), much of this collapse likely reflects a precautionary contraction in loan demand. In the low credit score counties (column 3), the economic impact of uncertainty is about half that obtained in column 2.

The evidence on the average price of newly originated mortgage credit continues to suggest that the negative impact of local uncertainty on loan originations likely reflects decreased demand in high credit score counties but a contraction in loan supply in the low credit score counties. LPS reports the loan weighted average interest rate inside a county at the quarterly frequency, and the dependent variable in column 4 is the average mortgage interest rate for newly originated loans in high credit score counties. The sample period is 2009 Q1 through 2013 Q4, and we use county and year-by-quarter fixed effects, and cluster standard errors at the state-level.

We exploit the higher frequency LPS data and include up to two lags of the local uncertainty and local returns series. For the subsample of high credit score counties, the local uncertainty point estimate is statistically and economically insignificant. In contrast, for the low credit score counties, a one standard deviation increase in local-uncertainty is associated with a 17 basis point increase in the average cost of mortgage credit the next quarter inside the county (column 5).

Both the individual and county-level associations drawn from different data sources and collection methods suggest that increased uncertainty can affect mortgage credit at both the extensive and intensive margins. Default costs and underlying risk-shifting incentives across borrowers appear to be the main mechanism. Increased local uncertainty appears to increase the precautionary demand for financial flexibility among high credit score borrowers, making these borrowers far less willing to demand mortgage credit. Lenders respond to local uncertainty mainly by cutting mortgage credit supply to low credit score areas and the equilibrium cost of credit also increases.

However, other channels could be at work. Most notably, liquidation values for homes could decline in response to increased uncertainty within a county. This variation in the underlying collateral value could also help explain bank and borrower behavior at the different margins. And since HMDA does not directly report borrower credit scores, inference based on county-level median scores cannot exclude these other possible mechanisms. Therefore, 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, including credit scores, that can help us isolate better the underling mechanism.

IIIB. Local uncertainty and consumer credit

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 individual-level observables such as age, and the previous year's average Equifax Risk score, along with individual fixed effects and year-by-quarter fixed effects; individual fixed effects absorbs possibly time invariant individual level factors such as risk aversion, 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 line 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 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 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. From column 2, 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 5.5 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 10.45 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 4.02 percent increase in the size of credit lines.

Column 4 uses the log of the number of credit cards as the dependent variable. Among high risk borrowers, a one standard deviation increase in local-uncertainty is associated with a 1.1 percent decline in the number of active cards. But among the above median Risk score individuals, the implied impact suggests a 0.8 percent increase in the number of cards—these borrowers increase their buffer stock of liquidity when uncertainty rises. Therefore, while increased uncertainty appears to be associated with an increase in spending and a decline in consumer debt capacity among the less credit worthy borrowers—an increase in credit utilization—the exact opposite appears to be the case for low risk borrowers.

To understand how these results might vary across the pre-crisis period as well as the period incorporating the financial crisis and its aftermath, we take advantage of the longer time period in Equifax to split the sample between the relatively quiet 2002Q1-2006Q4 period and 2007Q1-2013Q4. Table 8 shows that the effects of uncertainty on credit decisions remain statistically significant across the two sample periods, but the economic magnitudes are considerably larger during the more turbulent 2007Q1-2013Q4 period. For example, in column 2, a one standard deviation increase in the local uncertainty index suggests a 4.3 percent decline the size of credit lines—6 percentage points less than in 2007-2013; and the implied increase in credit lines among the high Risk score borrowers is about half that of the crisis sample. Taken together, these results suggest that while uncertainty features in consumer credit decisions, its effects might be especially strong during a financial crisis and its aftermath.[9]

Because the local uncertainty measure is derived from financial market volatility, differences across individuals in their exposure to equity and financial markets can further identify the impact of uncertainty on consumer credit decisions. This approach is motivated by the fact that for individuals whose net worth is mainly comprised of financial assets, increased uncertainty derived from equity markets will likely have a bigger impact on their net worth. Standard arguments then observe that these individuals would be more likely to postpone entering into longer-term debt contracts like mortgages and other credit arrangements. In contrast, for individuals whose net worth contains relatively little financial assets, their credit decisions might be less sensitive to economic uncertainty, as measured by the fluctuations in stock prices.

Unfortunately, while the Equifax panel includes rich information on liabilities, it contains no data on assets. We can however construct indirect tests of this hypothesis by matching zip code level tax data from the IRS to the location of the individual in the Equifax panel. For each zip code, the IRS reports the number of income tax returns, total income from salaries and wages; and importantly, total

[9] 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 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.

income from ordinary dividends and net capital gains. Using this data, we can compute the ratio of dividends and net capital gains to total adjusted income.

In cases where individuals have little exposure to financial markets, this ratio is likely to be close to zero in those zip codes. While in zip codes where individuals have larger financial portfolios, we would expect this ratio to be larger. We use the 2005 tax year version of this dataset. There is substantial variation in this ratio across zip codes. For the median zip code in the sample, capital gains and ordinary dividends account for about five percent of adjusted gross income. But in the top decile, this ratio more than doubles, while in the bottom decile of zip codes, the ratio of net capital gains and ordinary dividends to adjusted gross income is about 1.5 percent.

Moreover, we can exploit the geographic information in Equifax and match the tax data to both zip code and age in order to measure better an individual's potential exposure to uncertainty. There is considerable evidence that exposure to equity markets fluctuates over the life cycle (Calvet, Campbell and Sodini (2007, 2009). Agents gradually accumulate assets early in their life cycle, increase their exposure to equity markets mid-life, and then gradually shift their portfolios towards less risky assets nearing retirement. Individuals in mid-life then would likely be maximally exposed to equity market based measures of uncertainty. And if our results reflect the impact of financial market uncertainty on debt decisions, then we would expect that individuals in their 40s and 50s who live in an above median zip code should evince the greatest sensitivity to equity market uncertainty.

To implement this test, we create indicator variables for whether an individual lives in a zip code with an above median ratio of capital gains and dividend income to adjusted gross income. We then interact this indicator with the uncertainty and returns series. Because this tax ratio might proxy for income differences, we also include an analogous indictor for whether an individual lives in a zip code with an above median income, and create interaction terms based on this variable as well. We then estimate separately this specification by age categories.

The estimates from these specifications are in Table 9. They suggest that exposure to financial markets might be another key channel through which this source of uncertainty affects credit decisions. In particular, we focus on the log of credit card balances, where we continue to control for borrowing capacity and the other baseline controls in Table 6, column 2. An increase in local uncertainty is associated with a significant decline in credit card balances among individuals in their 50s—those likely to be at the peak of their exposure to financial markets—as well as among individuals in their 70s—those most likely to be retired and dependent on financial markets for their income. During the period 2002-2006, these results vanish (Table 10), suggesting again that the effects on uncertainty on credit decisions might be especially powerful during a financial crisis and its aftermath.

III. Identification through Mortgage Contract Design

The accretion of evidence suggests that local-uncertainty impacts consumer debt decisions. However, the variation in the local uncertainty measure is non-random and we cannot be certain whether these results reflect uncertainty, related county-level first moment shocks or some other unobserved feature of decision making. Even if these results reflect the causal impact of uncertainty, it is possible that they might be specific to the form of uncertainty used in the analysis, and might not generalize easily to other uncertainty measures.

To address these concerns, we turn to the exogenous timing of the interest rate resets in a large panel of adjustable rate mortgage (ARMs) contracts to isolate better the causal impact of economic uncertainty on individual spending decisions (Di Maggio, Kermani and Ramcharan (2016)). Specifically, our sample consists of borrowers with adjustable rate mortgages (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 adjustable rate mortgage contracts can help causally identify the role of uncertainty. After the reset, borrowers experience a sizeable decline in monthly mortgage payments, and this can boost current spending (DiMaggio et. al (2016)). 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.

We would therefore expect that an increase in local uncertainty—greater employment or portfolio risk—might then moderate a borrower's spending response around the mortgage reset window. For example, in response to increased local uncertainty, a borrower with high default cost— a high credit score—might spend less in order increase financial flexibility during the reset window relative to other time periods and otherwise similar borrowers who are exposed to less local 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 mortgage payments.

Moreover, because the decision to obtain a mortgage in our sample precedes current spending and credit decisions by some 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 on 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 monthly mortgage payments and 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 adjust easily 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 be 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.[10] Liquidity constraints or habit

[10] For the various measures of uncertainty, Table IA4 reports the results from a series of 6th order autoregressive models using monthly data. For some types of uncertainty, there is evidence of persistence, but this is limited to the two month

persistence could also delay any consumption response to the local uncertainty shocks until very close to the reset date.

In column 1 of Table 11A, 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 is positively associated with larger balances two quarters after the reset. But 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 full 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, only slightly less than the OLS results obtained using the full Equifax sample over the same time period.

Also in keeping with our previous results, borrowers with below median FICO 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 important for consumer credit decisions. Nevertheless, these results could be an artifact of the local uncertainty measure, or reflect some latent first moment shock that co-moves with this particular local uncertainty variable.

Therefore, rather than the local uncertainty index, we now use 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 uncertainty words. It is also likely to affect credit decisions through a very different channel than the local uncertainty measure. An increase in monetary

horizon. That is, while some types of uncertainty might be forecastable, these simple AR(6) models suggest that this forecastability might be limited, at least beyond the two month horizon.

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, high credit score borrowers should target greater financial flexibility, and we should expect to observe a decline in credit card balances for this subsample when monetary policy uncertainty increases. The monthly frequency of the MPU series can also help us understand better the timing of an individual's response to uncertainty.

The difference-in-difference results using the monthly MPU series for the full sample of borrowers are in Table 11B; 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 economic magnitudes are large. 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 FICO 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.

Table 12 considers 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 12, the impact of 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. The MPU results are unchanged. As a further robustness check, column 3 includes interaction terms with the 10-year Treasury rate. 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 next control for realized interest rate volatility using the monthly standard deviation of the three-month Treasury computed daily (column 4) and the 10 year Treasury (column 5). The evidence continues to strongly suggest that increased MPU around the reset date, especially the month before the reset, tends to have a large negative impact on credit card balances.

We now include other standard time series indicators of uncertainty within the difference-in-difference framework. Column 1 of Table 13 adds the VIX and the related reset-timing interaction terms 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 positive sign. The MPU variable is however little changed. The remaining columns of Table 13 uses 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.

IV. Conclusion

This paper has used several comprehensive individual-level datasets of debt and credit decisions to understand the role of economic uncertainty in shaping these decisions. To identify better the role of uncertainty in individual-level credit decisions, we also created a new equity-based measure of local uncertainty at the county level. 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. Specifically, in both the mortgage and unsecured credit markets, high-credit-score decrease their demand for credit, cutting back on mortgage applications and credit card balances. Lenders however either maintain the supply of credit, or in the case of credit cards, increase credit lines. To wit, these high-credit-score borrowers appear to target successfully higher liquidity when uncertainty increases.

Risk shifting best describes the response of low-credit-score borrowers to increase uncertainty. Their mortgage applications decline by far less when uncertainty increases, while lenders ration mortgage credit more aggressively. Similarly, the credit card balances of low-credit-score borrowers increase with uncertainty, while their credit lines are cut. These effects are especially strong during financial crisis and its aftermath, and they suggest not only that uncertainty might drive economic fluctuations, in part through credit markets, but these effects can vary starkly across individuals.

V. Tables and Figures

TABLE 1. LOCAL AND AGGREGATE UNCERTAINTY, CORRELATIONS

Correlation, 2002-2013					
	Local Uncertainty, 10th percentile	Local Uncertainty, 50th percentile	Local Uncertainty, 90th percentile	VIX	BBD Index
Local Uncertainty, 10th percentile	1.00	0.96	0.76	0.71	0.08
Local Uncertainty, 50th percentile	0.96	1.00	0.84	0.75	0.17
Local Uncertainty, 90th percentile	0.76	0.84	1	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, 10th percentile	Local Uncertainty, 50th percentile	Local Uncertainty, 90th percentile	VIX	BBD Index
Local Uncertainty, 10th percentile	1.00	0.37	0.24	-0.15	-0.42
Local Uncertainty, 50th percentile	0.37	1.00	0.92	0.42	0.44
Local Uncertainty, 90th 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

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).

TABLE 2A. SUMMARY STATISTICS: BASIC CORRELATIONS BETWEEN SECTORAL UNCERTAINTY AND EMPLOYMENT

	Log employment in sector	
	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 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

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.

TABLE 2B. SUMMARY STATISTICS: BASIC CORRELATIONS BETWEEN LOCAL UNCERTAINTY AND COUNTY-LEVEL EMPLOYMENT OUTCOMES

	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

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.

TABLE 3. SUMMARY STATISTICS

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	47.6	696.6	187653.8	16738.1	6195.4	0.71
Median	48	724	133434	12500	3042	0.88
25th percentile	35	620	75867	5000	1016	0.45
75th percentile	59	789	228074	21990	7563	1.00
min	18	284	55	1	3	0.00
max	80	841	8938310	817704	239832	1.00
Std Deviation	15.78	108.64	217628.64	20653.21	10700.26	0.34

Black Box Logic, 2005-2013

	Vantage Risk Score	Credit Card Balance	Credit Card Limit	Utilization Rate: Balance/Limit	Loan to Value Ratio, Origin	Interest Rate, Origin	Mortgage, Origin
Mean	736.87	11280.41	34027.33	0.35	77.09	5.85	362291.74
Median	719.00	5096.00	24700.00	0.27	80.00	6.38	293000.00
25th percentile	690.00	799.00	10080.00	0.07	75.00	5.75	186918.42
75th percentile	754.00	14573.00	47273.00	0.59	80.00	6.88	467461.67
min	658.00	0.00	0.00	0.00	5.00	0.00	10000.00
max	9999.00	912240.00	1005712.00	2.47	148.53	14.00	8196501.00
Std Deviation	356.67	18053.91	34742.87	0.32	10.05	2.13	271928.36

TABLE 4A. LOCAL-UNCERTAINTY AND MORTGAGE CREDIT DEMAND: LOAN AMOUNT DEMANDED

	(1)	(2)	(3)	(4)	(5)	(6)
	2004-2013	2009-2013				
VARIABLES		Full Sample	High credit score	Low credit score	High credit score	Low credit score
					County-fixed effects	
local-uncertainty	-3.174	-13.63**	-17.54**	-12.90*	-15.38***	-8.923**
	(6.011)	(6.043)	(7.033)	(7.116)	(5.686)	(3.881)
Observations	28,632	14,316	6,746	7,570	6,746	7,570
R-squared	0.981	0.985	0.986	0.988	0.998	0.998

The unit of observation is the county-year. The dependent variable is the total volume of mortgage credit listed in loan applications in each county-year. Columns 1-4 includes demographic variables observed in 2007-2010 from the American Community Survey: Log of African-American population; white population; total population; area of county; median income; Gini coefficient; as well as year and state fixed effects. Columns 5 and 6 use county fixed effects and year fixed effects. All columns also include local returns. The point estimate on local uncertainty in column 2 is statistically different from the full sample in column 1: estimating the full sample and allowing the coefficient on local-uncertainty and weighted local returns to differ during the 2009-2013 time period yields an interaction term with a coefficient of -29.46 (p-value=0.03) in the case of local-uncertainty; the corresponding interaction term on local weighted returns is not significant. "High credit score" denotes the sample of counties where the median credit score in the county in 2006 is higher than 680—the median credit score across all counties in 2006. "Low credit score" is the sample of counties where the median credit score in the county in 2006 is less than 680. Each regression is weighted by population. Standard errors (in parenthesis) are clustered at the state level and *** p<0.01, ** p<0.05, * p<0.1.

TABLE 4B. LOCAL-UNCERTAINTY AND MORTGAGE CREDIT DEMAND: NUMBER OF LOAN APPLICATIONS

	(1)	(2)	(3)	(4)	(5)	(6)
	2004-2013	2009-2013				
VARIABLES		Full Sample	High credit score	Low credit score	High credit score	Low credit score
					County-fixed effects	
local-uncertainty	-7.334	-12.64	-23.92***	-2.774	-19.58**	-8.426*
	(7.668)	(8.419)	(7.889)	(10.33)	(9.231)	(4.890)
Observations	28,630	14,316	6,746	7,570	6,746	7,570
R-squared	0.981	0.982	0.982	0.986	0.997	0.997

The unit of observation is the county-year. The dependent variable is the total number of mortgage applications submitted in each county-year. Columns 1-4 includes demographic variables observed in 2007-2010 from the American Community Survey: Log of African-American population; white population; total population; area of county; median income; Gini coefficient; as well as year and state fixed effects. Columns 5 and 6 use county fixed effects and year fixed effects. All columns also include local returns. The point estimate on local uncertainty in column 2 is statistically different from the full sample in column 1: estimating the full sample and allowing the coefficient on local-uncertainty and weighted local returns to differ during the 2009-2013 time period yields an interaction term with a coefficient of -29.46 (p-value=0.03) in the case of local-uncertainty; the corresponding interaction term on local weighted returns is not significant. "High credit score" denotes the sample of counties where the median credit score in the county in 2006 is higher than 680—the median credit score across all counties in 2006. "Low credit score" is the sample of counties where the median credit score in the county in 2006 is less than 680. Each regression is weighted by population. Standard errors (in parenthesis) are clustered at the state level and *** p<0.01, ** p<0.05, * p<0.1.

TABLE 5. LOCAL-UNCERTAINTY AND MORTGAGE CREDIT SUPPLY: PROBABILITY OF APPLICATION DENIAL

	(1)	(2)	(3)	(4)
VARIABLES	Full Sample	high credit score	low credit score	subprime
local-uncertainty	0.983**	0.868	1.091*	1.925**
	(0.433)	(0.521)	(0.626)	(0.825)
Requested loan amount, logs	-0.0333***	-0.0228***	-0.0430***	-0.0502***
	(0.00528)	(0.00273)	(0.00801)	(0.00746)
Applicant income, logs	-0.0401***	-0.0388***	-0.0412***	-0.0443***
	(0.00238)	(0.00230)	(0.00328)	(0.00407)
male	0.00688***	0.00670***	0.00668***	0.00605***
	(0.000969)	(0.000843)	(0.00159)	(0.00193)
white	-0.0384***	-0.0269***	-0.0476***	-0.0541***
	(0.00485)	(0.00371)	(0.00583)	(0.00595)
Local returns	0.450	-0.192	0.652	-2.959
	(1.810)	(1.955)	(2.656)	(3.325)
Observations	21,374,080	10,651,505	10,722,575	6,758,504
R-squared	0.042	0.027	0.052	0.062

The dependent variable equals 1 if an individual loan application is denied, and 0 if approved by the lender. “Male” and “White” are indicator variables for gender and race respectively. “high credit score” denote the sample of borrowers in counties with median FICO scores above 680; “low credit score” denote the sample of borrowers in counties with a median FICO score less than 680. Subprime includes the sample of borrowers in counties with a median FICO score below 660. FICO scores are observed in 2006. All regressions include county and year fixed effects, and standard errors (in parenthesis) are clustered at the state-level. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 6. LOCAL-UNCERTAINTY AND MORTGAGE CREDIT: LOAN ORIGINATION AND PRICE

	(1)	(2)	(3)	(4)	(5)	(6)
	Mortgage origination volume, log			Average interest rate on new mortgages		
VARIABLES	full sample	high credit score	low credit score	full sample	high credit score	low credit score
Local-uncertainty, year average	-15.04***	-20.75***	-9.995*			
	(3.737)	(3.880)	(5.278)			
Local-uncertainty, contemporaneous quarter				-11.19	-16.34	-0.683
				(11.98)	(17.22)	(4.474)
Local-uncertainty, 1 quarter lag				7.991***	3.082	12.30***
				(2.660)	(3.708)	(3.590)
Local-uncertainty, 2 quarter lag				0.279	-0.136	0.612
				(4.555)	(4.137)	(6.103)
Observations	15,474	7,646	7,758	31,048	17,286	13,762
R-squared	0.994	0.993	0.995	0.889	0.902	0.876

The dependent variable in columns 1-3 is the log total volume of mortgages originated within a county-year period; the panel extends from 2009-2013. Columns 1-3 also include "local returns" and year and county fixed effects as controls. Column 2 restricts the sample to "high credit score" denote the sample of borrowers in counties with median FICO scores above 680; "low credit score" denote the sample of borrowers in counties with a median FICO score less than 680. FICO scores are observed in 2006. In columns 4-6, the dependent variable is the loan-size weighted average interest rate in the county-quarter; the sample period extends from 2009 Q1-2013 Q4.. Controls include local returns, up to two lags, county fixed effects and year-quarter fixed effects. Standard errors are clustered at the state-level. Column 5 restricts the sample to the set of counties with median FICO scores above 680 (observed in 2006). Column 6 restricts the sample to the set of counties with median FICO scores below 680 (observed in 2006). Standard errors (in parenthesis) are clustered at the state level and all regressions are weighted by population. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 7. LOCAL-UNCERTAINTY AND CONSUMER CREDIT DECISIONS, 2002Q1-2013Q4

	(1)	(2)	(3)	(4)
	Credit Card Balances, log	Credit Card Balances, log	Credit Card Limit, log	No of Credit Cards, log
Local uncertainty	-2.14	7.38***	-6.67**	2.01*
	(2.33)	(2.73)	(2.62)	(1.12)
Local uncertainty*Low Risk Borrower		-15.1***	-4.12**	-8.14***
		(1.19)	(1.94)	(0.62)
Credit Card Limit, log	0.080***	0.082***		
	(0.0035)	(0.0035)		
Observations	5617195	5601041	7269576	7269576
R-squared	0.589	0.590	0.438	0.537

This table examines the impact of local uncertainty on consumer credit outcomes from Equifax over the sample period 2002 Q1-2013 Q4. 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 2-4 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 2-4 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. The full table is available in a supplementary online appendix.

TABLE 8. LOCAL-UNCERTAINTY AND CONSUMER CREDIT DECISIONS, CRISIS AND QUIESCENT PERIODS

	(1)	(2)	(3)	(4)	(5)	(6)
	2007Q1-2013Q4			2002Q1-2006Q4		
	Credit Card Balances, log	Credit Card Limit, log	No of Credit Cards, log	Credit Card Balances, log	Credit Card Limit, log	No of Credit Cards, log
Local Uncertainty	7.86**	-9.57***	-1.16	12.7***	-3.09	3.65***
	(3.07)	(2.90)	(0.97)	(3.01)	(3.63)	(1.14)
Local Uncertainty*Low Risk Borrower	-12.8***	7.53***	0.68*	-27.3***	8.82***	-7.35***
	(1.06)	(1.26)	(0.36)	(1.08)	(1.03)	(0.29)
Observations	3109246	4181333	3099233	2488673	3086794	3086794
R-squared	0.686	0.550	0.651	0.673	0.577	0.758

This table examines the impact of local uncertainty on consumer credit outcomes from Equifax over the crisis period 2007 Q1-2013 Q4 and the quiescent period 2002 Q1-2006 Q4. 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. 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. Local returns is also interacted 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. Columns 1 and 4 also include the log of the credit card limit as a regressor. Standard errors are clustered at the state-level. *** p<0.01, ** p<0.05, * p<0.1. The full table is available in a supplementary online appendix.

TABLE 9. LOCAL UNCERTAINTY AND FINANCIAL MARKET EXPOSURE, 2007Q1-2013Q4.

	(1)	(2)	(3)	(4)	(5)	(6)
	Age 20s	Age 30s	Age 40s	Age 50s	Age 60s	Age 70s
Local weighted returns	-26.7	-21.9	-36.5*	-7.85	-14.1	-24.1
	(50.6)	(22.3)	(21.1)	(22.1)	(26.1)	(35.9)
Local Uncertainty	-2.79	-3.83	-0.83	-2.14	4.13	12.1
	(9.93)	(3.45)	(5.68)	(5.09)	(5.26)	(8.96)
Local weighted returns* Financial Market Exposure	-8.64	-20.6	-3.43	-9.10	-6.93	7.03
	(20.4)	(15.8)	(12.7)	(9.95)	(11.7)	(24.9)
Local Uncertainty* Financial market exposure	-3.92	2.50	-2.35	-5.16***	-2.18	-6.77*
	(3.11)	(2.07)	(1.48)	(1.42)	(2.00)	(3.88)
Local weighted returns* High Income	44.6	5.66	41.0*	-8.25	8.14	26.0
	(55.4)	(21.4)	(23.9)	(18.3)	(24.8)	(37.8)
Local Uncertainty* High Income	-3.89	-4.29	-2.69	1.04	-5.15	-8.10
	(6.92)	(2.87)	(3.71)	(3.65)	(3.65)	(6.81)
Observations	125368	526154	682378	719988	537947	320106
R-squared	0.646	0.650	0.688	0.704	0.730	0.758

The dependent variable is the log of credit card balances. All regressions include the individual's average Risk score the previous year; and 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. "Financial Market Exposure" equals one if an individual lives in a zip code with an above median ratio of capital gains and dividend income to adjusted gross income and zero otherwise. "High Income" equals one if an individual lives in a zipocde with an above median adjusted gross income and zero otherwise. Both these variables enter linearly as well. The regressions also control for the log of the credit line in quarter. The sample period is 2007Q1 through 2013 Q4. The basic regression is estimated separately for individuals in different age cohorts.

TABLE 10. LOCAL UNCERTAINTY AND FINANCIAL MARKET EXPOSURE, 2002Q1-2006Q4.

	(1)	(2)	(3)	(4)	(5)	(6)
	Age 20s	Age 30s	Age 40s	Age 50s	Age 60s	Age 70s
Local weighted returns	91.6	-92.2**	-37.2	56.8*	3.32	53.3
	(59.3)	(42.2)	(35.6)	(32.1)	(43.6)	(52.1)
Local Uncertainty	-14.8**	-3.59	13.7**	-3.53	18.9***	12.9
	(7.35)	(6.81)	(5.53)	(5.05)	(6.96)	(8.67)
Local weighted returns* Financial Market Exposure	-74.6***	-3.90	-2.26	-9.53	-14.5	16.2
	(25.0)	(15.4)	(17.3)	(16.1)	(21.3)	(31.8)
Local Uncertainty* Financial market exposure	0.99	-2.96	0.77	-1.07	0.92	3.71
	(2.05)	(1.86)	(2.16)	(1.85)	(3.30)	(4.43)
Local weighted returns* High Income	-72.3	75.0*	54.4	-50.3**	1.71	-91.2
	(54.6)	(43.5)	(34.2)	(24.9)	(39.9)	(58.5)
Local Uncertainty* High Income	9.73	4.17	-11.5**	2.05	-6.95	-6.66
	(5.88)	(5.39)	(5.24)	(4.40)	(5.19)	(10.1)
Observations	302997	477711	577174	496891	300103	207712
R-squared	0.599	0.626	0.663	0.696	0.721	0.740

The dependent variable is the log of credit card balances. All regressions include the individual's average Risk score the previous year; and 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. "Financial Market Exposure" equals one if an individual lives in a zip code with an above median ratio of capital gains and dividend income to adjusted gross income and zero otherwise. "High Income" equals one if an individual lives in a zipocde with an above median adjusted gross income and zero otherwise. Both these variables enter linearly as well. The regressions also control for the log of the credit line in quarter. The sample period is 2007Q1 through 2013 Q4. The basic regression is estimated separately for individuals in different age cohorts.

TABLE 11A. LOCAL UNCERTAINTY AND ADJUSTABLE RATE MORTGAGE INTEREST RATE RESETS

	(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

This table estimates the impact of local uncertainty around the two quarters 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 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 score at loan origination above 720—the median in the sample. Column 3 includes individuals with a FICO score at loan origination below the 720 median.

TABLE 11B. MONETARY POLICY UNCERTAINTY AND ADJUSTABLE RATE MORTGAGE INTEREST RATE RESETS

	(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

This table estimates the impact of the Baker Bloom and Davis (2016) monthly monetary policy index around the 6 month 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 score at loan origination above 720—the median in the sample. Column 3 includes individuals with a FICO score at loan origination below the 720 median.

Table 12. Monetary Policy Uncertainty and Adjustable Rate Mortgage Interest Rate Resets: Robustness 1

	(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

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.

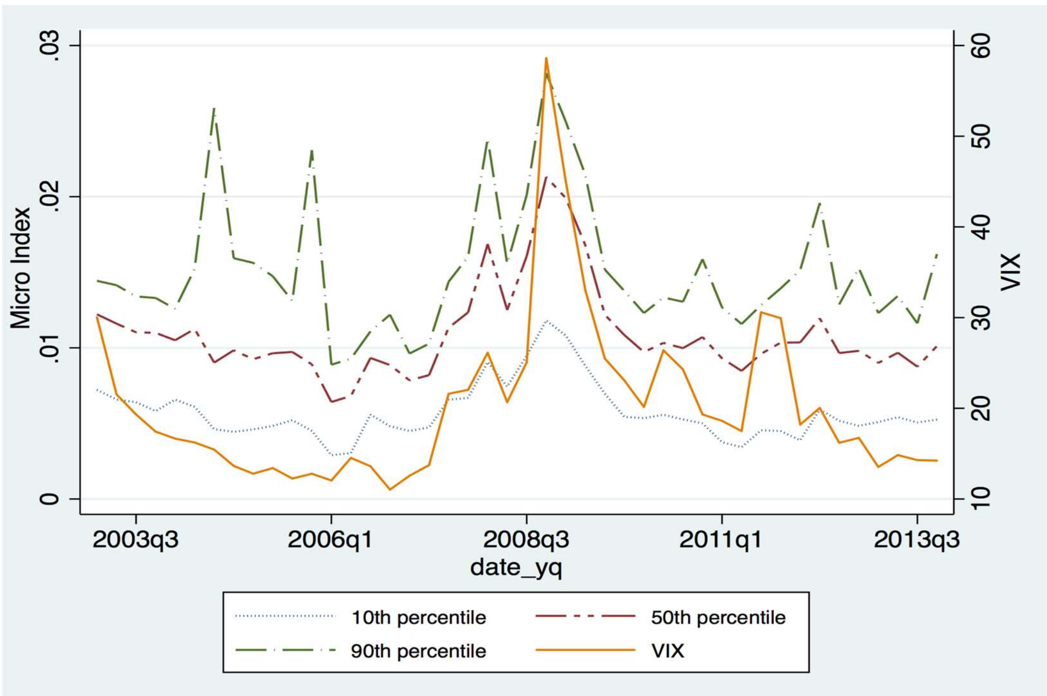
TABLE 13. CREDIT CARD BALANCES AROUND THE MORTGAGE RESET DATE, AND OTHER ECONOMIC POLICY UNCERTAINTY CATEGORIES: ROBUSTNESS 2

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

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. Columns 2, 3, 4, 5, 6 and 7 interact the reset indicators with the following categorical uncertainty measures: fiscal policy; financial regulation; sovereign crises; trade policy; entitlement policy and health care policy. Standard errors are clustered at the state level.

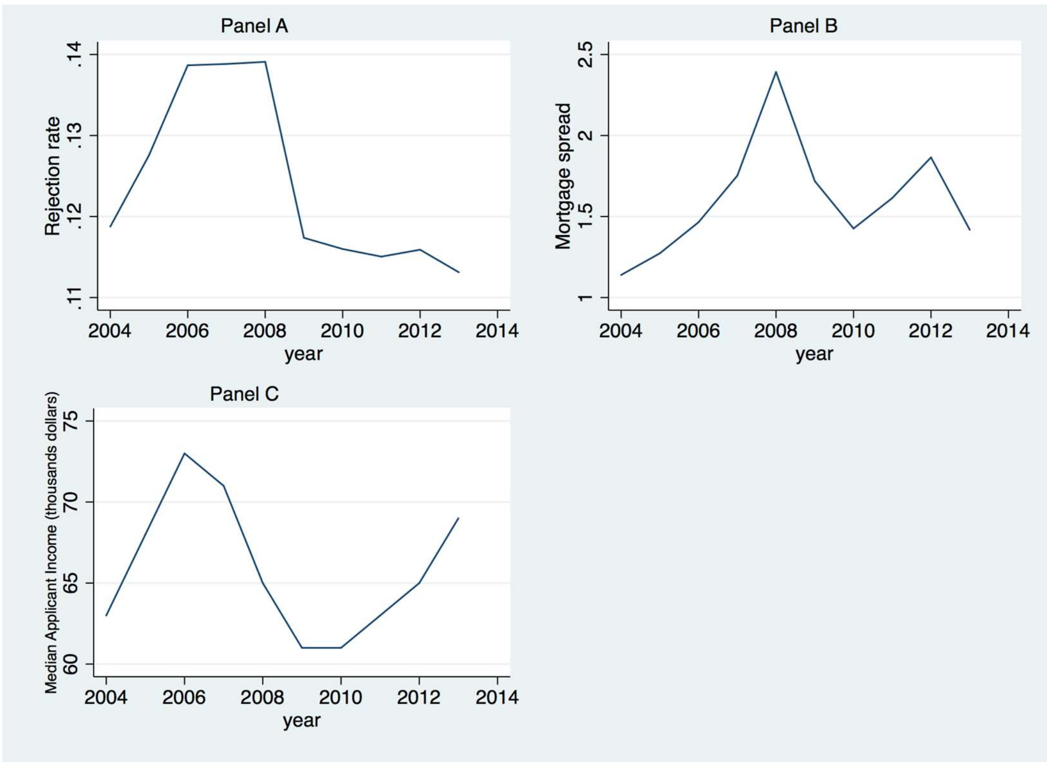
Figures

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.

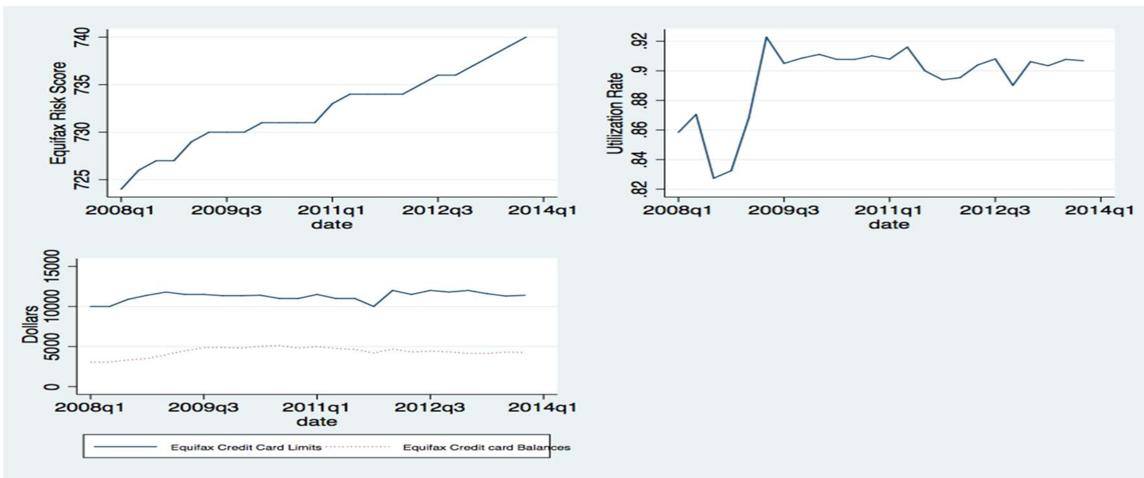
FIGURE 2. MORTGAGE CREDIT, OVER TIME.



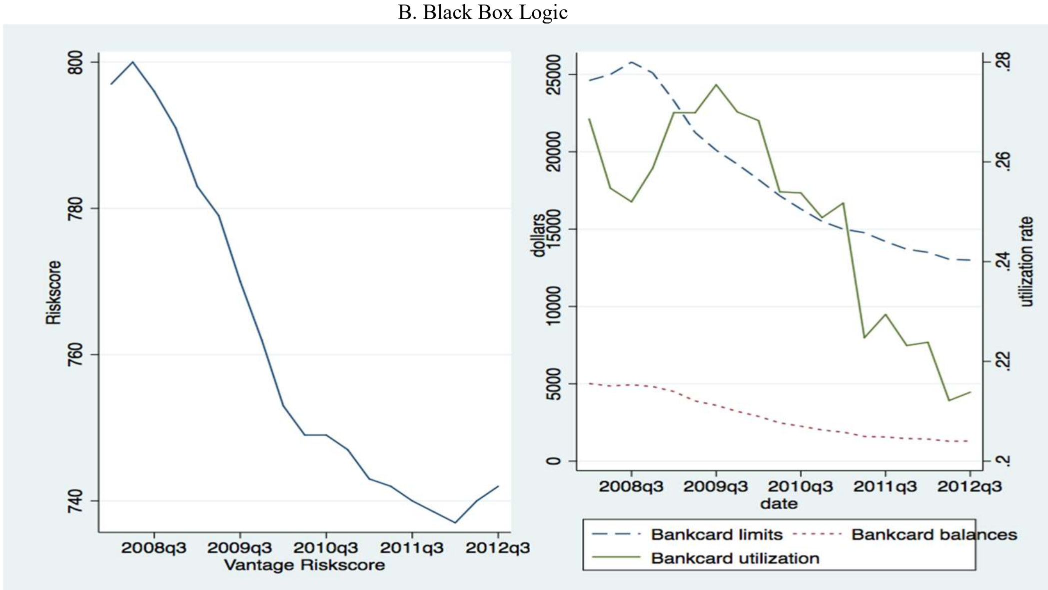
Panel A plots the fraction of mortgage applications denied over time (HMDA). Panel B shows the average spread between the mortgage interest rate (30 fixed term) and the 10 year Treasury Rate for newly originated loans (LPS). Panel C plots the median income of mortgage applicants (HMDA)

FIGURE 3. CONSUMER CREDIT USAGE OVER TIME

A. Equifax

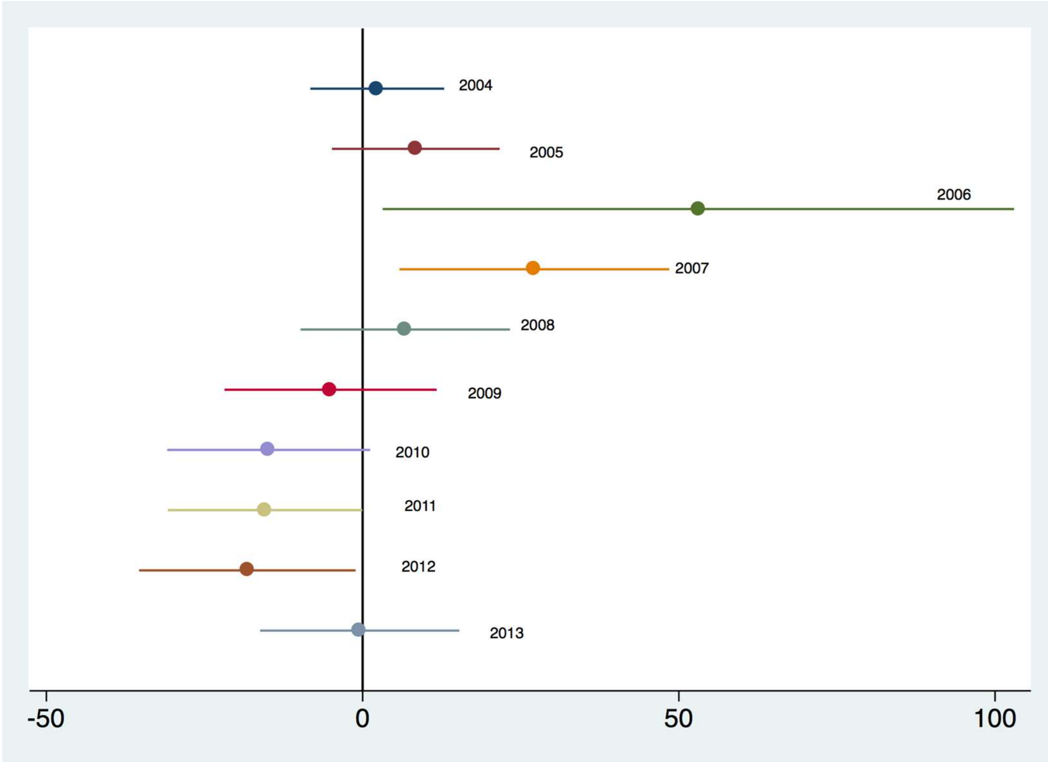


B. Black Box Logic



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

FIGURE 4. THE IMPACT OF LOCAL UNCERTAINTY ON MORTGAGE CREDIT, 2004-2013.



Using a specification similar to column 1 of Table 4A, this figure reports the coefficient (dots) and confidence bands (lines) for the local uncertainty variable in each year of the sample period 2004-2013. The dependent variable is the total volume of mortgage credit in loan applications for each county-year, and the controls are as in column 1 of Table 4A.

Internet Appendix

TABLE IA1 UNCERTAINTY: INDIVIDUAL-LEVEL EVIDENCE

	(1)	(2)	(3)
	Home	Home	Home
VIX	-0.000096***		-0.000089***
	(0.000022)		(0.000022)
Policy-related Uncertainty (BBD Index))		-0.000049***	-0.000048***
		(0.0000040)	(0.0000040)
S&P 500 (change)	0.28***	0.21***	0.054
	(0.054)	(0.056)	(0.058)
Average Risk Score Previous Year	0.0022*	0.0022*	0.0022*
	(0.0012)	(0.0012)	(0.0012)
Age (Log)	0.045***	0.044***	0.030***
	(0.0030)	(0.0030)	(0.0031)
GDP growth	-0.00024***	-0.00011***	-0.00024***
	(0.000043)	(0.000027)	(0.000043)
3 month Treasury yield	0.0011***	0.00068**	-0.000063
	(0.00039)	(0.00031)	(0.00043)
10 year Treasury yield	0.0013***	0.00025	0.00016
	(0.00017)	(0.00020)	(0.00021)
Observations	4895978	4895978	4895978
R-squared	0.054	0.054	0.054

This table reports regressions from an individual level quarterly panel (2008-2013). "Home" is the probability that an individual obtains a first mortgage; Standard errors are clustered at the state level, and all regressions include individual fixed effects. "policy

TABLE IA2. DEPENDENT VARIABLE: LOCAL UNCERTAINTY, 2002-2013.

VARIABLES	(1) first moment	(2) unemployment	(3) form of credit	(4) demographic controls	(5) demographic controls changes	(6) county-fixed effects
Local weighted returns	0.918***	0.930***	0.930***	0.262*	0.263*	0.465***
	(0.147)	(0.144)	(0.144)	(0.147)	(0.147)	(0.135)
unemployment rate		9.55e-05***	9.60e-05***	2.73e-05	2.26e-05	-1.52e-05
		(2.50e-05)	(2.50e-05)	(3.10e-05)	(3.14e-05)	(3.35e-05)
non-bank dependence			0.00114	-6.18e-06	1.53e-05	
			(0.00109)	(0.00107)	(0.00109)	
population, log				8.46e-05	-0.000159	
				(0.000611)	(0.000617)	
area, log				-0.000227*	-0.000275**	
				(0.000115)	(0.000107)	
median income, log				-0.00162***	-0.00237***	
				(0.000518)	(0.000634)	
African-American population, log				-2.84e-05	5.71e-06	
				(6.65e-05)	(6.27e-05)	
White Population, log				0.00107*	0.00135**	
				(0.000561)	(0.000602)	
poverty rate				2.64e-05	7.09e-05**	
				(1.74e-05)	(3.32e-05)	
inequality				-9.92e-05	-0.00140	
				(0.00177)	(0.00273)	
change in income, 2000-2008					0.00209**	
					(0.00102)	
change in inequality, 2000-2008					0.00185	
					(0.00553)	
change in African-American population, 2000-2008					-0.000162*	
					(8.82e-05)	
change in population					-0.000297	
					(0.00142)	
change in poverty rate					-0.000997*	
					(0.000570)	
Observations	66,841	66,841	66,841	66,841	66,841	66,841
R-squared	0.044	0.046	0.047	0.347	0.349	0.574

The unit of observation is the county-quarter, observed from 2002-20013. Local weighted returns is the first moment analog of the Local uncertainty index: sectoral stock returns weighted by employment shares in the county. All regressions include year and quarter fixed effects, and standard errors are clustered at the state-level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE IA 3. LOCAL UNCERTAINTY, AGGREGATE UNCERTAINTY AND CREDIT CARD BALANCES, 2007-2013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log
BBD Index or sub-index	BBD Index	BBD News	BBD Government	BBD CPI Inflation	BBD Tax	Economic Policy	Monetary Policy	Fiscal Policy	Tax Policy
Local weighted returns	-15.1***	-15.6***	-25.2***	-13.2**	-14.6***	-14.9***	-20.0***	-16.0***	-15.8***
	(5.49)	(5.45)	(5.82)	(5.41)	(5.42)	(5.48)	(5.87)	(5.57)	(5.54)
Local uncertainty	9.15**	9.32***	9.65***	8.73**	10.7***	9.21**	9.93***	8.68**	9.00**
	(3.48)	(3.47)	(3.54)	(3.40)	(3.56)	(3.47)	(3.52)	(3.43)	(3.46)
Local weighted returns * Low risk borrower	10.7**	11.2**	27.3***	7.41*	9.97**	10.1**	18.6***	12.1***	11.7**
	(4.44)	(4.44)	(5.42)	(4.41)	(4.48)	(4.32)	(4.94)	(4.42)	(4.54)
Local uncertainty * Low risk borrower	-21.5***	-21.8***	-22.3***	-20.8***	-24.0***	-21.6***	-22.8***	-20.7***	-21.3***
	(2.02)	(2.02)	(2.10)	(1.95)	(2.11)	(2.01)	(2.10)	(1.96)	(2.00)
Three month treasury yields * Low risk borrower	-0.0083**	-0.0021	-0.027***	-0.0087**	-0.011***	-0.00032	-0.0044	-0.00056	-0.0029
	(0.0038)	(0.0043)	(0.0045)	(0.0041)	(0.0039)	(0.0044)	(0.0043)	(0.0044)	(0.0043)
Ten year yields * Low risk borrower	-0.16***	-0.15***	-0.16***	-0.15***	-0.17***	-0.15***	-0.16***	-0.15***	-0.16***
	(0.012)	(0.011)	(0.011)	(0.0098)	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)
GDP growth * Low risk borrower	0.0020	0.0047***	0.0066***	0.0025	0.0024	0.0055***	0.0040**	0.0058***	0.0040**
	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0016)
BBD index or sub-index * Low risk borrower	-0.013***	0.012***	-0.065***	-0.011***	-0.022***	0.014***	0.012***	0.015***	0.0033
	(0.0046)	(0.0024)	(0.0092)	(0.0038)	(0.0037)	(0.0026)	(0.0027)	(0.0023)	(0.0023)
Observations	3115407	3115407	3115407	3115407	3115407	3115407	3115407	3115407	3115407
R-squared	0.685	0.685	0.685	0.685	0.685	0.685	0.685	0.685	0.685

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log	Credit Card Balances, log
BBD Index or sub-index	Government Spending	Healthcare	National Security	Entitlement Programs	Regulation	Financial Regulation	Trade Policy	Sovereign Debts, Currency Crisis
Local weighted returns	-14.4***	-16.6***	-14.6**	-16.7***	-14.7***	-12.3**	-15.6***	-15.0***
	(5.38)	(5.50)	(5.56)	(5.67)	(5.47)	(5.57)	(5.48)	(5.54)
Local uncertainty	8.19**	8.24**	9.34***	8.72**	9.05**	9.68***	9.08**	9.03**
	(3.39)	(3.38)	(3.44)	(3.42)	(3.45)	(3.44)	(3.48)	(3.45)
Local weighted returns * Low risk borrower	9.39**	12.8***	9.88**	13.1***	9.82**	5.88	11.3**	10.4**
	(4.30)	(4.44)	(4.21)	(4.62)	(4.24)	(4.38)	(4.41)	(4.61)
Local uncertainty * Low risk borrower	-19.9***	-20.0***	-21.8***	-20.8***	-21.4***	-22.4***	-21.4***	-21.3***
	(1.93)	(1.92)	(1.98)	(1.96)	(2.00)	(2.02)	(2.02)	(2.02)
Three month treasury yields * Low risk borrower	-0.00043	0.0022	-0.0012	-0.0026	0.0025	0.00059	-0.0036	-0.0025
	(0.0044)	(0.0045)	(0.0044)	(0.0044)	(0.0041)	(0.0042)	(0.0044)	(0.0050)
Ten year yields * Low risk borrower	-0.15***	-0.16***	-0.15***	-0.15***	-0.16***	-0.16***	-0.16***	-0.16***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.014)
GDP growth * Low risk borrower	0.0046***	0.0055***	0.0085***	0.0045***	0.0050***	0.0037**	0.0034**	0.0034**
	(0.0015)	(0.0015)	(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0015)	(0.0016)
BBD index or sub-index * Low risk borrower	0.019***	0.015***	0.059***	0.0073***	0.012***	0.012***	0.0063	-0.0033
	(0.0021)	(0.0022)	(0.0057)	(0.0023)	(0.0017)	(0.0020)	(0.0056)	(0.0048)
Observations	3115407	3115407	3115407	3115407	3115407	3115407	3115407	3115407
R-squared	0.685	0.685	0.685	0.685	0.685	0.685	0.685	0.685

The dependent variable is the log of credit card balances, observed between 2007 Q1 and 2013 Q4. The other control variables included but suppressed are the same as in Table 3, column 2.

TABLE IA 4. LOCAL UNCERTAINTY AND MORTGAGE APPLICATIONS

VARIABLES	(1) full sample	(2) 2004-2007	(3) 2008-2013	(4) 2008-2013: low dti	(5) 2008-2013: high dti	(6) 2008-2013: high dti & bank fixed effects	(7) 2008-2013: high dti & bank fixed effects & county fixed effects
Debt to income ratio (dti)	0.000681***	0.000305**	0.00139***	-0.111***	-0.000210***	-0.000222***	-0.000221***
	(0.000185)	(0.000132)	(0.000256)	(0.00850)	(7.74e-05)	(6.63e-05)	(6.45e-05)
Loan amount, log	-0.0232***	-0.0176***	-0.0363***	0.0492***	0.125***	0.151***	0.148***
	(0.00402)	(0.00270)	(0.00768)	(0.0104)	(0.00856)	(0.00784)	(0.00637)
Income of applicant, log	-0.0398***	-0.0410***	-0.0365***	-0.131***	-0.175***	-0.186***	-0.184***
	(0.00475)	(0.00532)	(0.00268)	(0.0121)	(0.0112)	(0.00931)	(0.00914)
male	0.00474**	0.00299	0.00834***	0.00360***	0.0107***	0.00647***	0.00670***
	(0.00207)	(0.00230)	(0.00132)	(0.00118)	(0.00164)	(0.00163)	(0.00156)
white	-0.0397***	-0.0409***	-0.0386***	-0.0412***	-0.0333***	-0.0315***	-0.0296***
	(0.00510)	(0.00578)	(0.00452)	(0.00438)	(0.00512)	(0.00419)	(0.00421)
Local weighted mean returns	-7.706	-18.41	-10.63***	-9.018***	-11.96***	-7.392**	-9.457***
	(7.952)	(20.68)	(3.054)	(2.381)	(3.602)	(2.765)	(3.045)
Local uncertainty	2.469	4.479	1.820	1.126	2.360*	3.617***	2.459**
	(1.774)	(2.590)	(1.653)	(1.132)	(1.399)	(1.012)	(1.038)
Observations	62,695,816	36,362,078	26,333,738	11,546,738	14,787,000	8,448,224	8,448,207
R-squared	0.021	0.018	0.028	0.046	0.033	0.081	0.086

The dependent variable is the probability that a loan application is denied. Column 1 uses the full-sample (2004-2013) of all loans that were either approved or denied by a bank. Column 2 restricts the sample to applications filed between 2004-2007. Column 3 focuses on the 2008-2013 sample. Column 4 uses the subsample of applications in 2008-2013 filed by borrowers with below median loan-to-income ratios (DTI). Column 5 restricts the sample to above median DTI applicants. Column 6 uses bank fixed effects, while column 7 uses both bank and county fixed effects. All regressions also use year fixed effects and standard errors are clustered at the state level. Columns 1-6 include state fixed effects as well.

REFERENCES

Baker, S. R., Bloom, N., & Davis, S. J. (2012). Measuring economic policy uncertainty. Policyuncertainy.com.

Benmelech, Ephraim, Ralf Meisenzahl and Rodney Ramcharan. The Real Effects of Liquidity During the Financial Crisis: Evidence from Automobiles, forthcoming, *Quarterly Journal of Economics.*

Bloom, Nicholas (2009). The impact of uncertainty shocks. Econometrica, 77(3), 623–685. http://doi.org/10.3982/ECTA6248

Caldara, Dario, Cristina Fuentes-Albero, Simon Gilchrist and Egon Zakrajsek. (2016). The Macroeconomics Impact of Financial and Uncertainty Shocks. NBER Working Paper 22058

Campbell, J. Y., Giglio, S., & Pathak, P. (n.d.). Forthcoming.“Forced Sales and House Prices..” *American Economic Review*

Chodorow-Reich, Gabriel, “The Employment Effects of Credit Market Disruptions: Firm-Level Evidence from the 2008–9 Financial Crisis,” *Quarterly Journal of Economics,* 129 (2014), 1–59.

Christiano, Lawrence J., Roberto Motto and Massimo Rostagno. 2014. "Risk Shocks." *American Economic Review*, 104(1): 27-65.

DeMarzo, P. M., Kaniel, R., & Kremer, I. (2004). Diversification as a public good: Community effects in portfolio choice. *The Journal of Finance*.

Fama, Eugene F., and French Kenneth R. (1992). The Cross-Section of Expected Stock Returns, *The Journal of Finance* 47.2: 427-65.

Grinblatt, M., & Keloharju, M. (2001). How distance, language, and culture influence stockholdings and trades. *The Journal of Finance*, *56*(3), 1053–1073.

Gilchrist, S., Sim, J. W., & Zakrajšek, E. (2014). Uncertainty, Financial Frictions, and Investment Dynamics. http://doi.org/10.3386/w20038

Gissler, Stefan, Jeremy Oldfather, and Doriana Ruffino (Forthcoming). "Lending on Hold:

Regulatory Uncertainty and Bank Lending Standards," *Journal of Monetary Economics*.
Hong, H., Kubik, J. D., & Stein, J. C. (2005). Thy neighbor's portfolio: Word of mouth effects in the holdings and trades of money managers. *The Journal of Finance*.
Kelly, Bryan, Lubos Pastor and Pietro Veronesi. The Price of Political Uncertainty: Theory and Evidence from the Option Market, forthcoming, *Journal of Finance.*
Kozeniauskas, Nicholas, Anna Orlik, and Laura Veldkamp, (2016). The Common Origin of Uncertainty Shocks, NBER Working Papers 22384, National Bureau of Economic Research, Inc.
Ludvigson, Sydney C, Sai Ma, and Serena Ng (2015). Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?, NBER Working Papers 21803, National Bureau of Economic Research, Inc.
Mian, Atif, and Sufi, Amir, *House of Debt: How They (and You) Caused the Great Recession, and How We Can Prevent It from Happening Again* (Chicago: University of Chicago Press, 2014).
PÁSTOR, L., & VERONESI, P. (2012). Uncertainty about Government Policy and Stock Prices. The Journal of Finance, 67(4), 1219–1264. http://doi.org/10.1111/j.1540-6261.2012.01746.x
Pool, Veronika K., Noah Stoffman, and Scott E. Yonker, (2012). No Place Like Home: Familiarity in Mutual Fund Manager Portfolio Choice, *Review of Financial Studies*, vol. 25(8), pages 2563-2599.
Ramcharan, Rodney, Stephane Verani, and Skander Van den Heuvel, (2014). From Wall Street to main street: the impact of the financial crisis on consumer credit supply. *The Journal of Finance*. http://doi.org/10.1111/jofi.12209
Satyajit, Chatterjee, Dean Corbae, Makoto Nakajima, and Jose-Victor Rios-Rull, (2007). A Quantitative Theory of Unsecured Consumer Credit with Risk of Default, *Econometrica*, 1–65.
Shale, Amity, (2008). The Forgotten Man: A New History of the Great Depression, Harper Perennial

Taschereau-Dumouchel, Mathieu, Edouard Schaal, and Pablo Fajgelbaum, (2013) Uncertainty Traps, Society for Economic Dynamics 2013 Meeting Papers 677

Van Nieuwerburgh, Stijn, and Laura Veldkamp, (2006). Learning Asymmetries in Real Business Cycles, *Journal of Monetary Economics, May 2006, v.53(4), p.753-772.*

Christiano, Lawrence J, Roberto Motto, and Massimo Rostagno, 2014, Risk Shocks †, *American Economic Review* 104, 27–65.

Davis, Steven J, R Jason Faberman, John Haltiwanger, Ron Jarmin, and Javier Miranda, 2010, Business Volatility, Job Destruction, and Unemployment, *American Economic Journal: Macroeconomics* 2, 259–287.

Gilchrist, Simon, Jae W Sim, and Egon Zakrajšek, 2014, Uncertainty, Financial Frictions, and Investment Dynamics.

Mian, Atif, Kamalesh Rao, and Amir Sufi, 2013, Household Balance Sheets, Consumption, and the Economic Slump*, *The Quarterly Journal of Economics* 128, 1687–1726.

Morse, A, 2011, Payday lenders: Heroes or villains? *Journal of Financial Economics* 102, 28–44.

Mortensen, Dale T, and Christopher A Pissarides, 1994, Job Creation and Job Destruction in the Theory of Unemployment, *The Review of Economic Studies* 61, 397–415.

PÁSTOR, ĽUBOŠ, and PIETRO VERONESI, 2012, Uncertainty about Government Policy and Stock Prices, *The Journal of Finance* 67, 1219–1264.

Ramcharan, Rodney, STEPHANE VERANI, and SKANDER J van den HEUVEL, 2016, From Wall Street to Main Street: The Impact of the Financial Crisis on Consumer Credit Supply, *The Journal of Finance* 71, 1323–1356.

Satyajit Chatterjee, Dean Corbae Makoto Nakajima Jose-Victor Rios-Rull, 2007, A Quantitative Theory of Unsecured Consumer Credit with Risk of Default,, 1–65.

Shoag, Daniel, and Stan Veuger, 2016, Uncertainty and the geography of the great recession, *Journal of Monetary Economics* 84, 84–93.