## Financial Volatility and Household Consumption

By Marco DiMaggio, Amir Kermani, Rodney Ramcharan and Edison Yu<sup>1</sup>

Abstract (Prelimanary, do not quote)

How does uncertainty affect consumer credit decisions? Using a unique panel of consumer debt decisions, this paper shows that during periods of increased economic uncertainty, consumers are less likely to enter into long-term debt contracts, and there is a sharp decline in new car and home purchases. Greater uncertainty is also associated with a more general reduction in leverage. We find that these effects are largest for individuals with portfolios most exposed to financial markets. This evidence suggests that by increasing the precautionary savings motive among consumers, financial volatility and increased policy uncertainty might have an independent effect on economic activity.

<sup>&</sup>lt;sup>1</sup> DiMaggio: Columbia Business School; Kermani: University of California, Berkley, Haas School of Business; Ramcharan: University of Southern of California, Price School of Public Policy and Marshall School of Business (rodney.ramcharan@gmail.com); Yu: Federal Reserve Bank of Philadelphia. The views in this paper does not necessarily reflect those of the Federal Reserve System.

## Introduction

Financial crises increase uncertainty. Firms and households are forced to revise their investment and consumption plans as demand and credit supply fluctuate sharply ((Chodorow-Reich, 2013), Mian and Sufi, 2014), (Ramcharan, Vernani, and van den Heuvel, 2014), Benmelech, Meisenzahl and Ramcharan (forthcoming)). Government responses to these events further compound uncertainty (Pastor and Veronesi (2013)). Political uncertainty makes it difficult for economic actors to predict how government policies might change in response to these large shocks. Congress for example first rejected TARP before approving it two weeks later. And potential policy responses are sometimes kept deliberately opaque to avoid moral hazard. Even after a policy is agreed upon, the impact of the policy response itself is often uncertain and can project economic uncertainty far into the future (Gissler, Oldfather and Ruffino (2016)). For example, new rule-making emanating from the substantial regulatory response to a crisis emerge gradually over time and are frequently modified in response to legal challenges and new information about its impact.<sup>2</sup>

The increase in economic and political uncertainty around a financial crisis might significantly affect economic activity. There is a sizeable theoretical literature that expands upon the idea that economic uncertainty can increase the real option value of delaying difficult to reverse investment and hiring decisions. These delays could then have a large economic impact, potentially amplifying the real cost of a financial crisis and delaying the pace of any recovery. 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

<sup>&</sup>lt;sup>2</sup> See for example the legal debate over Metlife's designation as a systemically important financial institution: http://www.wsj.com/articles/why-the-metlife-case-bears-watching-well-beyond-wall-street-1460585479.

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.

However, although the evidence is suggestive that second moment shocks might shape firm-level decisions along with economic and financial aggregates, much less is known about how uncertainty might affect the economic decisions of individuals. In particular, individual debt decisions are of enormous economic importance. From the Federal Reserve's Flow of Funds data, the stock of mortgage debt and consumer credit in the US economy was around 10 trillion and 4 trillion dollars respectively in 2015. Also, the reduction in the use of consumer debt in the wake of the financial crisis has been implicated as one of the key factors shaping the slow pace of post-crisis economic growth. To help fill this gap, this paper investigates the impact of uncertainty on individual level debt decisions using a large panel of consumers and their credit history. Our main dataset spans the period before the crisis, the 2008-2009 financial crisis, and through 2013. And it contains information on major debt decisions such as mortgages, car purchases and the use of revolving debt.

Given the long term nature and partial irreversibility of many consumer debt contracts, well known economic arguments would predict that these debt decisions are likely be highly sensitive to the level of uncertainty that the individual perceives. Mortgages and other standard consumer debt contracts typically require a borrower to commit to a sequence of relatively large payments over a long period. These debt contracts are difficult to abrogate. Selling houses involve very high transaction costs, and discounts can be sizeable when attempting quick sales ((Campbell, Giglio, and Pathak, 2014), Rajan and Ramcharan (forthcoming). Failing to make these contractual payments can also cause long term damage to a borrower's credit reputation (Gross and Souleles (2002a)). Intuitively then, during periods of increased uncertainty, individuals might postpone obtaining a mortgage or other large debt obligations.

Uncertainty might also shape consumer borrowing constraints. Increased uncertainty can cause borrowers' net worth to fluctuate, increasing the default risk and potentially making mortgage credit less available. Similarly, providers of revolving lines of credit might also preemptively reduce credit line limits (Gross and Souleles (2002b)). This pre-emptive behavior could in turn increase consumer borrowing constraints, and lead to a pro-cyclical reduction in expenditures. Holding constant the borrowing limit, increased uncertainty and the precautionary saving motive could also induce consumers to utilize less of their remaining borrowing capacity, again leading to a pro-cyclical reduction in expenditures. Therefore, increased uncertainty might both reduce the demand for highly levered debt contracts among individuals, and also lead to a reduction in the supply of consumer credit as well.

Identifying these hypothesized channels is difficult. Second moment shocks to economic processes often coincide with first moment shocks, making it difficult to disentangle the effects of uncertainty from a first moment shock that might also independently shape debt decisions. For example, stock prices might become extremely volatile after a drop in oil prices, as investors gradually update their priors about the path of future cash flows at public firms. But it is the drop in commodity prices—a first moment shock—that might directly impact household debt decisions. More generally, uncertainty can also increase after a period of weak economic activity, as governments consider changes to economic policy. This again makes it hard to disentangle the effects of uncertainty from the broader economic and political conditions that might precipitate the introduction of new policies and regulations.

We construct a series of tests showing that economic uncertainty might feature prominently in consumer debt decisions, and can have sizeable aggregate implications. To measure uncertainty, we use both the VIX—a measure of economic uncertainty derived from the volatility of equity prices—along with the policy uncertainty index in Baker, Bloom and Davis (2016) (BBD index) based on references to uncertainty in newspaper articles. In the aggregate, we find that both these uncertainty measures are negatively associated with new home mortgages and car financing at the county level.

Such broad aggregate movements can be difficult to interpret. And we show that at the individual level increased economic and political uncertainty are associated with a decreased probability that an individual enters into a mortgage or obtains automotive financing. We further exploit the fact that there is substantial heterogeneity across individuals in their exposure to economic and political uncertainty. In particular, the debt decisions of individuals whose networth is mainly comprised of financial assets is likely to be more sensitive to financial volatility and political uncertainty relative to others less exposed to these assets. Using IRS tax data, we find evidence consistent with this prediction: Increased uncertainty is associated with a sharper decline in the probability of entering longer term debt contracts among individuals more likely to have portfolios comprised of financial assets. These effects are also greater among individuals in their 40s and 50s—those most likely to be holding equity in their portfolios.

Aggregate measures of uncertainty might still nosily capture the uncertainty faced by an individual and we also develop a local time varying county level uncertainty index. For all the public firms in each three digit NAIC category, we create a market capitalization weighted portfolio of stock returns. We then weight the volatility of this portfolio by the corresponding employment shares inside the county. This index is less likely to be conflated with broader aggregate trends, and we again find that local uncertainty is associated with a decline in the use of consumer longer-term debt contracts. We also find evidence that consumer credit lines are also more likely to be curtailed when uncertainty spikes. This evidence

suggests then that the uncertainty associated with financial crises might independently lead to a contraction in economic activity, as consumers delay home and durable good purchases, and lenders reduce credit limits. In section 2 of the paper we discuss the empirical framework and data; Section 3 presents the main results and Section 4 concludes.

#### **II.** Empirical Framework and Data

We study the impact of economic uncertainty on consumer debt decisions. Our main hypothesis is that because mortgages, and to a lesser extent durable goods debt contracts such as automobiles, are long-term obligations that are difficult to abrogate, economic theory suggests that the real-option value of waiting to enter into these types of contracts is likely to be higher during periods of increased economic uncertainty. For example, when stock market volatility is high, households, especially those with a higher fraction of their wealth denominated in stocks, might face greater uncertainty about the present value of their expected net-worth. And rather than committing to a contract requiring a series of payments extending far into the future, it might be optimal to reduce or altogether postpone these obligations until uncertainty abates.

To be sure, uncertainty can also shape the supply of credit. Lenders might be unwilling to enter into longer term debt contracts with some types of borrowers during times of increased uncertainty. Lenders for example might discount the present value of consumer wealth at a higher rate during times of increased uncertainty. Such risk aversion can be more pronounced at banks with thinner capital buffers (Ramcharan et al., 2014). Similarly, lenders that find it difficult to diversify away risk—those that are smaller for instance or lack access to broader financial markets—might also restrict credit to some types of borrowers during periods of increased economic uncertainty.

The effects of uncertainty on debt decisions might also vary across individuals. For individuals with limited access to external finance, increased uncertainty about future cash flow might induce these borrowers to reduce their utilization of existing credit card lines as a hedge against the increased risk of negative income shock. However, borrowers with plentiful sources of external finance might evince less precautionary behavior in response to increased uncertainty. But apart from its impact on the borrower's expected net worth, well known models also observe that aggregate uncertainty about the future value of real estate can also make it optimal for potential buyers to delay purchase (Titman (1985)).

Although economic theory posits that uncertainty might play a large role in shaping consumer debt decisions, the existing evidence is limited. This reflects in part the fact that second moment shocks to economic processes often coincide with first moment shocks, making it difficult to disentangle the effects of uncertainty from a first moment shock that might also independently shape debt decisions. Measures of aggregate uncertainty such as the VIX—the implied volatility of the S&P 500 index options—might co-vary with first moment economic and political shocks. These shocks could in turn have an independent effect on consumer debt decisions. The relatively limited data on individual level debt decisions linked to their location has also hampered research in this area.<sup>3</sup>

We address these challenges using detailed microeconomic data on consumer debt decisions from a one percent random sample of the NY Fed's Equifax Consumer Credit Panel (CCP). With these data we can measure with relative precision the impact of economic uncertainty shocks, such as stock market volatility, on individual debt decisions over time, holding constant a number of

<sup>&</sup>lt;sup>3</sup> Some recent notable work in this area includes Keys et. al (2016) and Aggarwal et. al (2016)

important characteristics such as the individual's level of risk aversion and other potentially time invariant preferences, along with credit access, and age and local economic conditions. In addition, we can also control for a myriad of first moment shocks that are likely to co-vary with the VIX—a common measure of financial volatility. Individual level data also allow us to trace out heterogeneous responses to uncertainty shocks, helping us make progress in understanding the underlying mechanisms that might drive an individual's response to uncertainty.

Specifically, the one percent sample consists of a balanced panel of about 220,000 individuals, and includes comprehensive quarterly information on key dimensions of debt usage: mortgage, automotive, and credit card balances, as well as credit limits from 2002-2013. The panel also includes information on age, zip code of the primary residence, and FICO score; the latter is an important credit scoring index commonly used in credit decisions.

In our main empirical tests, we combine these micro-level data with the VIX along with the policy uncertainty index developed by Baker, Bloom and Davis (2016). As Figure 1 shows, while these two series tend to co-vary positively at the quarterly level, they do seem to measure different aspects of uncertainty. The policy uncertainty index for example increased sharply in the second half of 2011 and part of 2012, but financial volatility remained very low during this period.

However, because aggregate movements in these indices might well reflect broader macroeconomic and political shocks, we exploit the fact that we know the individual's zip code of residence in order to include location specific controls for economic uncertainty as well as local proxies for uncertainty itself. In the case of the latter, we use NAIC sectoral information on the employment structure of an individual's county of residence in order to create a time varying county level index of uncertainty using the VIX. For all the public firms in each three digit NAIC category, we create a market capitalization weighted portfolio of stock returns. We then compute the standard deviation of these weighted portfolio of returns as a proxy for uncertainty at the sector level. Finally, we use data from the Bureau of Labor Statistics on sectoral employment at the county level, and weight the sectoral standard deviation of stock returns by these employment shares.

Thus, when firms in the oil and gas sector face an increase in uncertainty, as measured by increase in the standard deviation of stock returns in that sector, this index will increase by more in counties where oil and gas employment is higher. With such an index then, we can hold constant aggregate macroeconomic and political developments, studying how local uncertainty might shape an individual's debt decisions.

Figure 2 plots the median and interquartile range of this local measure of uncertainty over time for each county-quarter observation; the figure also includes the aggregate VIX. There is substantial comovement over time at the local level, but sizeable differences in magnitudes in the cross-section of counties. The interquartile range for example is large, especially during times of significant uncertainty. During the financial crisis, the employment weighted standard deviation of stock returns for counties in the 75<sup>th</sup> percentile was almost 66 percent higher than at the 25<sup>th</sup> percentile. Five years after the crisis, this gap fell by about 20 percentage points.

<u>Table 1</u> reports basic summary statistics for some of the individual variables, observed in 2008 Q1. The average credit card limit 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 panel of figures 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. Utilization rates fell sharply during the crisis, perhaps due to the precautionary saving motive, before rebounding sharply. But it might also reflect an increase in post-crisis credit supply: There is also some evidence that the median credit limit spiked after the crisis, though there is no similar increase

in median credit balances during this period. Similarly, car and mortgage balances also rose sharply in the post-crisis period. There is also some evidence that the median credit limit spiked after the crisis, though there is no similar increase in median credit balances during this period.

#### III. Main Results

#### III.A Basic Associations

In this subsection, we offer the first tentative evidence that economic uncertainty might influence aggregate fluctuations through consumer debt decisions. To this end, for each quarter through 2008-2013, we compute the fraction of new mortgages originated in each county by aggregating the individual-level information in Equifax. We then report correlations between this fraction and movements in the VIX, controlling for time invariant county level observables using county fixed effects; standard errors are clustered at the statelevel. The results are reported in Table 2.

In column 1, there is a significant negative associated between the VIX and the county-level fraction of new mortgages in each quarter. A one standard deviation increase in the VIX is associated with a 0.2 percentage point drop in the fraction of new mortgages originated in the county. The VIX covaries with first moment shocks that are likely to independently affect these debt decisions, and in column 2 we include the mean change in the S&P 500 stock index in the quarter, the mean three month Treasury interest rate; the mean 10 year Treasury rate; and GDP growth in the quarter. The impact of the VIX remains negative and significant. Column 3 uses the fraction of new cars financed inside the county in that quarter. The point estimate remains negative and significant.

In addition to the VIX, we now consider the popular measure of political uncertainty developed by Baker Bloom and Davis (2016) (BBD index). Unlike

the VIX, which primarily captures uncertainty through financial market volatility, the BBD index is based on references to political uncertainty in newspaper articles. Columns 5 and 6 replace the VIX with the BBD index, using the fraction of new home purchases (column 5) and automobiles financed (column 6) as the dependent variables, respectively.

As with the VIX, the BBD index enters negatively, and it suggests that a one standard deviation increase in the BBD index is associated with a 0.08 standard deviation decline in the fraction of new home purchases; in column 6, a similar increase in the BBD is associated with a 0.05 drop in the fraction of new car purchases. Columns 7 and 8 use both the VIX and the BBD index jointly. There is evidence that both economic uncertainty, as measured by the VIX, and political uncertainty—the BBD index—independently affect consumer debt decisions. However, the economic impact of the VIX appears much larger, suggesting that equity market volatility might spill over into other asset markets like housing.

In Table 3, we repeat this exercise using disaggregated individual level data. We can thus absorb time invariant individual level characteristics such as risk aversion in individual fixed effects; we can also control for key observables such as age and credit score—the Equifax Risk Score. The evidence continues to suggest at this more disaggregated level that aggregate uncertainty might shape consumer debt decisions. Both the VIX and the BBD index are significant when entered separately, as well as when included jointly along with the suite of aggregate proxies for first moment shocks. All this suggests that economic and political uncertainty might feature in consumer debt decisions.

However, before making too much of these results, unobserved aggregate economic shocks that correlate with movements in the VIX and the BBD index could still drive these results. To make progress then, we pursue a two-pronged strategy. We construct measures of uncertainty at the county level. This allows us to exploit the spatial variation in uncertainty, while absorbing aggregate first moment shocks in year-by-quarter fixed effects. We also combine these local uncertainty measures with tests based on the fact that exposure to financial markets likely varies across individuals, and this heterogeneity can be another way to identify the impact of uncertainty on debt decisions.

## III.B Portfolios, the life cycle and uncertainty

In this subsection, we develop tests of the impact of uncertainty on debt decisions based on potential differences in portfolio composition across individuals. This approach is motivated by the fact that for individuals whose net worth is mainly comprised of financial assets, increased financial volatility or political uncertainty will likely have a bigger impact on their net worth. And as uncertainty over their own net worth increases, standard arguments observe that these individuals would then be more likely to postpone entering into longer-term debt contracts like mortgages and car purchases. In contrast, the net worth of individuals with little financial assets is likely to be less sensitive to increased financial volatility or political uncertainty. Therefore, if the negative correlation between the decision to use debt and the VIX and the BBD index reflects the causal effect of uncertainty, then this correlation should be larger for individuals whose net worth is consists of a greater fraction of financial assets.

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 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. And as Table 4 shows, 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.

In Table 5 we examine whether the impact of movements in the VIX on the household mortgage decision varies depending on the extent to which an individual might be exposed to equity markets. We create an indicator variable that equals one if a household lives in a zip code with above median capital gains ratio and zero otherwise. This indicator is then interacted with the VIX. We also interact the indicator variable with the mean change in the S&P 500 to address first moment shocks that might affect differentially those with more financial assets. Moreover, because these interaction terms exploit variation across time and zip code, we can include year by quarter fixed effects to absorb aggregate shocks that vary by quarter and that affect individuals in all counties equally. We continue to include individual-level controls such as age and the last year's average RISK score; all regressions also include individual fixed effects and standard errors are clustered at the state-level.

In column 1 of Table 5, the dependent variable is the probability that an individual obtains a first mortgage. An increase in the VIX appears to have a statistically significant and negative impact on the probability of obtaining a first mortgage among individuals living in above median capital gains zip code. Column 2 uses the change in the mortgage balance. Again, the interaction term between the VIX and the above median indicator is large, negative and

statistically significant. It suggests that a one standard deviation increase in the VIX is associated with a 0.05 percentage decrease in mortgage balances among individuals in above median zip codes relative to those living elsewhere. The interaction term is also negative in the case of automobiles, which we disaggregate by those financed by banks and non-banks, but it is not statistically significant. The remaining columns of Table 5 repeat the exercise using the BBD index. There is some indication that aggregate policy uncertainty might influence more the debt decisions of individuals with significant financial assets, but these results are not statistically significant at conventional levels; the p-value in the case of the growth in mortgage debt is 0.13.

The evidence is suggestive that uncertainty, especially as measured by financial volatility, might matter for consumer debt choices. But zip code level tax data is likely to be a noisy proxy for an individual's exposure to financial markets. We therefore build on the considerable evidence that exposure to equity markets fluctuates over the life cycle. Agents gradually accumulate assets early in their life cycle, increase their exposure to equity markets mid-life, and then gradually dissave and shift their portfolios towards less risky assets during and nearing retirement. Building on this literature, we combine our information about age with the zip code level tax data to measure better the role of uncertainty in shaping debt decisions.

In particular, we create a series of binary variables that indicate whether an individual is in their 20s, 30s, 40s, 50s, 60s, and older than 70. We then interact these age indicator variables with an indicator variable that equals 1 if an individual lives in a zip code above the median dividend and capital gains ratio. Finally, we create a triple interaction term by using the VIX. 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. As before, by

exploiting this individual level variation in the dataset, we can include year-by quarter fixed effects in order to absorb aggregate shocks that vary by quarter in our sample. We also continue to include the log age of the individual along with the person's Equifax Risk Score, lagged by one year.

In column 1 of Table 6, the dependent variable is the probability that an individual obtains a first mortgage in the quarter. The results are striking. Among those individuals living in above median capital gains zip code, the negative association between the VIX and the probability of obtaining a mortgage is negative and statistically significant beginning with those cohorts in their 40s. The negative effect of uncertainty peaks among individuals in their 50s—those usually with portfolios most exposed to the financial markets—and then begins to decline among the cohort in their 60s. Among those in their 70s and older, uncertainty no longer has a significant effect on the mortgage decision.

When using the change in the mortgage balance as the dependent variable (column 2), the negative effects of uncertainty begins among those in their 30s, and peaks among the cohort in their 40s. This approach also reveals a statistically negative and significant impact of financial volatility on car purchases among cohorts in their 40s living in above median capital gains zip code (column 3). Column 4 uses the log of the credit limit as the dependent variable. There is now evidence that not only is increased volatility associated with a decline in mortgage and automotive debt among individuals most exposed to financial markets, but also the limits on credit card lines of credit tend to decline when uncertainty increase. This suggests that while some of the decline in debt usage might be driven by the precautionary motive on the part of the consumer, some of it might also be caused by a precautionary contraction in credit supply.

To gauge the relative importance of financial volatility—the VIX—versus the BBD policy uncertainty index, Table 6B includes the BBD Index interacted with the zip code indicator variable along with the various age cohort variables. In the

case of mortgages and automotive debt, there is evidence that both financial volatility as well as policy uncertainty might have independent negative effects on the use of long term debt contracts. In the case of policy uncertainty however, these effects tend to present themselves even among cohorts in their 30s. There are however important and suggestive differences on the part of credit limits. While increased policy uncertainty is associated with an *increase* in these limits among cohorts likely to have a large exposure financial markets, actual financial market volatility is associated with a decline in these credit limits.

#### III.C Local uncertainty

The evidence suggests that aggregate financial volatility might be an important factor in consumer debt decisions, especially for those consumers with portfolios heavily exposed to these markets. But movements in the aggregate VIX might still be a noisy measure of an individual's exposure to equity market uncertainty, even allowing for heterogeneity across age. There is now substantial evidence of home bias in portfolio holdings, as individuals, and even professional money managers tend to disproportionally weight geographically proximate companies in their portfolios ((DeMarzo, Kaniel, & Kremer, 2004), (Hong, Kubik, & Stein, 2005),(Grinblatt & Keloharju, 2001), Pool, Stoffman and Yonker (2015). Therefore, in the presence of home bias, aggregate stock market volatility might matter little for households with equity holdings weighted towards the local economy. Beyond the portfolio channel, aggregate financial market volatility might also capture uncertainty about future labor income will likely vary across individuals depending on their occupation.

To help address this concern, we link the Quarterly Employment Survey (QES) which lists employment in each county by the three digit sectoral industrial classification code (SIC) with the individual's county of residence from Equifax.

We then use the QES data to create an index of economic volatility by county: We compute the standard deviation of stock prices by SIC code, and then weight this series by a county's employment shares in that sector. Figure 3 shows the spatial variation in this series at the beginning of the sample in 2007 and then again in 2013 at the end of the period. Many agricultural counties in the upper Mid-West do not have employment in sectors with publicly listed firms, and for these counties, the index is missing. We should emphasize however there is no significant relationship between this local uncertainty index and the ratio of capital gains and dividends to AGI (Figure 4). This local volatility index thus offers us a potentially independent source of variation to measure the impact of uncertainty on household debt decisions.

Table 7A builds on the analysis from the previous section. We include interaction terms between this local measure of uncertainty, whether an individual lives in a zip code with an above median dividend/capital gains to AGI ratio, and an indicator for the age cohort. We also include separate interaction terms between the age cohort and the zip code indicator variable; the latter cohort variables also enter linearly in the regression along with the log of the individual's age. These regressions also include interaction terms between the weighted mean stock returns for the county, the age cohort indicator and the above median zip code variable. and The results are striking. For individuals in their 20s, the triple interaction term is positive but insignificant. This coefficient becomes negative for individuals in their 30s, but is significant. It however increases in absolute value by about 3.5 times for individuals in their 40s and gradually tapers off for older cohorts.

While increased volatility is associated with a significant reduction in the probability of entering into mortgage contract for those individuals most exposed to equity markets, there is also evidence of asset market integration. Higher average returns in equity markets, weighted by local employment sectoral shares, are associated with an increased likelihood of purchasing a home among the segment of the population likely to be most exposed to these markets. As before, this coefficient peaks for those in their 40s and declines steadily for older cohorts.

In column 2, the dependent variable is the change in the mortgage balance. In the case of uncertainty, we continue to see evidence that at the intensive margin, the impact remains negative and significant among individuals likely to be most sensitive to this source of uncertainty. However, using this intensive margin measure, the impact of increase in mean stock returns is negative, suggesting that individuals might reduce their debt exposure when the value of their equity market holdings rise.

The results on car buying are imprecise (column 3), but the evidence in column 4 suggests that greater uncertainty in financial markets are associated with a significant reduction in credit limits for those individuals likely to be most exposed to equity markets. In particular, an increase in stock prices is associated with an increase in the credit limit for individuals in their 40s and below. But greater volatility in the local uncertainty measure suggests a decline in these limits that is largest for individuals in their 50s.

In Table 7B, we include both the local uncertainty index and the BBD index. As with the local index, an increase in policy uncertainty is associated with a decline in the probability of obtaining a mortgage, and faster repayment. However, unlike the local uncertainty index based on financial volatility and potential fluctuations in net worth, an increase in policy uncertainty is associated with a significant increase in credit lines limits. This suggests that while credit card companies might pre-emptively curtail these lines when an individual's net worth is likely to fluctuate, individuals might increase the demand for these lines when there is greater policy uncertainty.

## **IV.** Conclusion

Financial crises are associated with a collapse in consumption and economic activity. There is now substantial evidence that much of this collapse stems from both a decline in demand as consumers adjust to balance sheet shocks, as well as a decline the availability of credit, as financial institutions also react to balance sheet impairments and funding disruptions. But crises are also associated with a substantial increase in economic and policy uncertainty. And consistent with models of decision making under uncertainty, there is growing aggregate evidence that uncertainty might also explain some of the collapse in consumption and output after these events.

This paper has used a large comprehensive individual level dataset of debt and credit decisions to understand the role of economic uncertainty in shaping these decisions. We find evidence that an increase in either economic or policy uncertainty is associated with a decline in the use of mortgage credit, and to a lesser extent automotive credit. These effects are largest for individuals most likely to be exposed financial markets—those living in zip codes where capital gains and dividend income are larger relative to earnings. Among these individuals, the effects are largest among those in their 40s and 50s—those with the largest share of their portfolio in financial assets.

While the evidence is suggestive that individuals might delay entering into these long lived and difficult to reverse debt contracts, there is also evidence that increased financial volatility is associated with a decline in credit card limits. That is, providers of credit lines might pre-emptively curtail credit availability when economic uncertainty increases and the net worth of individuals fluctuate. Interestingly, an increase in policy uncertainty is associated with an increase in these limits.

# V. Figures and Tables









FIGURE 3. MEDIAN INDIVIDUAL LEVEL OUTCOMES







FIGURE 5. THE CORRELATION BETWEEN TAX RATIOS AND LOCAL UNCERTAINTY

			-							
	Obs.	Mean	Std Dev	Min	р5	p25	p50	p75	p95	Max
Age	816709	46	16	18	22	34	46	58	74	80
Risk Score	825984	690	111	286	485	608	715	787	823	844
First Mortgage Balance	279687	194109	226572	0	31794	78724	134999	231967	534127	9411239
Auto Bank Loan Balance	875838	2251	7074	0	0	0	0	0	16773	576942
Credit Card Limit	558984	24347	27185	0	500	5000	15800	34000	77300	908784
Credit Card Balance	626436	6011	14548	0	0	340	1694	6163	26086	3176911
Credit Card Utilization	493193	0	0	0	0	0	0.10	0.42	0.92	1.00

TABLE 1. SUMMARY STATISTICS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Home	Home	Car	Home	Car	Home	Car
VIX	-0.000065*** (0.000012)	-0.000077*** (0.000020)	-0.00018*** (0.000034)			-0.000045** (0.000021)	-0.00016*** (0.000033)
Policy Uncertainty Index				-0.000038*** (0.0000055)	-0.000039*** (0.000012)	-0.000034*** (0.0000057)	-0.000026** (0.000012)
S&P 500 (change)		0.15 (0.12)	-0.94*** (0.19)	0.11 (0.11)	-0.80*** (0.20)	0.040 (0.11)	-1.03*** (0.20)
Average Risk Score Previous Year		0.0035 (0.0051)	0.0013 (0.010)	0.0033 (0.0050)	0.0024 (0.010)	0.0029 (0.0051)	0.00083 (0.010)
GDP growth		-0.000099 (0.000072)	0.00021 (0.00013)	-0.00000055 (0.000062)	0.00051*** (0.00011)	-0.000084 (0.000072)	0.00022* (0.00013)
3 month Treasury yield		0.00076** (0.00035)	0.0035*** (0.00087)	0.00047 (0.00040)	0.0038*** (0.00093)	0.00026 (0.00039)	0.0031*** (0.00088)
10 year Treasury yield		0.00021 (0.00017)	-0.0025*** (0.00035)	-0.00053*** (0.00016)	-0.0036*** (0.00045)	-0.00032** (0.00014)	-0.0029*** (0.00043)
Obs R-squared	75166 0.083	74901 0.083	74901 0.093	74901 0.084	74901 0.093	74901 0.084	74901 0.093

TABLE 2. AGGREGATE IMPACT OF UNCERTAINTY, COUNTY-LEVEL

This table reports regressions from a county-level quarterly panel (2008-2013). "Home" is the fraction of first mortgages originated in the county among the sample of individuals in Equifax that live in the county in the quarter; "Car" is the fraction of new cars financed among the sample of individuals in Equifax that live in the county in that quarter. Standard errors are clustered at the state level, and all regressions include county fixed effects.

(1)	(2)	(3)	(4)	(5)	(6)
Home	Car	Home	Car	Home	Car
-0.000096*** (0.000022)	0.000011 (0.000017)			-0.000089*** (0.000022)	0.0000097 (0.000017)
		-0.000049*** (0.0000040) 0.000049***	0.000011** (0.0000049)	-0.000048*** (0.0000040)	0.000011** (0.0000049)
0.28***	-0.65***	0.21***	-0.62***	0.054	-0.60***
(0.054)	(0.082)	(0.056)	(0.083)	(0.058)	(0.082)
0.0022*	0.052***	0.0022*	0.052***	0.0022*	0.052***
(0.0012)	(0.0020)	(0.0012)	(0.0020)	(0.0012)	(0.0020)
0.045***	0.052***	0.044***	0.054***	0.030***	0.055***
(0.0030)	(0.0048)	(0.0030)	(0.0039)	(0.0031)	(0.0047)
-0.00024***	0.00040***	-0.00011***	0.00039***	-0.00024***	0.00040***
(0.000043)	(0.000060)	(0.000027)	(0.000051)	(0.000043)	(0.000060)
0.0011***	0.0049***	0.00068**	0.0051***	-0.000063	0.0052***
(0.00039)	(0.00051)	(0.00031)	(0.00049)	(0.00043)	(0.00049)
0.0013***	-0.0011***	0.00025	-0.00083***	0.00016	-0.00082***
(0.00017)	(0.00018)	(0.00020)	(0.00021)	(0.00021)	(0.00021)
4895978	4895978	4895978	4895978	4895978	4895978
0.054	0.072	0.054	0.072	0.054	0.072
	<ul> <li>(1)</li> <li>Home</li> <li>-0.000096***</li> <li>(0.000022)</li> <li>0.28***</li> <li>(0.0054)</li> <li>0.0022*</li> <li>(0.0012)</li> <li>0.045***</li> <li>(0.0030)</li> <li>-0.00024***</li> <li>(0.000043)</li> <li>0.0011***</li> <li>(0.00039)</li> <li>0.0013***</li> <li>(0.00017)</li> <li>4895978</li> <li>0.054</li> </ul>	(1)         (2)           Home         Car           -0.000096***         0.000011           (0.000022)         (0.000017)           0.28***         -0.65***           (0.00022)         (0.00017)           0.28***         -0.65***           (0.0012)         (0.082)           0.0022*         0.052***           (0.0012)         (0.0020)           0.045***         0.052***           (0.0030)         (0.0048)           -0.00024***         0.00040***           (0.000043)         (0.00040)           0.0011***         0.0049***           (0.00013)         -0.0011***           (0.00017)         (0.00018)           4895978         4895978           0.054         0.072	(1)         (2)         (3)           Home         Car         Home           -0.000096***         0.000011         -0.000049***           (0.000022)         (0.000017)         -0.000049*** $-0.000049^{***}$ 0.000017)         -0.000049***           0.28***         -0.65***         0.21***           (0.054)         (0.082)         (0.056)           0.0022*         0.052***         0.0022*           (0.0012)         (0.0020)         (0.0012)           0.045***         0.052***         0.044***           (0.0030)         (0.0048)         (0.0030)           -0.00011***         0.00049***         0.00068**           (0.00039)         (0.00051)         (0.00027)           0.0013***         -0.0011***         0.00025           (0.0017)         (0.0018)         (0.00020)           4895978         4895978         4895978           0.054         0.072         0.054	(1)         (2)         (3)         (4)           Home         Car         Home         Car           -0.000096***         0.000011         -0.000049***         0.000011**           (0.000022)         (0.000017)         -0.000049***         0.000011** $-0.000049^{***}$ 0.000011**         (0.0000049)         -0.62*** $0.000049^{***}$ 0.000011**         -0.62***         0.000049*** $0.000049^{***}$ 0.000011**         -0.62***         0.022** $0.054^{***}$ 0.052***         0.0022*         0.052*** $0.0022^{*}$ 0.052***         0.0022*         0.052*** $0.0012$ (0.0020)         (0.0012)         (0.0020) $0.045^{***}$ 0.052***         0.0044***         0.054*** $(0.00043)$ (0.00040***         -0.00011***         0.00039) $0.0011^{***}$ 0.00049***         0.00068**         0.0051*** $(0.00039)$ (0.00031)         (0.00049)*         0.00068*** $0.0011^{***}$ 0.00013)         (0.00033)         0.00051) $0.0013^{***}$ -0.0011***         0.00025         -0.00083***	(1)(2)(3)(4)(5)HomeCarHomeCarHome $-0.000096^{***}$ $0.000011$ $-0.000089^{***}$ $0.000011^{***}$ $(0.000022)$ $(0.00017)$ $-0.000049^{***}$ $0.000011^{**}$ $-0.000049^{***}$ $0.000011^{***}$ $0.000011^{***}$ $(0.000040)$ $(0.0000040)$ $(0.0000040)$ $-0.000049^{***}$ $0.000011^{***}$ $0.000011^{***}$ $0.28^{***}$ $-0.65^{***}$ $0.21^{***}$ $-0.62^{***}$ $0.054$ $(0.054)$ $(0.082)$ $(0.056)$ $(0.083)$ $(0.058)$ $0.0022^{*}$ $0.052^{***}$ $0.0022^{*}$ $0.0022^{*}$ $0.0022^{*}$ $(0.0012)$ $(0.0020)$ $(0.0012)$ $(0.0020)$ $(0.0012)$ $0.045^{***}$ $0.052^{***}$ $0.0021^{***}$ $(0.00031)$ $-0.00024^{***}$ $0.00040^{***}$ $0.00011^{***}$ $-0.00024^{***}$ $(0.0003)$ $(0.00051)$ $(0.00027)$ $(0.00039)^{***}$ $(0.00043)$ $0.0011^{***}$ $0.00049^{***}$ $0.00068^{**}$ $0.0051^{***}$ $0.00016$ $(0.0003)$ $(0.00031)$ $(0.00043)$ $(0.00043)$ $0.0013^{***}$ $-0.0011^{***}$ $0.00025$ $-0.00083^{***}$ $0.00016$ $(0.00017)$ $(0.00018)$ $(0.00025)$ $-0.00083^{***}$ $0.00016$ $(0.00017)$ $(0.00018)$ $(0.0025)$ $-0.00083^{***}$ $0.00016$ $(0.00017)$ $(0.00018)$ $(0.0025)$ $-0.00083^{***}$ $0.00016$ $(0.00017)$ $(0.00018)$

TABLE 3	UNCERTAINTY.	INDIVIDUAL-LEVEL	EVIDENCE
IADLL J.	UNCERTAINT I.	INDIVIDUAL LLVLL	LIDLIGL

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

	Obs.	Mean	Standard Deviation	Min	р5	p25	p50	p75	p95	Max
Tax Patio										
(Zip										
Code)	2549	0.06	0.46	-24 69	0.00	0.02	0.05	0.08	0.19	20.26

 TABLE 4. THE RATIO OF CAPITAL GAINS AND DIVIDENDS TO ADJUSTED GROSS INCOME, IRS TAX DATA 2005.

TABLE 5A. UNCERTAINTY: VI	X AND ZIP CODE TAX	RATIOS		
	(1)	(2)	(3)	(4)
VARIABLES	Home	Mortgage Change	Car(Bank)	Car(Non-Bank)
age (log)	0.00694**	-0.211***	0.00203	0.0105***
	(0.00274)	(0.0379)	(0.00285)	(0.00365)
VIX*Top ratio	-2.54e-05**	-0.000361*	-5.35e-06	-5.15e-06
	(1.05e-05)	(0.000180)	(8.82e-06)	(9.90e-06)
S&P Change*Top ratio	0.0333	-1.596	0.0216	-0.0277
	(0.0568)	(1.046)	(0.0567)	(0.0653)
Average Risk score, previous year	-0.00266**	0.395***	0.0129***	0.0102***
	(0.00131)	(0.0420)	(0.00110)	(0.00128)
Observations	4,318,749	4,318,747	4,318,749	4,318,749
R-squared	0.062	0.017	0.067	0.063

TABLE 5B. UNCERTAINTY: POLICY UNC	ERTAINTY AND ZIP CO	DDE TAX RATIOS		
	(1)	(2)	(3)	(4)
VARIABLES	Home	Mortgage Change	Car(Bank)	Car(Non-Bank)
age (log)	0.00674**	-0.215***	0.00199	0.0105***
	(0.00274)	(0.0375)	(0.00285)	(0.00367)
Policy Uncertainty*Top ratio	-4.93e-06	-0.000115	-1.28e-06	-6.68e-07
	(4.77e-06)	(7.60e-05)	(3.62e-06)	(3.33e-06)
S&P Change*Top ratio	0.111*	-0.602	0.0375	-0.0110
	(0.0572)	(0.889)	(0.0441)	(0.0492)
Average FICO score, previous year	-0.00267**	0.395***	0.0129***	0.0102***
	(0.00130)	(0.0421)	(0.00110)	(0.00127)
Observations	4,318,749	4,318,747	4,318,749	4,318,749
R-squared	0.062	0.017	0.067	0.063

This table reports regressions from an individual level quarterly panel (2008-2013). "Home" is the probability that an individual obtains a first mortgage; "Car" is the probability that an individual finances a car from either a bank or non-bank. Top Ratio is an indicator that equals one if an individual lives in a zip code with a ratio of capital gains and dividend income that is above the median. Standard errors are clustered at the state level, and all regressions include individual fixed effects and year-quarter fixed effects.

TABLE 6A. VIX, AGE A	ND ZIP CODE TAX RATIO	OS		
	(1)	(2)	(3)	(4)
VARIABLES	Home	Mortgage Change	Car(Bank)	Credit Card Limit (Log)
age_20_top_vix	-0.000077**	0.000366	-0.00018***	0.00347***
	(0.000033)	(0.000319)	(0.000043)	(0.000457)
age_30_top_vix		-0.000915***		-0.000736*
	-0.00012***	(0.000332)	-0.00024***	(0.000428)
age_40_top_vix	(0.000028)	-0.000928***	(0.000043)	-0.00163***
		(0.000311)		(0.000488)
age_50_top_vix	-0.00019***	-0.000495	-0.00020***	-0.00191***
	(0.000029)	(0.000303)	(0.000036)	(0.000602)
age_60_top_vix		-0.000172		-0.00153***
	-0.00019***	(0.000343)	-0.00013***	(0.000496)
age_70_top_vix	(0.000023)	0.000213	(0.000035)	0.00261***
		(0.000200)		(0.000751)
Observations	4,724,440	4,724,437	4,724,440	4,724,384
R-squared	0.058	0.015	0.063	0.871

This table reports regressions from an individual level quarterly panel (2008-2013). "Home" is the probability that an individual obtains a first mortgage; "Car" is the probability that an individual finances a car from either a bank or non-bank. Top Ratio is an indicator that equals one if an individual lives in a zip code with a ratio of capital gains and dividend income that is above the median. Standard errors are clustered at the state level, and all regressions include individual fixed effects and year-quarter fixed effects. The variable "age\_x top\_vix" is a triple interaction term: "age\_x" is an indicator that equals 1 if an individual is in their "x" decade. Top is an indicator that equals one if an individual lives in a zip code with a ratio of capital gains and dividend income that is above the median. And VIX is the quarterly mean VIX. All regressions also include interaction terms between "age\_x" and "Top". All regressions also include interaction terms with the change in the S&P 500 index.

	(1)	(2)	(3)	(4)
VARIABLES	Home	Mortgage Change	Car(Bank)	Credit Card Limit (Log)
				·
age (log)	0.0169***	-0.0382	0.00117	6.222***
	(0.00242)	(0.0323)	(0.00272)	(0.221)
age_20_top_vix	-0.000049	0.000226	-0.00016***	0.00279***
	(0.000033)	(0.000320)	(0.000043)	(0.000570)
age_30_top_vix		-0.000437		-0.00176***
	-0.000068**	(0.000366)	-0.00023***	(0.000511)
age_40_top_vix	(0.000029)	-0.000668**	(0.000047)	-0.00232***
		(0.000286)		(0.000575)
age_50_top_vix	-0.00014***	-0.000315	-0.00021***	-0.00213***
	(0.000032)	(0.000314)	(0.000038)	(0.000658)
age_60_top_vix		-0.000199		-0.00127*
	-0.00015***	(0.000352)	-0.00015***	(0.000634)
age_70_top_vix	(0.000026)	7.35e-05	(0.000037)	0.00419***
		(0.000216)		(0.000904)
age_20_top_bbd_index	-0.000027***	0.000142	-0.0000085	0.000594***
	(0.0000094)	(0.000116)	(0.000018)	(0.000167)
age_30_top_bbd_index		-0.000533***		0.00103***
	-0.000050***	(0.000114)	-0.0000061	(0.000183)
age_40_top_bbd_index	(0.000011)	-0.000287***	(0.000017)	0.000738***
		(8.68e-05)		(0.000164)
age_50_top_bbd_index	-0.000056***	-0.000199*	0.000020	0.000262
	(0.000088)	(0.000104)	(0.000013)	(0.000171)
age_60_top_bbd_index		1.67e-05		-0.000211
	-0.000041***	(0.000118)	0.000014	(0.000260)
age_70_top_bbd_index	(0.000080)	0.000144	(0.000012)	-0.00163***
		(0.000113)		(0.000340)
Observations	4,724,440	4,724,437	4,724,440	4,724,384
R-squared	0.058	0.015	0.063	0.871

TABLE 6B. VIX AND POLICY UNCERTAINTY

This table reports regressions from an individual level quarterly panel (2008-2013). "Home" is the probability that an individual obtains a first mortgage; "Car" is the probability that an individual finances a car from either a bank or non-bank. Top Ratio is an indicator that equals one if an individual lives in a zip code with a ratio of capital gains and dividend income that is above the median. Standard errors are clustered at the state level, and all regressions include individual fixed effects and year-quarter fixed effects. The variable "age\_x\_top\_vix" is a triple interaction term: "age\_x" is an indicator that equals 1 if an individual is in their "x" decade. Top is an indicator that equals one if an individual is in their "x" decade. Top is an indicator that equals one if an individual lives in a zip code with a ratio of capital gains and dividend income that is above the median. And VIX is the quarterly mean VIX. All regressions also include interaction terms with the change in the S&P 500 index.

TABLE /A. LOCAL UNCERTAINTY						
VARIABLES	(1) Home	(2) Mortgage Change	(3) Car(Bank)	(4) Credit Card Limit (Log)		
		0				
age_20_top_sd	0.466	3.032	-0.308	12.72		
	(0.281)	(3.661)	(0.255)	(7.830)		
age_30_top_sd	-0.380	-2.449	0.0449	-29.89***		
	(0.306)	(4.807)	(0.270)	(6.517)		
age_40_top_sd	-1.311***	-8.423**	-0.0981	-26.03***		
	(0.246)	(3.318)	(0.229)	(6.883)		
age_50_top_sd	-1.186***	-5.386*	0.0711	-32.94***		
	(0.236)	(3.143)	(0.227)	(7.565)		
age_60_top_sd	-0.799**	-1.962	0.142	-6.376		
	(0.351)	(4.219)	(0.287)	(8.105)		
age_70_top_sd	0.331*	2.093	-0.0784	61.91***		
	(0.183)	(3.593)	(0.217)	(10.66)		
age_20_top_mean	-1.970**	-5.852	-2.497**	154.2***		
	(0.929)	(13.95)	(1.190)	(17.66)		
age_30_top_mean	3.377*	-30.03	0.738	76.85***		
	(1.807)	(26.50)	(1.197)	(17.83)		
age_40_top_mean	3.858***	-56.96**	-0.0843	57.54***		
	(1.369)	(23.30)	(1.196)	(21.10)		
age_50_top_mean	1.427	-28.20	1.166	26.77		
	(1.148)	(18.08)	(1.226)	(21.59)		
age_60_top_mean	0.870	20.07	0.801	-2.655		
	(1.398)	(18.28)	(1.474)	(25.12)		
age_70_top_mean	-1.075	25.79*	-0.506	-55.23		
	(1.030)	(15.11)	(0.756)	(36.87)		
Observations	4,318,749	4,318,747	4,318,749	4,318,697		
R-squared	0.062	0.017	0.067	0.877		

TABLE 7A. LOCAL UNCERTAINTY

This table reports regressions from an individual level quarterly panel (2008-2013). "Home" is the probability that an individual obtains a first mortgage; "Car" is the probability that an individual finances a car from either a bank or non-bank. Top Ratio is an indicator that equals one if an individual lives in a zip code with a ratio of capital gains and dividend income that is above the median. Standard errors are clustered at the state level, and all regressions include individual fixed effects and year-quarter fixed effects. The variable "age\_x\_top\_mean" is a triple interaction term: "age\_x" is an indicator that equals 1 if an individual is in their "x" decade. Top is an indicator that equals one if an individual is above the median. "mean" is the county-level uncertainty index derived from the VIX. All regressions also include interaction terms with the change in the S&P 500 index.

	(1)	(2) Mortgage	(3)	(4) Credit Card
VARIABLES	Home	Change	Car(Bank)	Limit (Log)
age_20_top_sd	0.397	1.594	-0.351	4.396
	(0.288)	(3.684)	(0.248)	(8.893)
age_30_top_sd	-0.165	1.400	0.111	-39.43***
	(0.344)	(5.135)	(0.271)	(7.290)
age_40_top_sd	-1.279***	-6.368*	-0.0490	-32.10***
	(0.252)	(3.190)	(0.240)	(7.700)
age_50_top_sd	-1.112***	-3.446	0.0947	-34.77***
	(0.229)	(3.174)	(0.241)	(8.465)
age_60_top_sd	-0.725**	-1.802	0.110	-3.296
	(0.355)	(4.012)	(0.297)	(9.379)
age_70_top_sd	0.325*	1.506	-0.115	75.10***
	(0.176)	(3.473)	(0.210)	(12.69)
age_20_top_mean	-1.807*	-2.288	-2.377**	169.8***
	(0.925)	(14.48)	(1.175)	(18.51)
age_30_top_mean	2.459	-46.62*	0.447	108.9***
	(1.704)	(26.47)	(1.234)	(19.09)
age_40_top_mean	3.761***	-64.55***	-0.267	79.15***
	(1.379)	(23.83)	(1.156)	(22.51)
age_50_top_mean	1.100	-36.33*	1.072	35.89
	(1.224)	(19.26)	(1.214)	(24.44)
age_60_top_mean	0.555	20.15	0.959	-13.09
	(1.319)	(19.30)	(1.479)	(27.30)
age 70 top mean	-1.006	29.38*	-0.320	-113.2**
	(1.077)	(16.06)	(0.776)	(43.10)
age_20_top_bbd	9.08e-06	0.000199	6.48e-06	0.000744***
	(8.29e-06)	(0.000124)	(7.59e-06)	(0.000168)
age_30_top_bbd	-3.45e-05***	-0.000625***	-1.07e-05	0.00121***
	(1.01e-05)	(0.000129)	(7.36e-06)	(0.000184)
age_40_top_bbd	-5.26e-06	-0.000315***	-7.26e-06	0.000861***
	(5.91e-06)	(0.000101)	(6.57e-06)	(0.000178)
age_50_top_bbd	-1.22e-05	-0.000303**	-3.53e-06	0.000359*
	(8.12e-06)	(0.000120)	(6.56e-06)	(0.000184)
age_60_top_bbd	-1.13e-05	-3.23e-05	4.57e-06	-0.000290
	(7.83e-06)	(0.000145)	(6.42e-06)	(0.000256)

TABLE 7B. LOCAL AND POLICY UNCERTAINTY

age_70_top_bbd	1.10e-06	9.31e-05	5.81e-06	-0.00184***
	(5.25e-06)	(0.000127)	(6.34e-06)	(0.000363)
Observations	4,318,749	4,318,747	4,318,749	4,318,697
R-squared	0.062	0.017	0.067	0.877

This table reports regressions from an individual level quarterly panel (2008-2013). "Home" is the probability that an individual obtains a first mortgage; "Car" is the probability that an individual finances a car from either a bank or non-bank. Top Ratio is an indicator that equals one if an individual lives in a zip code with a ratio of capital gains and dividend income that is above the median. Standard errors are clustered at the state level, and all regressions include individual fixed effects and year-quarter fixed effects. The variable "age\_x\_top\_mean" is a triple interaction term: "age\_x" is an indicator that equals 1 if an individual is in their "x" decade. Top is an indicator that equals one if an individual lives in a zip code with a ratio of capital gains and dividend income that is above the median. "mean" is the county-level uncertainty index derived from the VIX. "bbd: is the policy uncertainty measure. All regressions also include interaction terms with the change in the S&P 500 index.

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