Climate Risk is Financial Risk

Giacomo De Giorgi[*], Costanza Naguib[†‡]

Abstract

Extreme weather events are known to trigger workers' relocation. But climate risk also has a direct impact on financial risk. We measure the impact of natural disaster on a series of credit variables (defaults, foreclosures, credit card balance, ...) by using a unique proprietary dataset provided by Experian, who includes 1% of all the US population for the period 2004-2019 and we find evidence of negative and long-lasting impact of climatic shocks on the main credit variables.

Keywords: Natural disasters, Consumption, Income, Earnings persistence, Mobility

JEL codes: E21, D12

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1 Introduction

The aim of this paper is to investigate the impact of natural disasters on financial risk, as measured by a series of credit variables, such as current and new delinquencies, current and new foreclosures, chapter 13 and chapter 7 bankruptcy declarations, credit score and so on. The economic impact of natural disasters is currently a hot topic in both the economic and the political debate. According to the 2018 UN report, climate change will cause a dramatic rise in the frequency of natural disasters and in the subsequent economic losses in the next decades (UN, 2018). The contribution of this paper lies in the fact that we use high-quality US data from the credit scores recorded by the private firm Experian. The advantages of using this proprietary dataset are the following: (i) the level of geographical detail is notably fine, since we have information on individuals' staying and moving decisions at the level of the five-digit ZIP codes. Further (ii) we have information not only about individual income, but we can also exploit a measure of imputed consumption (based on credit card expenditure information). This allows us to examine how the impact of a natural disaster reverberates, respectively on income and on consumption and whether there are differences in these two impacts. Our data are panel, which allows us to control for individual and area-specific fixed effects. Further, a large number of credit variables, such as delinquencies, foreclosures, amount of mortgage, original price of car and so on are included in our dataset and hence available for analysis.

The remainder of this section presents an overview of the past literature on the economic impact of natural disasters. The United States are often chosen for analysis because: (i) their large geographical extension provides a wide richness of areas who are strongly and frequently hit by catastrophic natural events, whereas other areas are only mildly or barely hit at all, (ii) further, data availability both on meteorological and on economic data is usually excellent in the US. For this reason, in the present paper we will focus on the United States as well.

Contrary to what could be expected, there is currently no consensus in the literature on the sign of the impact of a natural disaster on migration flows. Indeed, Vigdor (2008) finds a negative impact of disasters on population size, whereas Boustan et al. (2012) find that the sign of the impact depends on the type of natural event. Hurricanes induce migration out of the area (see also Ouattara and Strobl (2014)), whereas floods attract population. The impact of natural disasters on labor market outcomes is also not clear-cut. Indeed, it mostly depends on whether individuals perceive climatic shocks as temporary or permanent, and on the existence and extent of public assistance programs and incentives for reconstruction (Belasen and Polachek (2008), Groen and Polivka (2008), McIntosh (2008), Belasen and Polacheck (2009), Strobl and Walsh (2009), Deryugina et al. 2018, Baker et al. 2019, Karbownik and Wray (2019), Gregory 2019). Further, natural disasters have been found to reduce the expected return on physical capital, but to increase incentives to accumulate human capital (Skidmore and Toya 2002).

Natural disasters have been found to cause a decline in economic growth (e.g. Noy and Nualsri (2011), Strobl (2011), Cavallo et al. (2013)), whereas several studies have found a positive or neutral association between extreme weather events and productivity (Leiter et al. (2009), Skidmore and Toya (2002)). Mohan et al. (2018) clarify that the different GDP components may respond in very different ways, both in sign and in size, to a natural disaster, and this explains why empirical evidence is mixed. In one of the few papers that study the impact of climate shocks on financial variables, Bourdeau-Brien and Kryzaniwski (2017) find that natural disasters in the US rarely have a significant impact on stock returns and that this impact is usually limited to firms which are based in disaster areas. With reference to Jamaican households, Henry et al. (2019) report that the impacts of extreme natural events on consumption are heterogeneous both across type of natural event and across household themselves (i.e. depending on their degree of partial insurance via savings). Brei et al. (2019) investigate the consequences of hurricanes on the banking sector in the Caribbean. In the US, floodings and similar events are associated with a spike in credit card borrowing and delinquencies; however, these phenomena are mostly short-lived and are usually followed by a reduction in total debt, fueled by flood insurances (Gallagher and Hartley (2017), Bleemer and van der Klaauw (2019)). Most literature on the topic of how climate shocks affect finance focus on how should central banks plan their strategy in view of an increasing number of extreme weather events in the future. On the contrary, the present paper aims at assessing the impact of natural disaster on credit reliability variables at the individual level.

The remainder of this paper is organized as follows: Section 2 presents the data, Section 3 is devoted to the presentation of the estimation methods employed and of the respective results obtained. Section 4 comments on these results and concludes.

2 Data and exploratory analysis

We rely on a unique proprietary dataset, which has been provided by Experian. This dataset includes information on the credit scores and ZIP codes of residence of around 1% of the total population of the US. Hence, we can rely on a huge sample size for our statistical analyses, as much as two million observations per year for the period 2004-2019.

Our data include a series of variables on number of trades made and several variables measuring credit reliability (i.e. number of bankruptcies, number of credit delinquencies, number of credit cards, average amount of credit and so on). Beyond this rich credit information (more than 400 variables), we have information on individual's age and a measure of imputed income, which has been computed by Experian. The reliability of this income imputation measure has been checked by comparing average income by age cohort with the PSID, and the results were plausible (see Appendix). Further, Lee and Van der Klaauw (2010) have shown validity and representativeness of the New York Fed Consumer Credit Panel, which is constructed on the basis of the same data source as our dataset.

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Credit Score	674.3781	112.0946	300	839	24,717,211
Income	50127.2	26866.57	1000	343000	24,717,211
Auto Balance	5912.833	12533.05	0	1.39e+07	24,717,211
Mortgage Balance	78406.96	170778	0	1.86e+07	24,717,211
Age	47.0412	12.2928	20	70	24,717,211
Consumption (w/zeros)	10256.24	20652.09	0	7744839	24,717,211
Move Zip dummy	0.1299	0.3362	0	1	24,717,211
Move Commuting Zone	0.0484	0.2147	0	1	24,717,211
Homeowner dummy	0.6255	0.4840	0	1	24,717,211
d90 current	0.3874	0.4872	0	1	24,717,211
d120 current	0.3751	0.4841	0	1	24,717,211
d90 new	0.0653	0.2470	0	1	24,717,211
d120 new	0.0619	0.2410	0	1	24,717,211
Forecl. current	0.0184	0.1343	0	1	24,717,211
Forecl. new	0.0055	0.0736	0	1	24,717,211
Ch 7 current	0.0671	0.2501	0	1	24,717,211
Ch 7 new	0.0108	0.1031	0	1	24,717,211
Ch 13 current	0.0156	0.1241	0	1	24,717,211
Ch 13 new	0.0033	0.0572	0	1	24,717,211

Table 1: Summary statistics of our main variables, 2004-2019

In Table 1 we report the summary statistics for our main credit variables, as well as for age, consumption and income.

For the natural disaster information, we resort to FEMA/HAZUS data, which provide detailed geographical information (to the level of the 5-digit ZIP code) on the areas affected by the extreme weather events. We distinguish between different types of natural disasters according to the FEMA classification: earthquake, fire, flood, hurricane, mud/landslide, severe storm, tornado, typhoon and volcano. In the next Section, we focus on a single type of disaster: storm. We select storms because they are the most common type of disaster in the US (they constitute around 62% of all the extreme weather events recorded in our period of analysis). In the regression analyses reported in Appendix B, we also consider the impact of a fire on our credit variables. The reason for this robustness check is that fires are unpredictale, so estimation results should not be distorted by anticipation effects. We consider as natural disasters all those recorded in the dataset FEMA: Disaster Declarations Summaries[1]. In the robustness checks reported in the Appendix, we measure extreme weather events by the monetary value in usd of the damage that they caused. This monetary value is taken directly from either the FEMA Housing Assistance Program Data for renters or from that for owners[2]. A FEMA disaster declaration is a political process, hence, there is no fixed definition of what is a storm or a severe storm. All requests for a disaster declaration have to be made by the governor of the affected State or district after a preliminary damage assessment is performed by the local FEMA office. This preliminary assessment aims at determining the extent of the disaster, its impact on individual and public facilities and the types of federal assistance that may be needed.

[1]Source: https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v1

[2]Sources: https://www.fema.gov/openfema-data-page/housing-assistance-program-data-owners-v1, https://www.fema.gov/openfema-data-page/housing-assistance-program-data-renters-v2

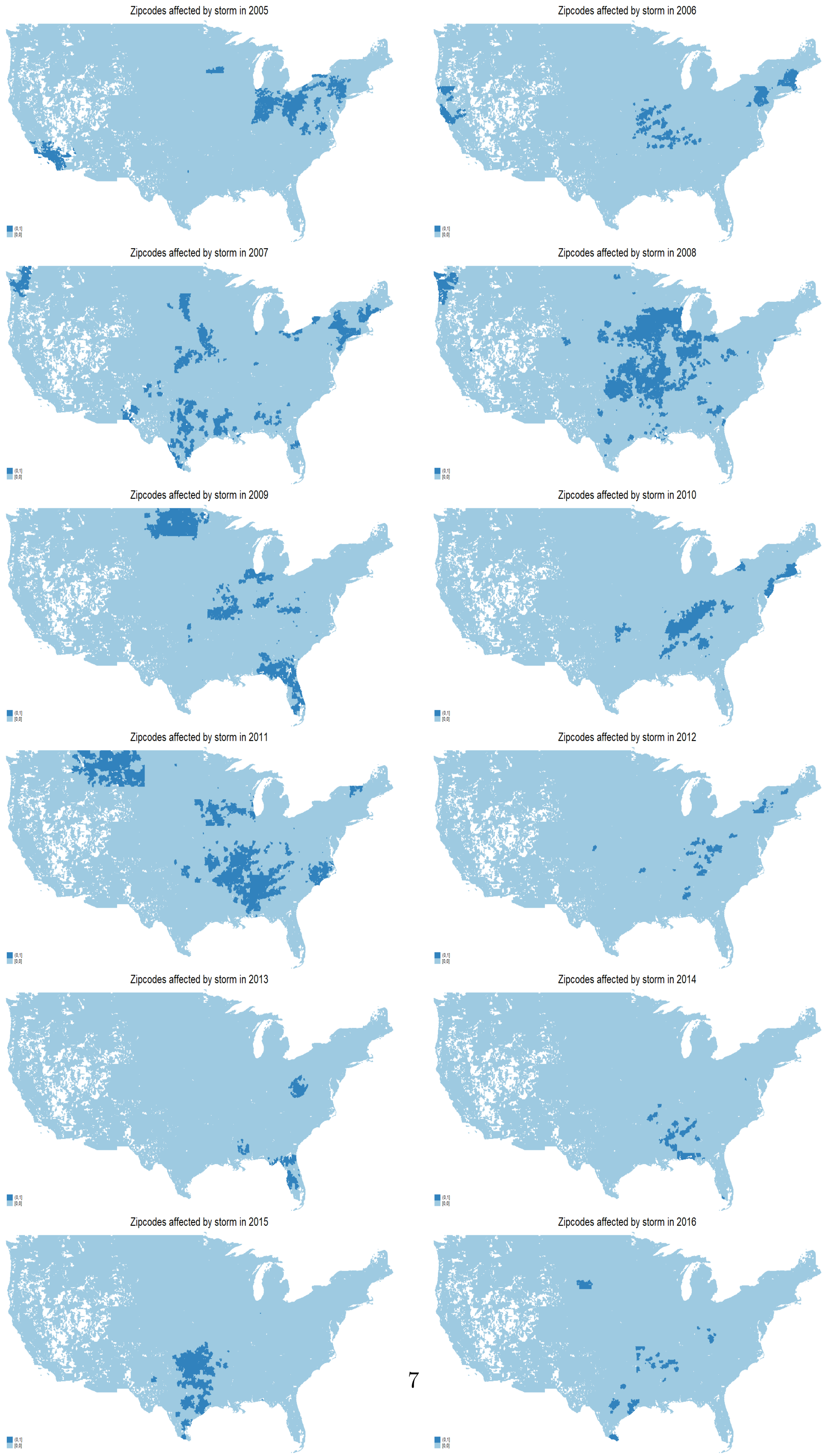

Figure 1: Zipcodes affected by storm, by year

In Figure 1, we report the zipcodes affected by storms, by year, in the period under scrutiny.The white areas in the graphs are remote areas which do not have a real zipcode[3].

Year	N of counties affected by Storm	N of zipcodes affected by Storm	Number of events
2005	302	2,880	31
2006	183	1,618	27
2007	382	3,069	29
2008	660	4,283	39
2009	320	2,183	28
2010	246	2,221	16
2011	517	3,029	25
2012	103	494	26
2013	73	707	14
2014	66	337	7
2015	164	1,136	6
2016	78	494	16

Of course, the number of disaster in itself only constitutes a very rough measure of natural disruption incidence, since it doesn't convey information about the intensity of the damage. For this reason, in some of the following analysis we will also resort to some measure of disaster intensity.

3 Event study results

In this section we present the results of a series of event studies in which we investigate the dynamic impact of a climate shock on each of our credit variables. We implement an event study design in the spirit of Athey and Imbens (2018), Callaway and Sant'Anna (2020). We estimate:

$$Y_{it} = \alpha_1 + \beta_t + \tau W_{it} + \varepsilon_{izt} \tag{1}$$

where Y is one of our credit variables, α_i are individual effects, β_t are time effects, W_{it} is the treatment. In this specification, the event is at the zipcode level, and follows individuals who were in that zip code at the time, so the analysis is at the event level.

[3]Note that, in the descriptive statistics, for each disaster we record the actual year in which it happened. However, since our credit data are recorded each year on the 30th of June, after merging them with the disaster data we increase by one the year of those disasters which happened after the 30th of June.

Two problems arise: (1) zipcodes are all hit by the storm at different times (some are never hit), and (2) Individuals can relocate in response to natural disasters We tackle these problems by re-initialiting the time variable according to each event and by fixing the zipcode population to what was before the disaster took place.

3.1 Housing Market

From Figure 5, we find evidence that a storm has a negative and statistically significant impact on the probability of having a mortgage. The impact is around the size of around 1-2% and lasts over time up to nine lags after the storm took place. From Figure 6, we find evidence that of a somehow positive impact of storms on mortgage balance. However, this effect is barely statistically significant at any of the time leads considered. We conclude that storms cause a decline in the probability of having a mortgage, but a (slight) increase in the amount of existing mortgages.

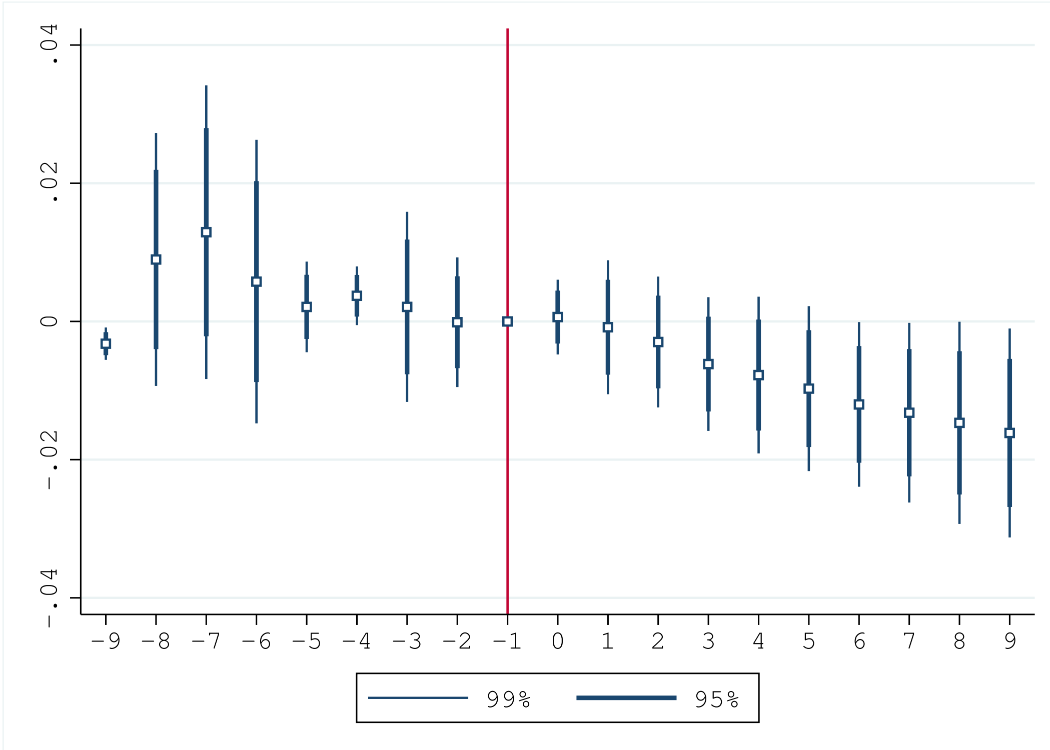

Figure 2: Event study, impact of storm on mortgage origination, data for the period 2004-2019, all variables are averages computed at the event-year level. Dots are point estimates, lines show 99% confidence intervals

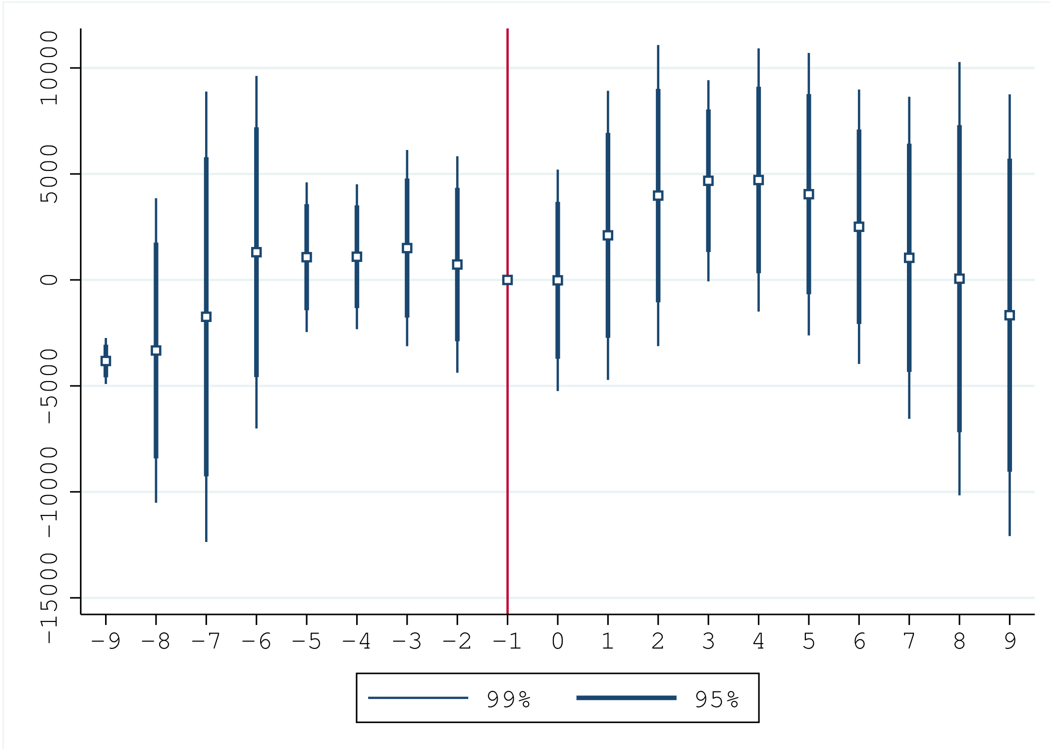

Figure 3: Event study, impact of storm on mortgage balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

3.1.1 Foreclosure

From Figure 7, we deduce that storms have a positive impact on the probability of having a foreclosure. The effect anyways is barely statistically significant. This may be due to the temporary relief/assistance programs which prevents individuals from having a foreclosure in the aftermath of a natural disaster.

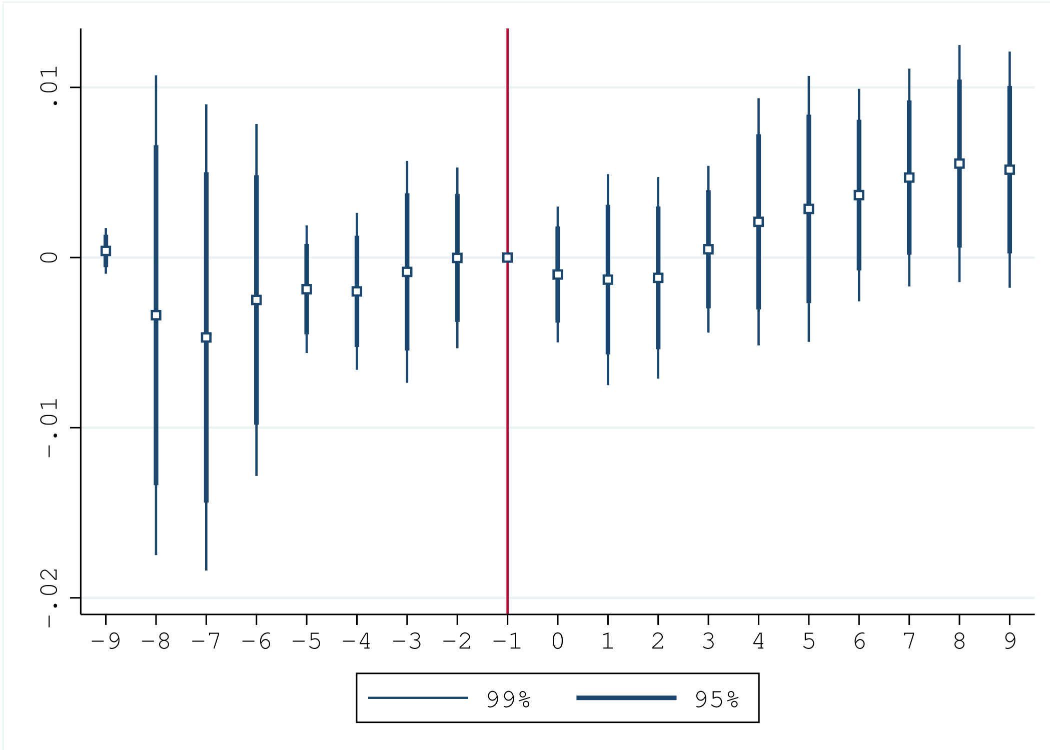

Figure 4: Event study, impact of storm on foreclosures, data for the period 2004-2019, all variables are averages computed at the zip code level.

3.2 Bankruptcy

Chapter 13. prevalence as in Table 1 is 1.6pp. so the effects are massive.[4]

As far as bankruptcy is concerned, from Figure 8 we find evidence that storms have a positive and statistically significant impact on the probability of declaring chapter 7 bankrupcy. This effect is still significant nine years after the adverse weather event.

[4] *A chapter 13 bankruptcy is also called a wage earner's plan. It enables individuals with regular income to develop a plan to repay all or part of their debts. Under this chapter, debtors propose a repayment plan to make installments to creditors over three to five years. If the debtor's current monthly income is less than the applicable state median, the plan will be for three years unless the court approves a longer period "for cause." (1) If the debtor's current monthly income is greater than the applicable state median, the plan generally must be for five years. In no case may a plan provide for payments over a period longer than five years. 11 U.S.C. 1322(d). During this time the law forbids creditors from starting or continuing collection efforts. This chapter discusses six aspects of a chapter 13 proceeding: the advantages of choosing chapter 13, the chapter 13 eligibility requirements, how a chapter 13 proceeding works, making the plan work, and the special chapter 13 discharge.* `https://www.uscourts.gov/services-forms/bankruptcy/bankruptcy-basics/chapter-13-bankruptcy-basics`

Please note that Chapter 7 declaration is usually more serious than Chapter 13 declaration, since the former leads to liquidation of assets, whereas the latter usually involves a reorganization of debts to be paid, e.g. giving more time to the debtor and laying out a plan for reimboursement. The impact of a storm on chapter 13 declaration is clearly higher than that on chapter 7 declarations, as we deduce from the comparison of Figure 8 and Figure 9. Further, the positive impact of the storm on chapter 13 declaration shows a sort of exponential growth from around year 3 up to year 9 after the natural disaster takes place.

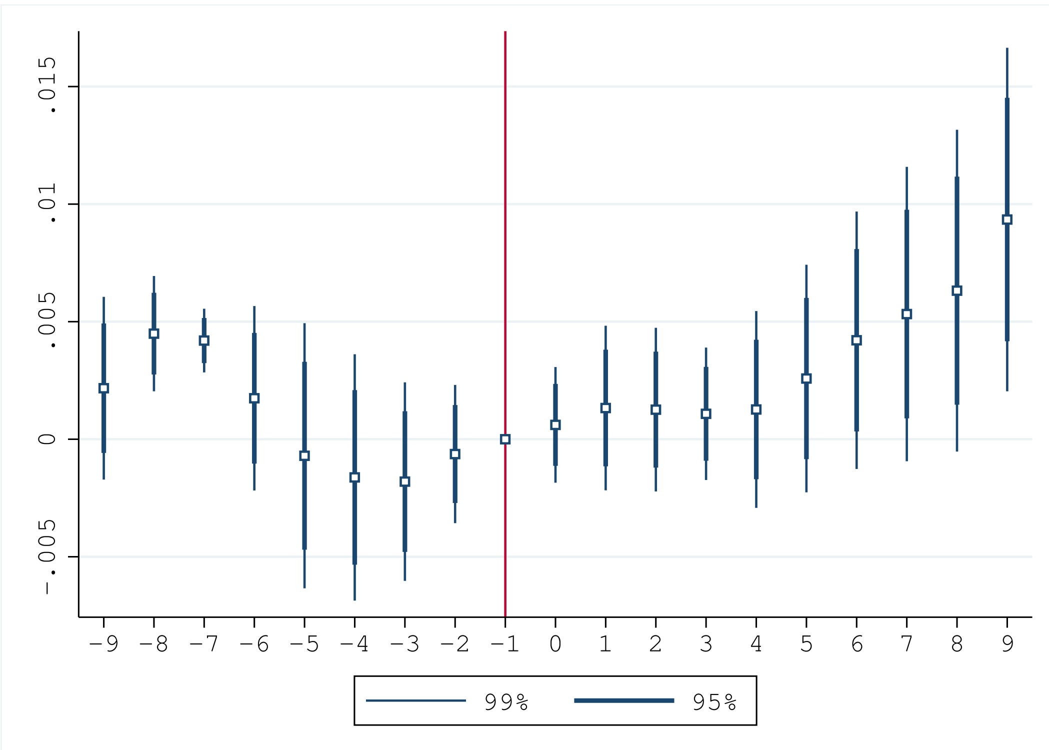

Figure 5: Event study, impact of storm chapter 7, data for the period 2004-2019, all variables are averages computed at the zip code level.

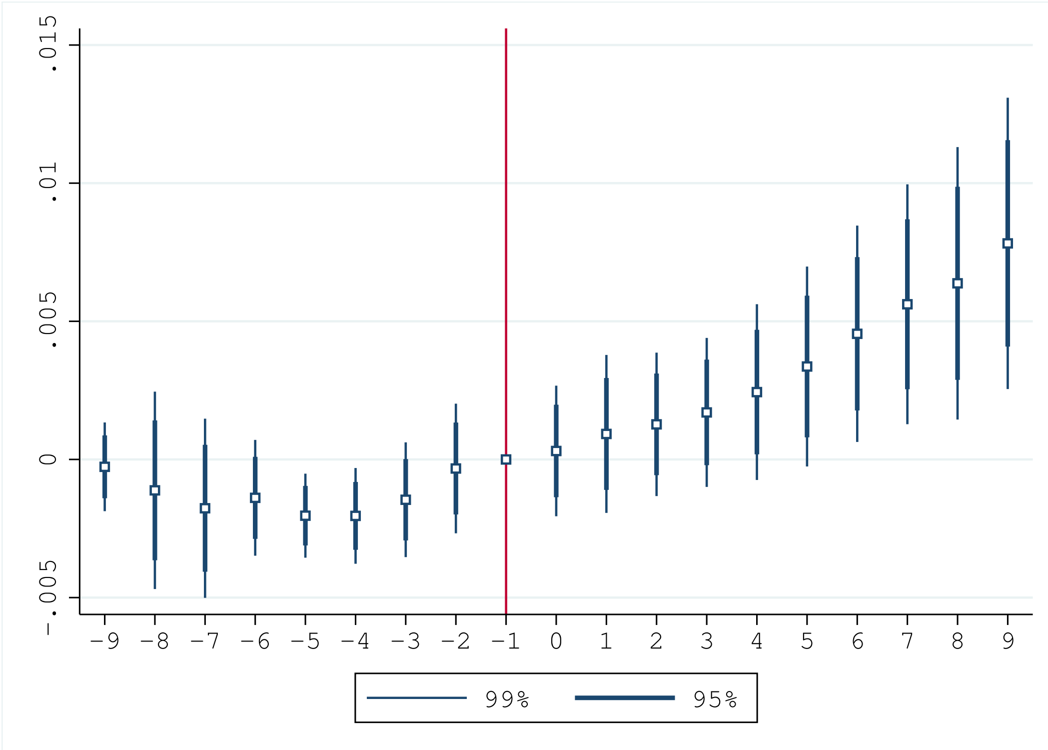

Figure 6: Event study, impact of storm chapter 13, data for the period 2004-2019, all variables are averages computed at the zip code level.

3.3 Credit Score

As expected, a storm has a negative, significant and long lasting impact on indvidual credit score. As credit scores in our dataset range from 300 to around 850 (the best), a storm causes a loss of 10 to 20 points over time, with the loss becoming larger and larger as time from the disaster passes (and probably, as the temporary relief and assistance programs are discontinued).

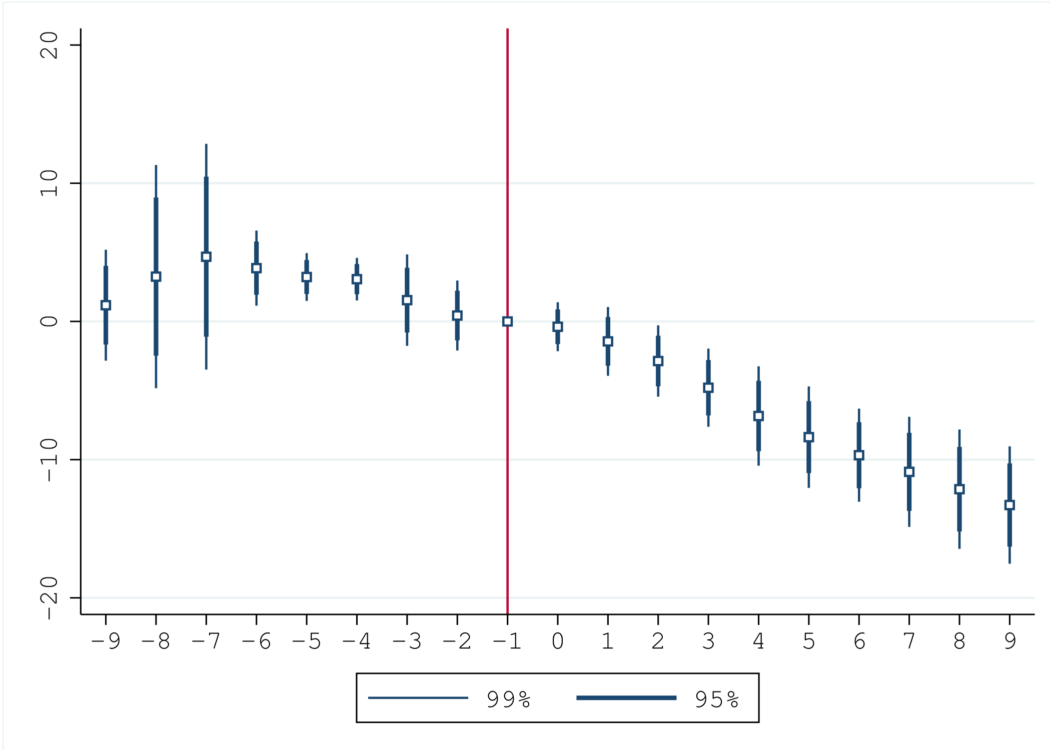

Figure 7: Event study, impact of storm on credit score, data for the period 2004-2019, all variables are averages computed at the zip code level.

3.4 Default on Revolving Credit

Another result in line with economic intuition is that about the impact of a storm on revolving credit. From Figure 11, we notice that a storm has a positive and significant impact on the probability of having 90-day default. This increase in probability amounts to around 1-4% and increases over time, reaching 4% at nine leads after the disaster happened. Further, from Figure 12 we find evidence of a positive impact of storms on 120-day delinquencies as well. Similarily to the previous case, the increase in probability is here around 1-4% and grows almost esponentially over time, as more and more time passes from the disaster date.

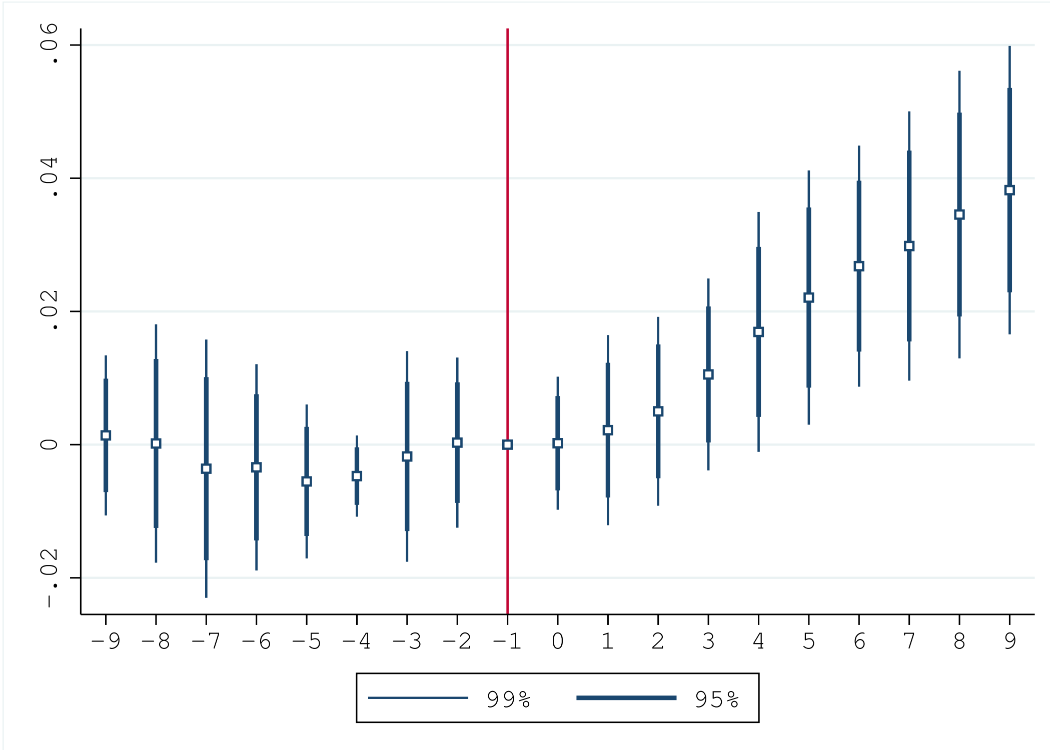

Figure 8: Event study, impact of storm on 90-day default, data for the period 2004-2019, all variables are averages computed at the zip code level.

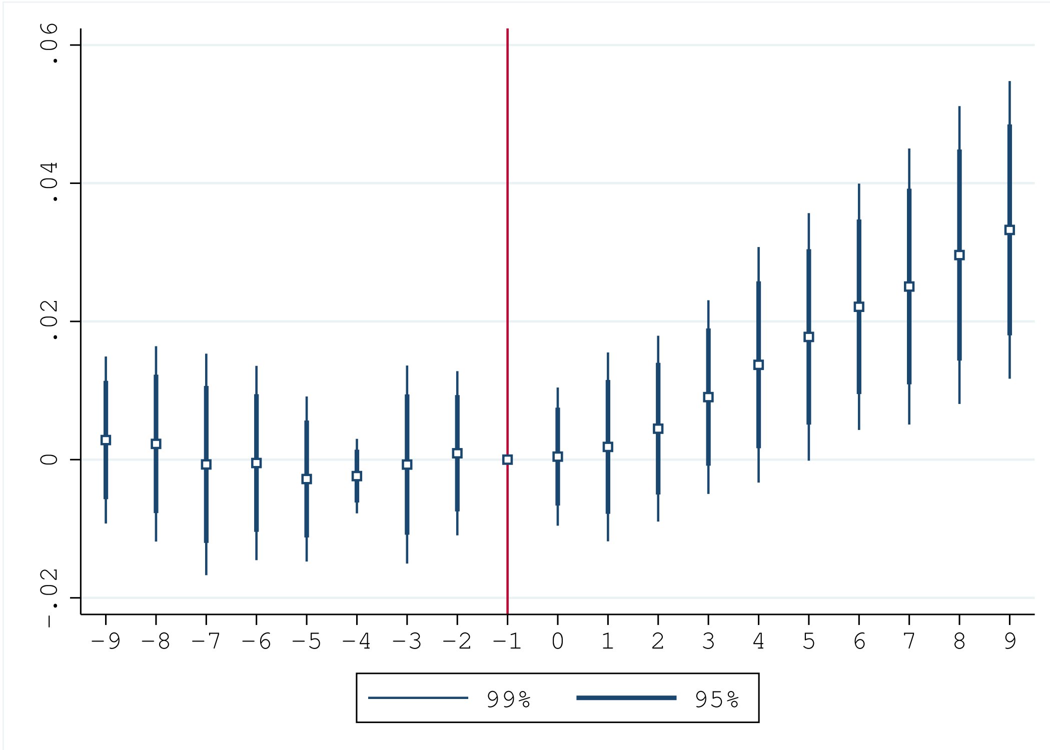

Figure 9: Event study, impact of storm on 120-day delinquencies, data for the period 2004-2019, all variables are averages computed at the zip code level.

3.5 Consumption

Let us now study the impact of storms on consumption. We do not have a comprehensive consumption measure in our dataset, but we have some information that we can use as a reasonable proxy for individual consumption. First, in Figure 13 we study the impact of storms on credit card balance. We find some evidence of a positive impact, especially up to 4-5 years after the disaster. Afterwards, however, this effect is no longer statistically significant. Second, in Figures 14 and 15 we study the impact of storms on auto loans. In Figure 14, we notice that a natural disaster has a negative and persistent impact on the probability of having an auto loan. This negative effect is around 1-2%, barely statistically significant but becoming more and more negative as time passes from the disaster date. Finally, in Figure 15 we find that storms have a negative impact on the amount of existing auto loans as well. This negative impact is not statistically significant in the first few periods after the disaster, but it becomes significant at leads 8 and 9. This negative impact ranges between, say, 200 usd and 1'000 usd.

3.5.1 Credit Card Balance as Consumption

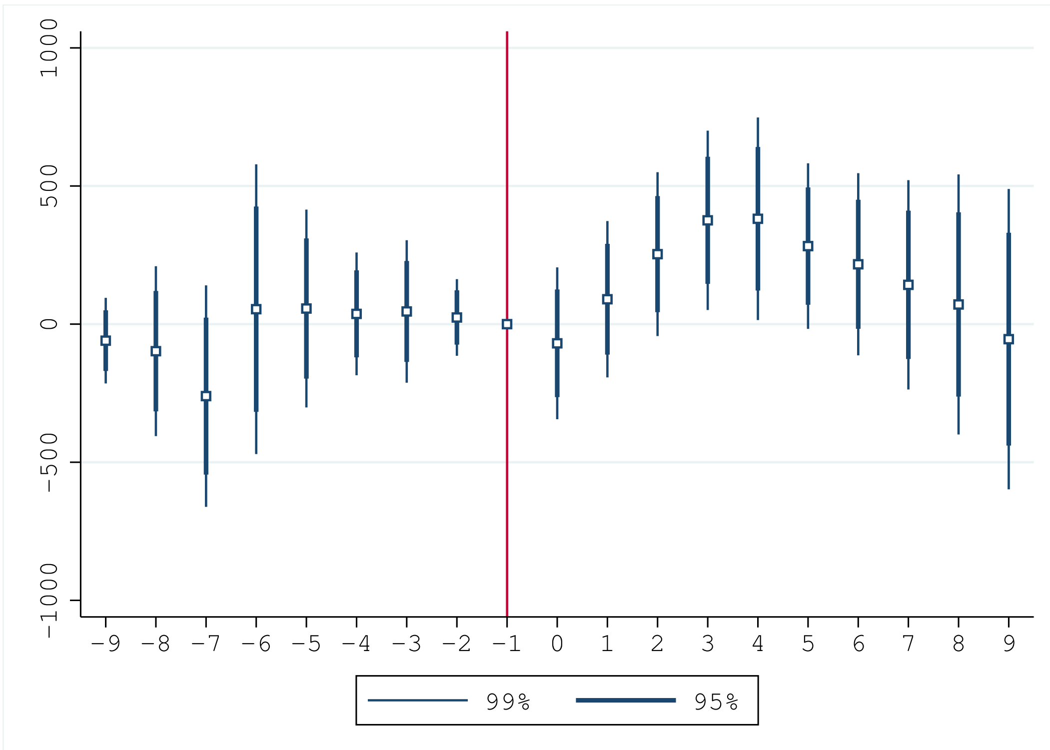

Figure 10: Event study, impact of storm on credit card balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

3.5.2 Auto Loan as Consumption

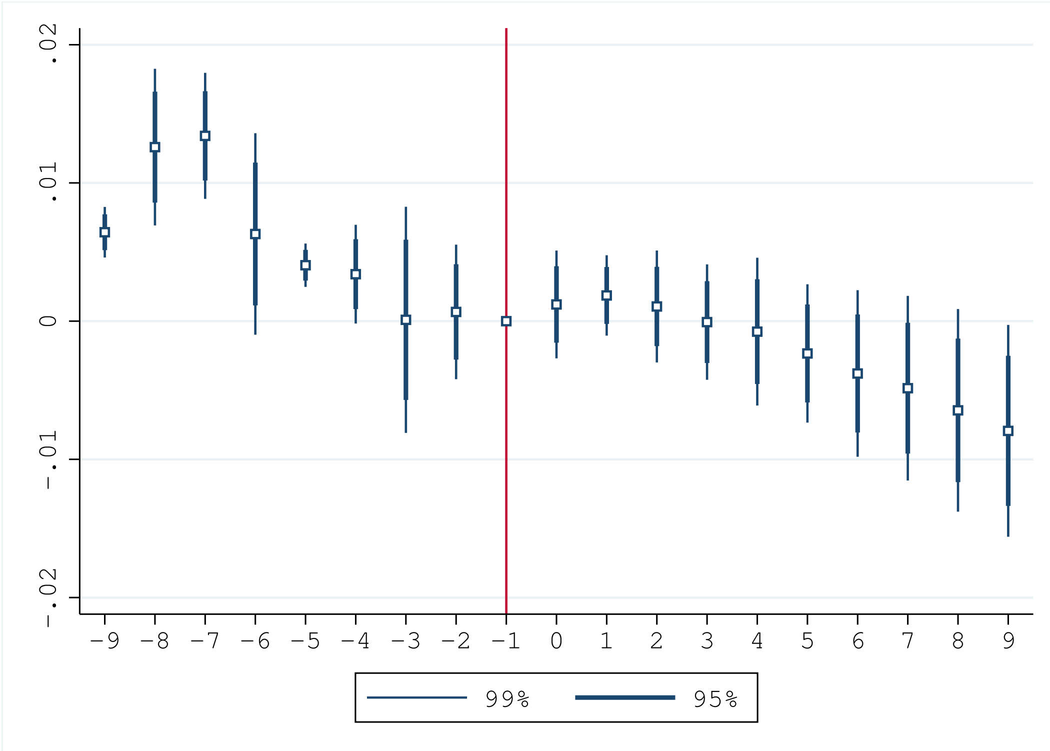

Figure 11: Event study, impact of storm on auto loan origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

3.5.3 Auto Balance as Consumption

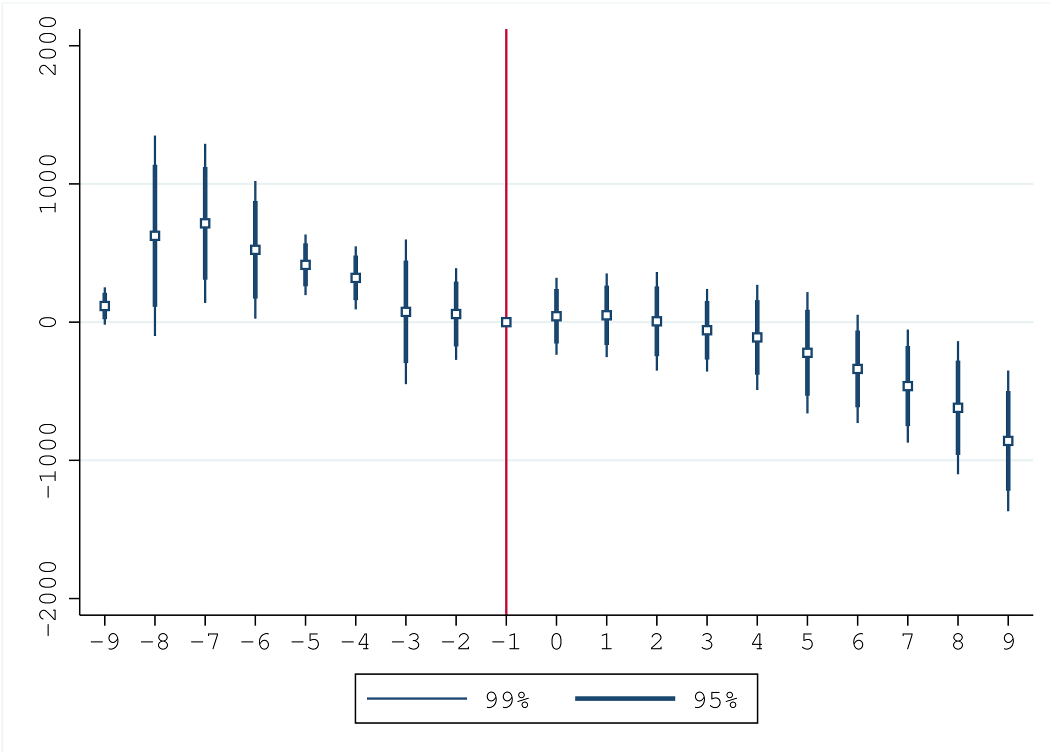

Figure 12: Event study, impact of storm on auto loan, data for the period 2004-2019, all variables are averages computed at the zip code level.

3.5.4 Auto Loan Delinquency

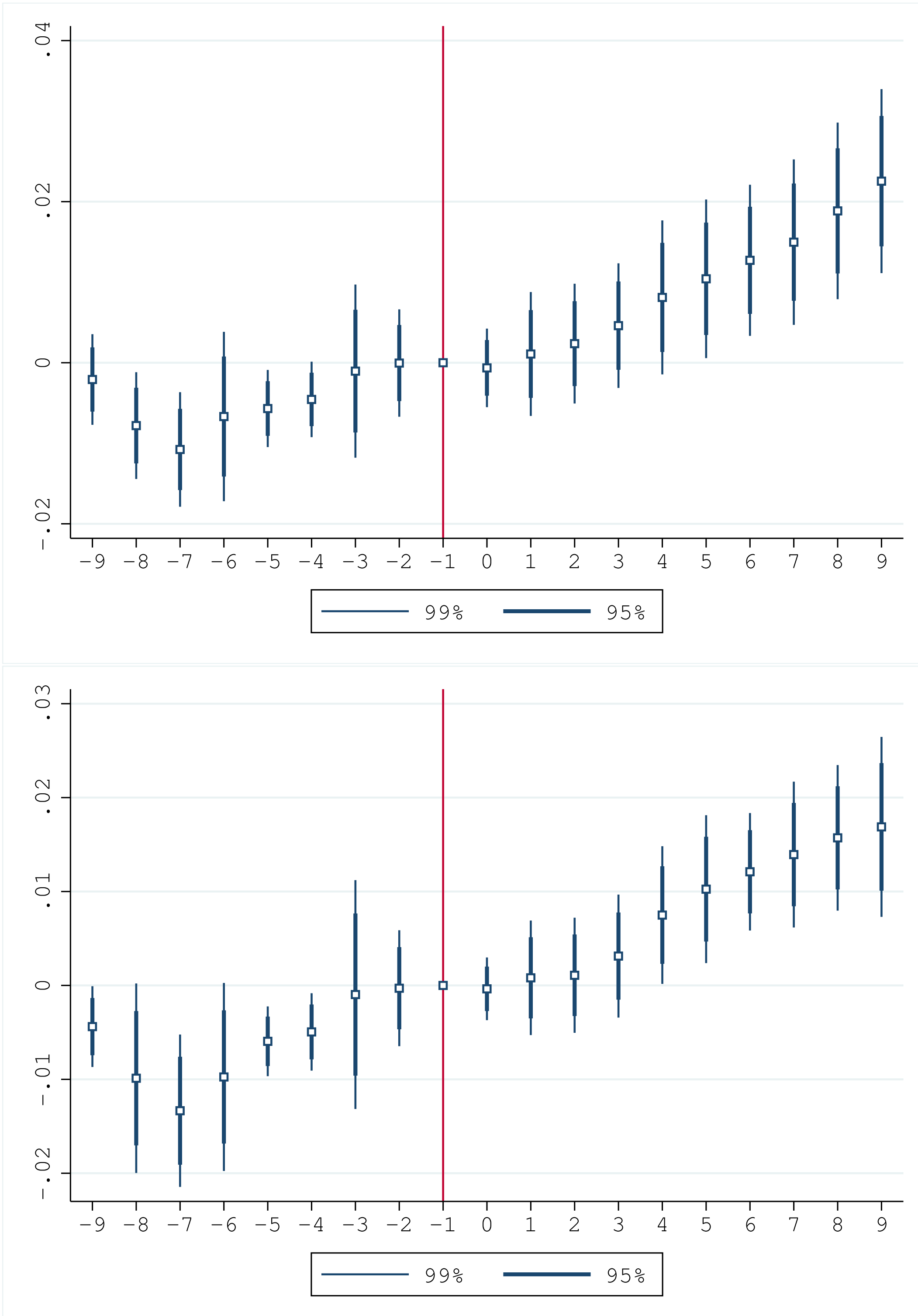

Figure 13: Event study, impact of storm on auto loan delinquencies (upper panel: 60 days, bottom panel: 90 days), data for the period 2004-2019, all variables are averages computed at the zip code level.

3.6 Migration

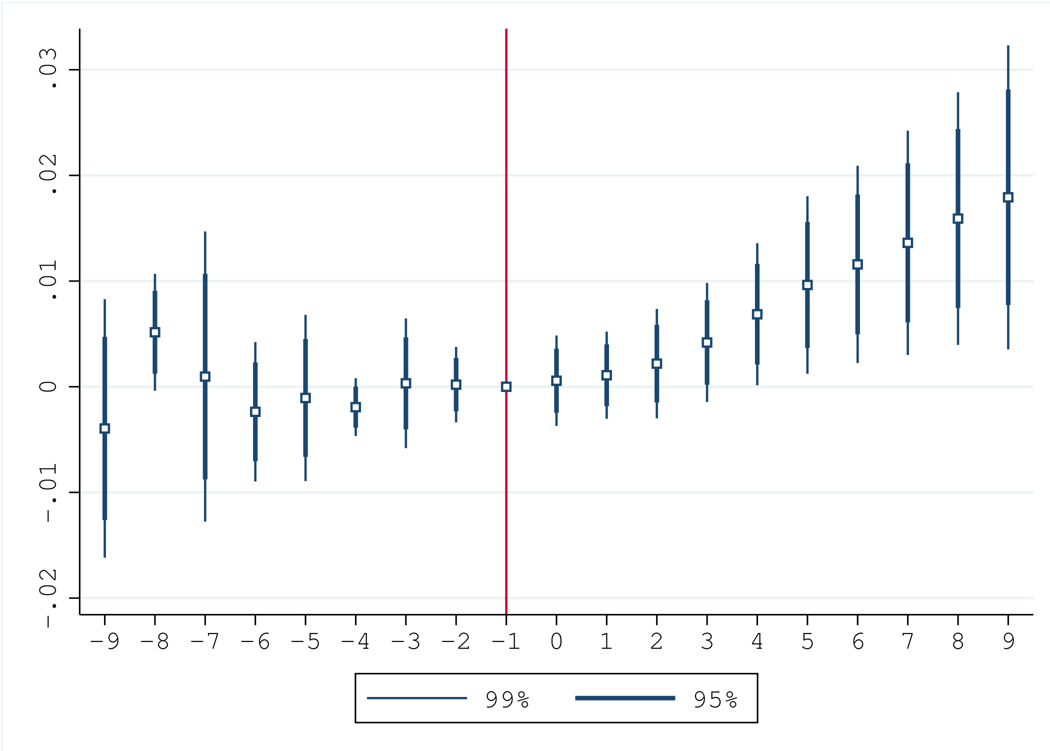

Figure 14: Impact of storms on the probability of moving out of the zipcode

4 Movers vs stayers

4.1 Housing Market

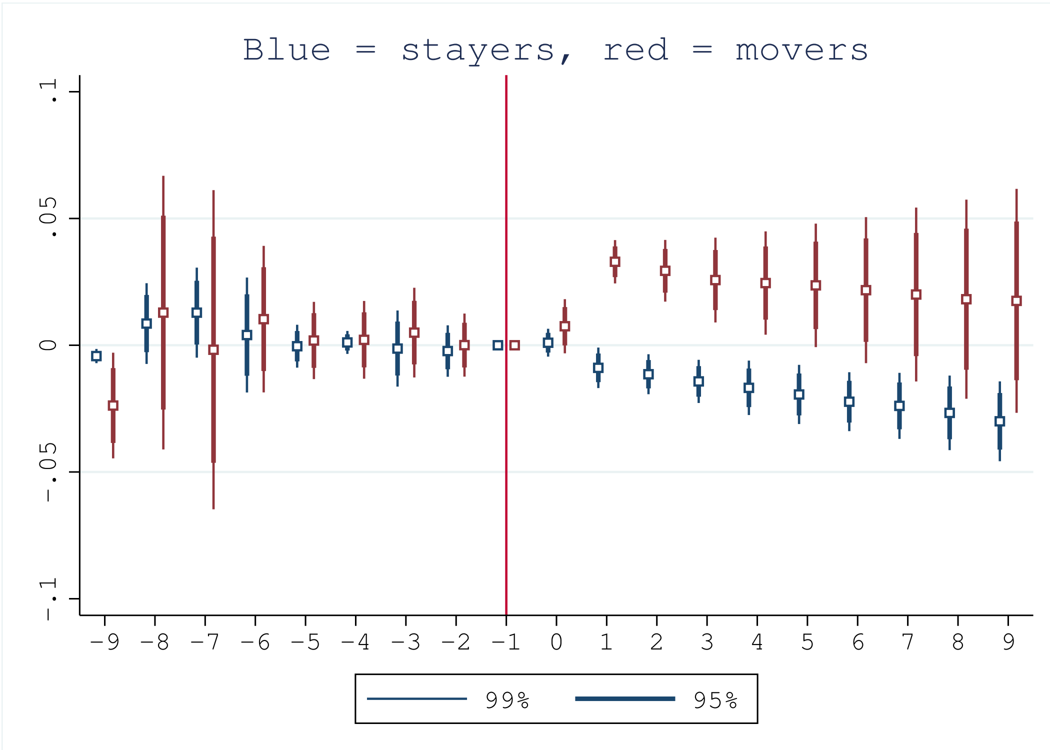

Figure 15: Event study, impact of storm on mortgage origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

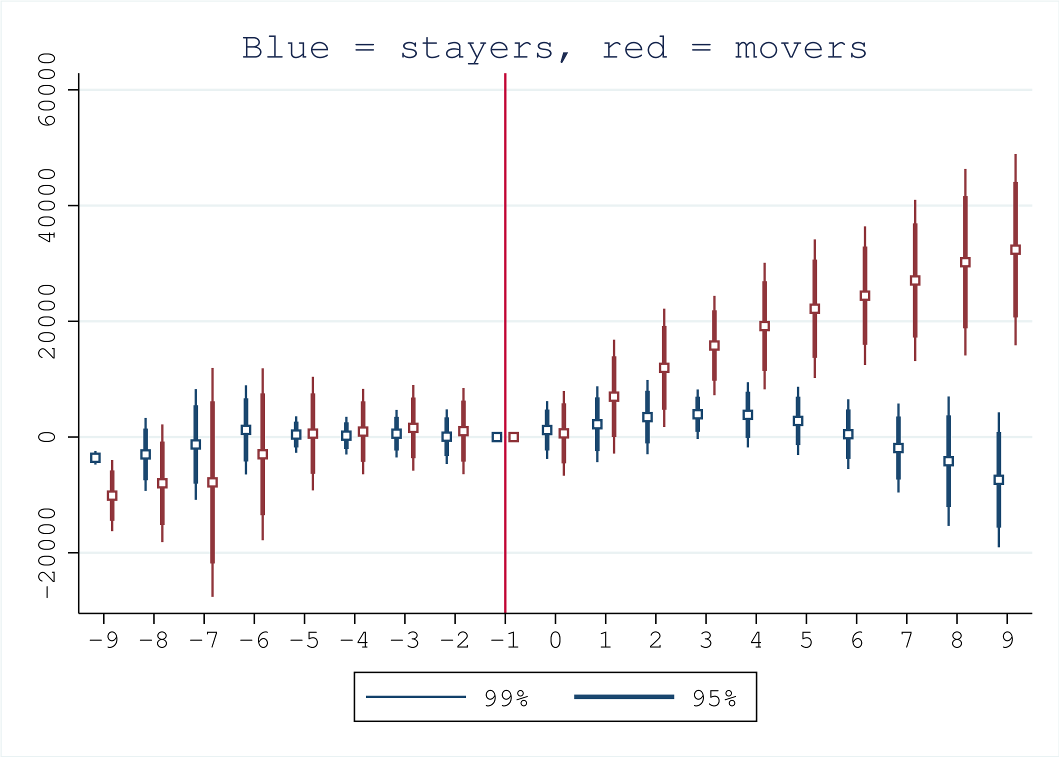

Figure 16: Event study, impact of storm on mortgage balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

4.1.1 Foreclosure

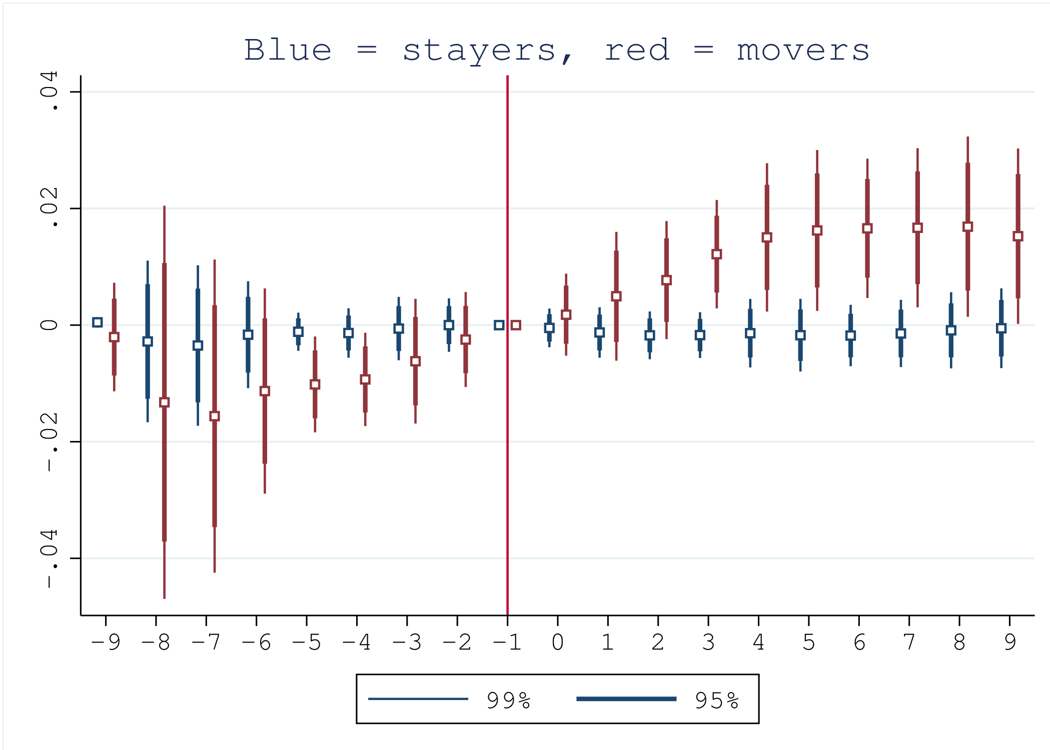

Figure 17: Event study, impact of storm on foreclosures, data for the period 2004-2019, all variables are averages computed at the zip code level.

4.2 Bankruptcy

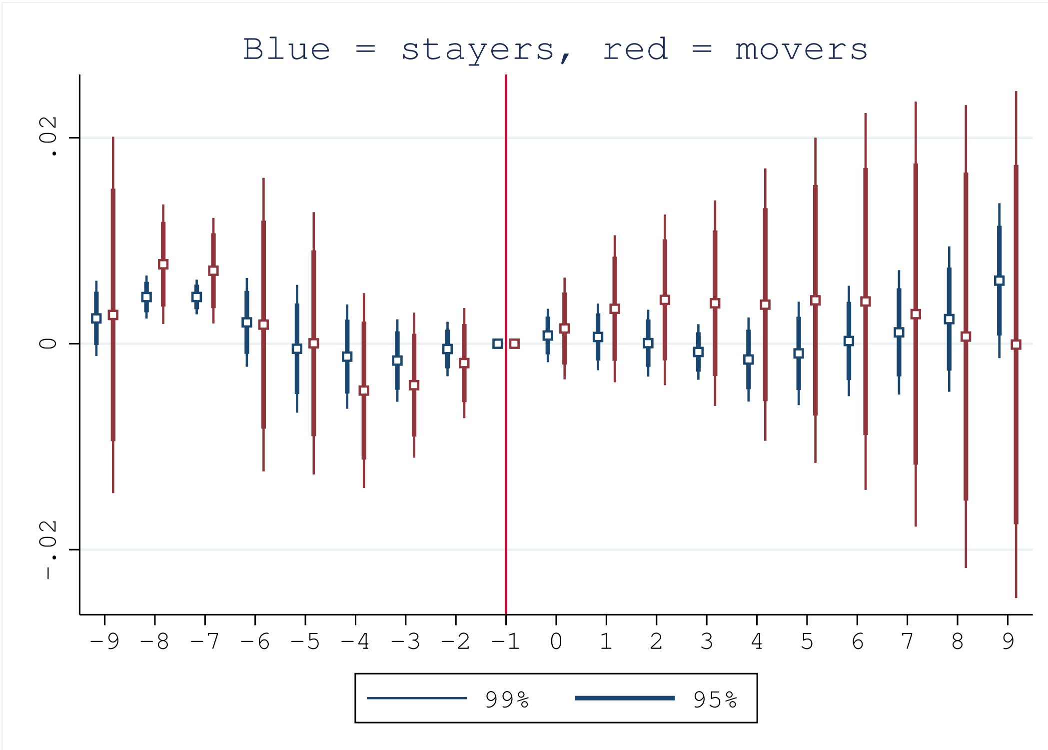

Figure 18: Event study, impact of storm chapter 7, data for the period 2004-2019, all variables are averages computed at the zip code level.

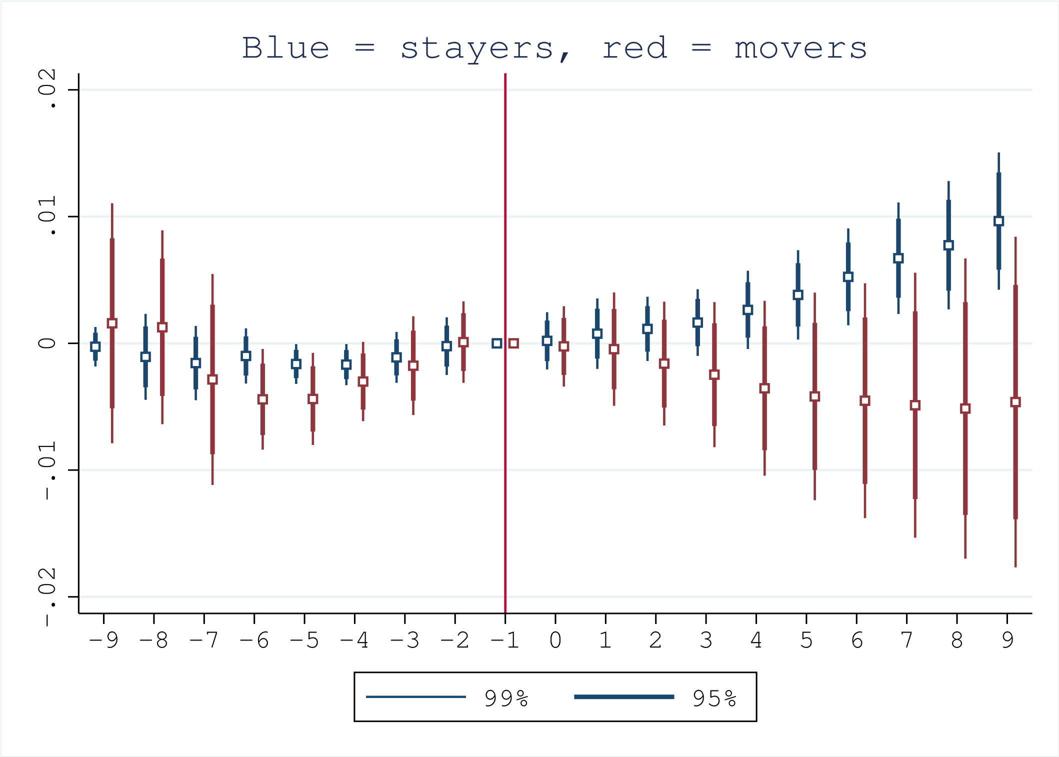

Figure 19: Event study, impact of storm chapter 13, data for the period 2004-2019, all variables are averages computed at the zip code level.

4.3 Credit Score

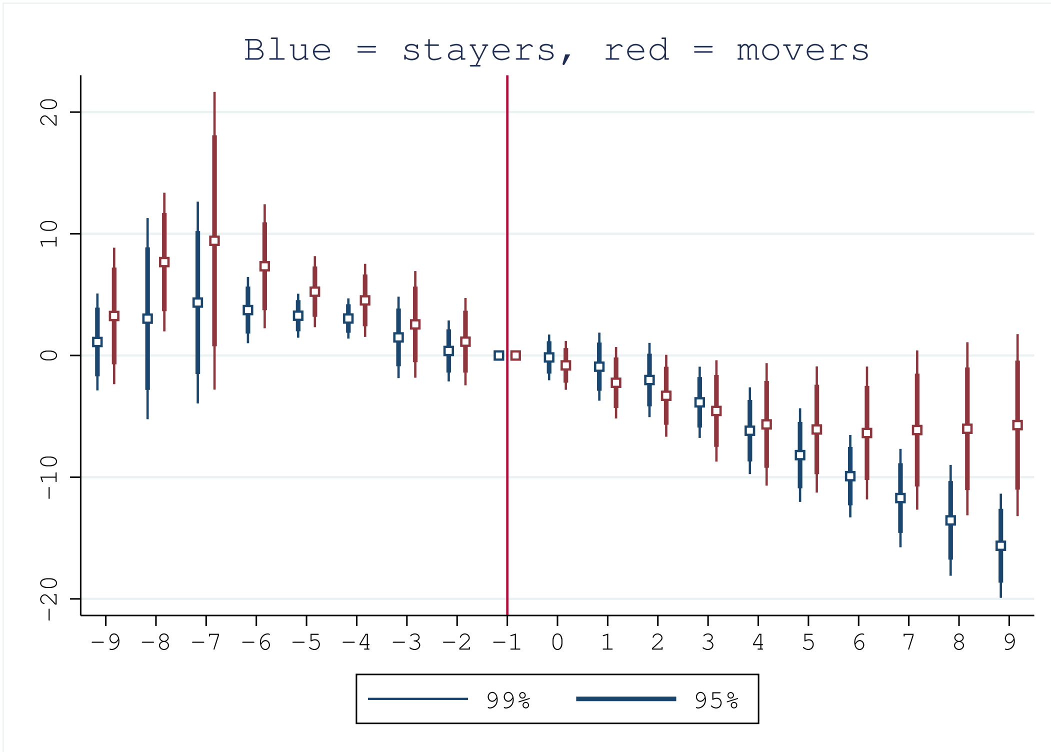

Figure 20: Event study, impact of storm on credit score, data for the period 2004-2019, all variables are averages computed at the zip code level.

4.4 Default on Revolving Credit

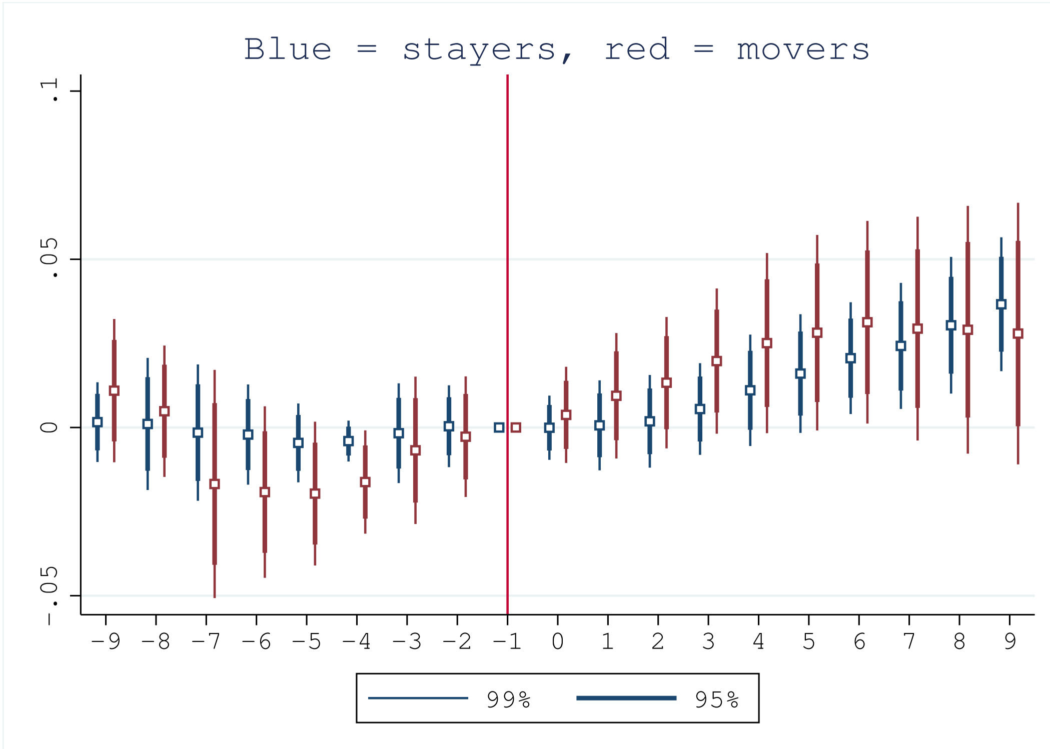

Figure 21: Event study, impact of storm on 90-day default, data for the period 2004-2019, all variables are averages computed at the zip code level.

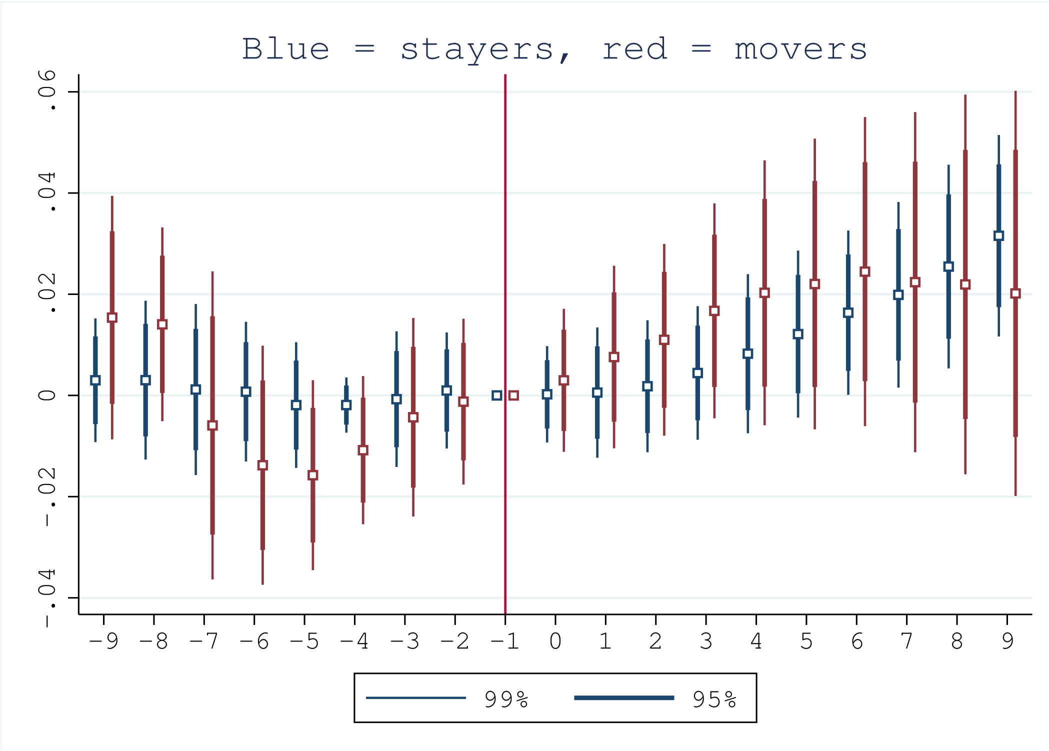

Figure 22: Event study, impact of storm on 120-day delinquencies, data for the period 2004-2019, all variables are averages computed at the zip code level.

4.5 Consumption

4.5.1 Credit Card Balance as Consumption

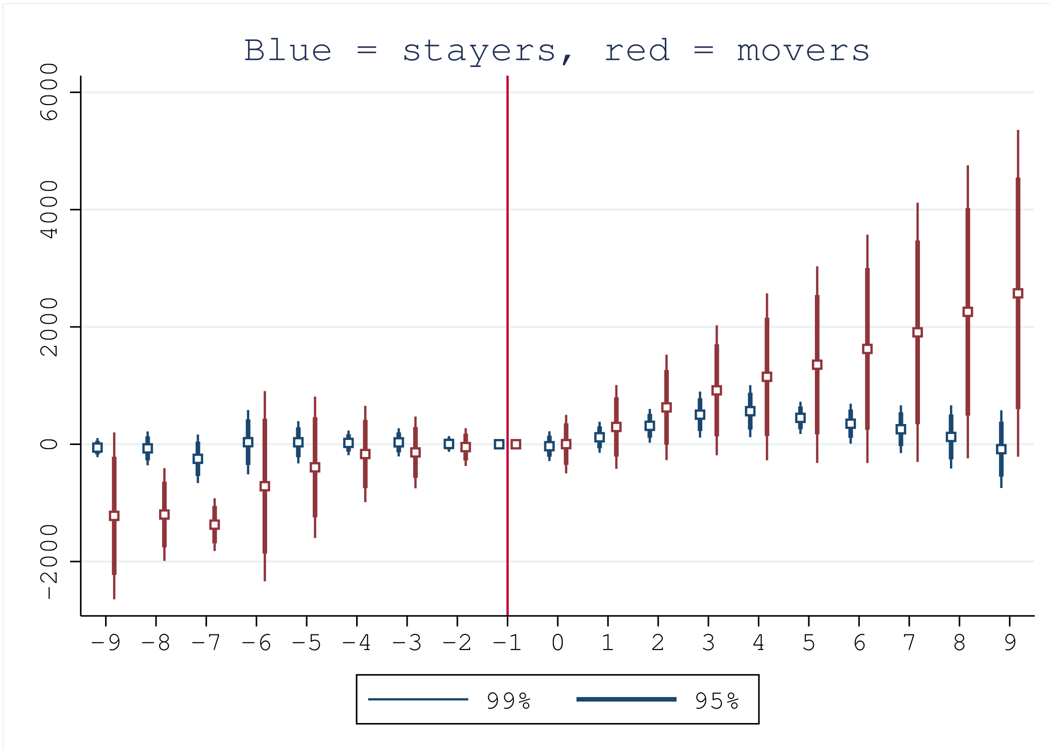

Figure 23: Event study, impact of storm on credit card balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

4.5.2 Auto Loan as Consumption

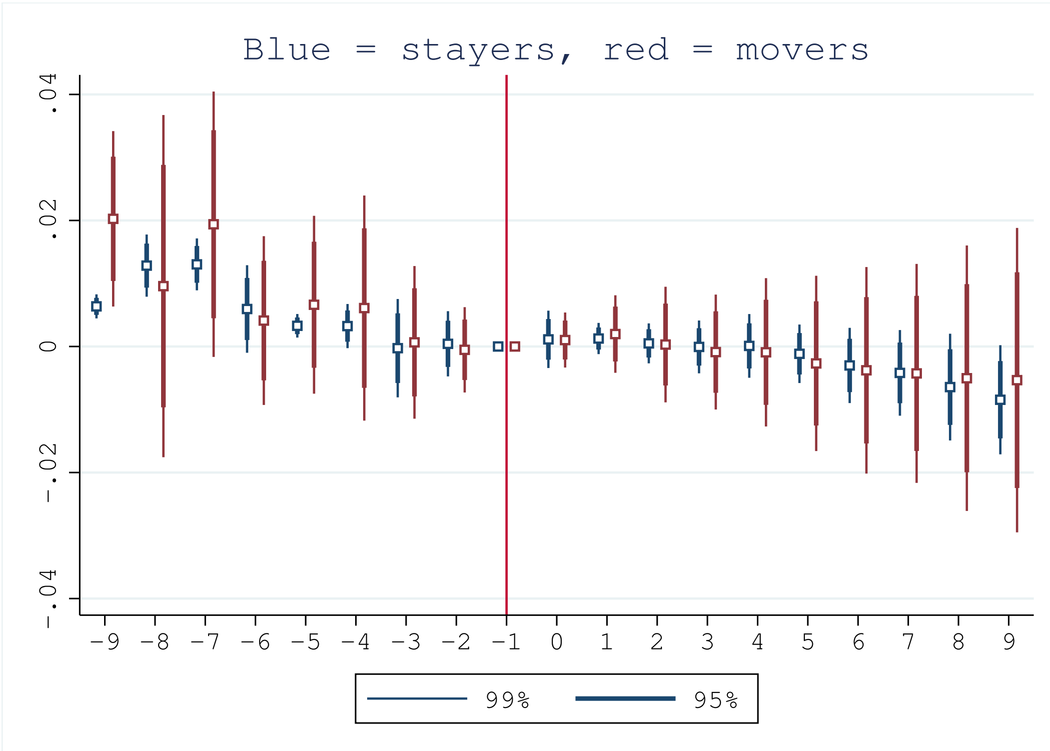

Figure 24: Event study, impact of storm on auto loan origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

4.5.3 Auto Balance as Consumption

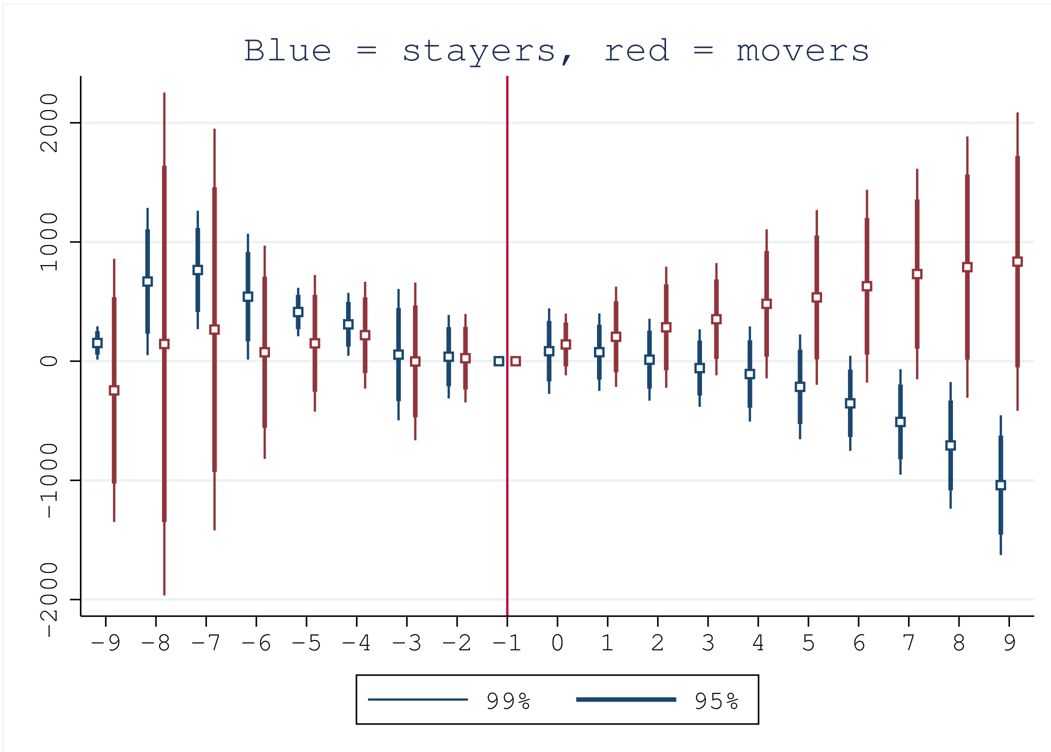

Figure 25: Event study, impact of storm on auto loan, data for the period 2004-2019, all variables are averages computed at the zip code level.

5 Homeowners vs renters

5.1 Housing Market

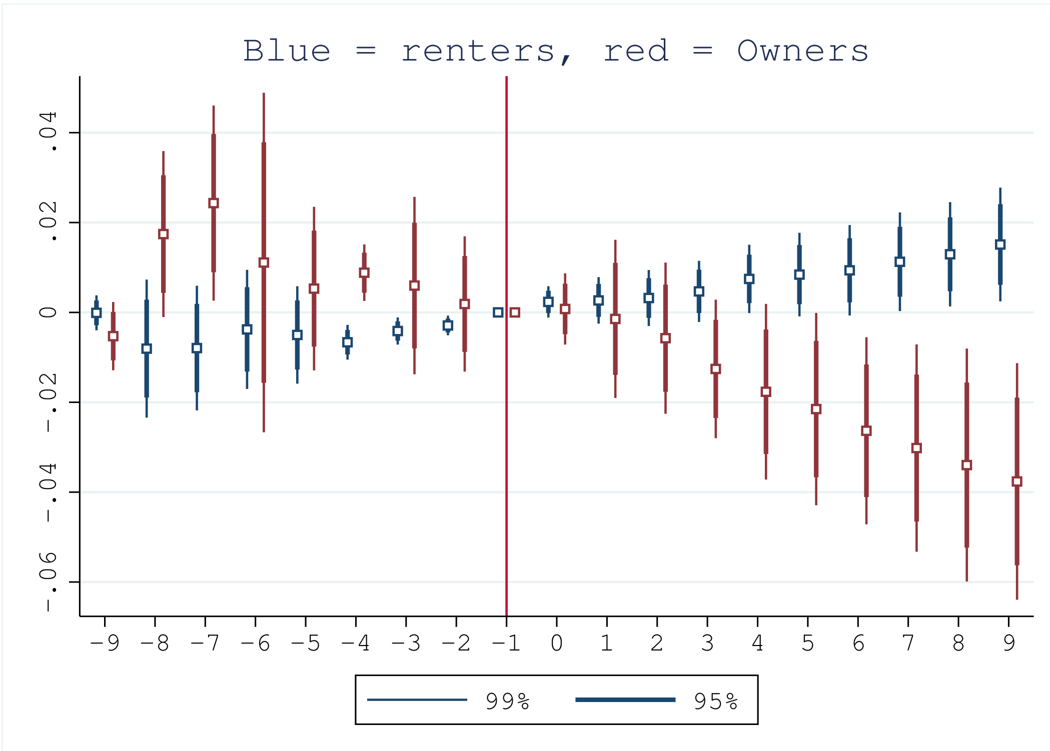

Figure 26: Event study, impact of storm on mortgage origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

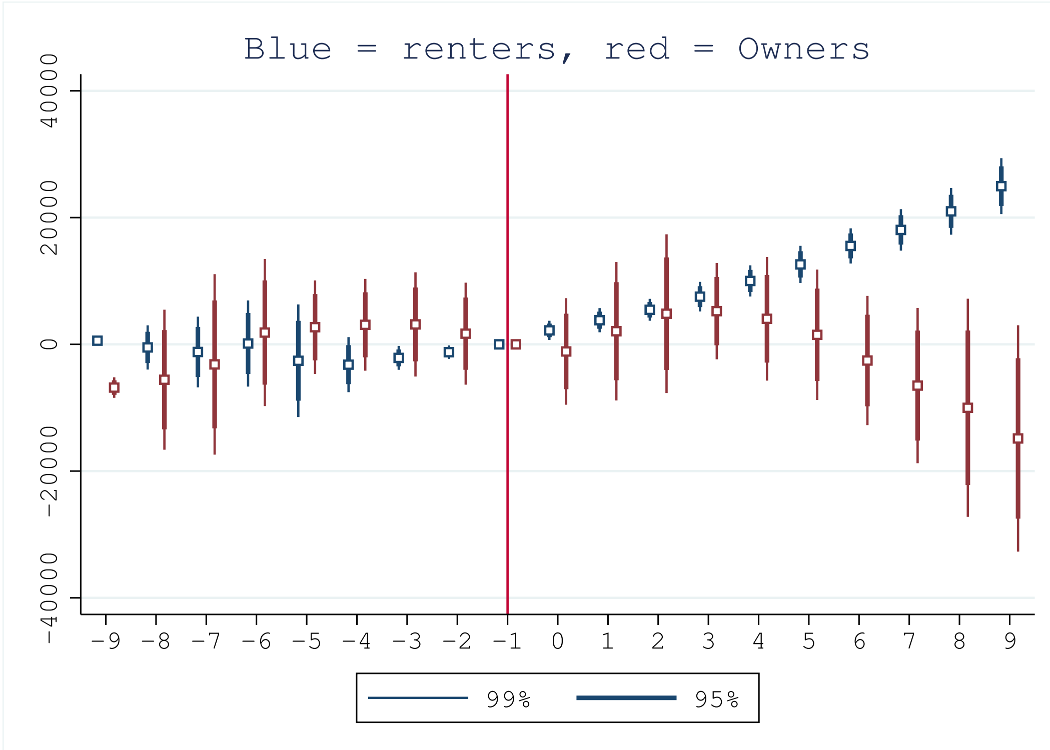

Figure 27: Event study, impact of storm on mortgage balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

5.1.1 Foreclosure

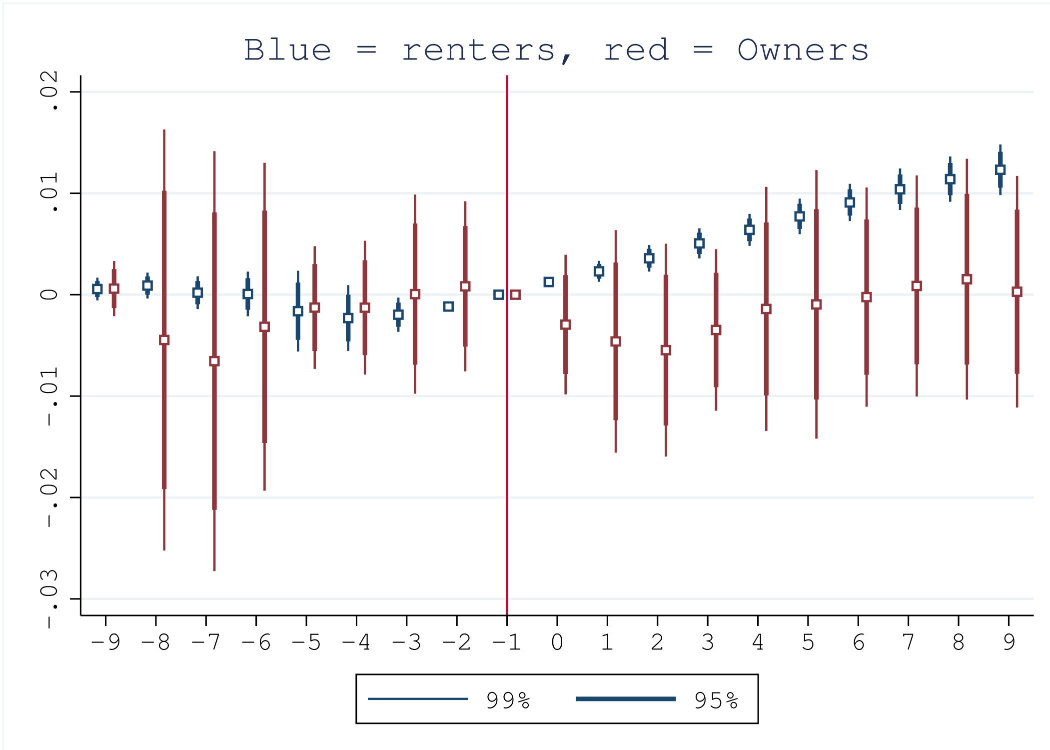

Figure 28: Event study, impact of storm on foreclosures, data for the period 2004-2019, all variables are averages computed at the zip code level.

5.2 Bankruptcy

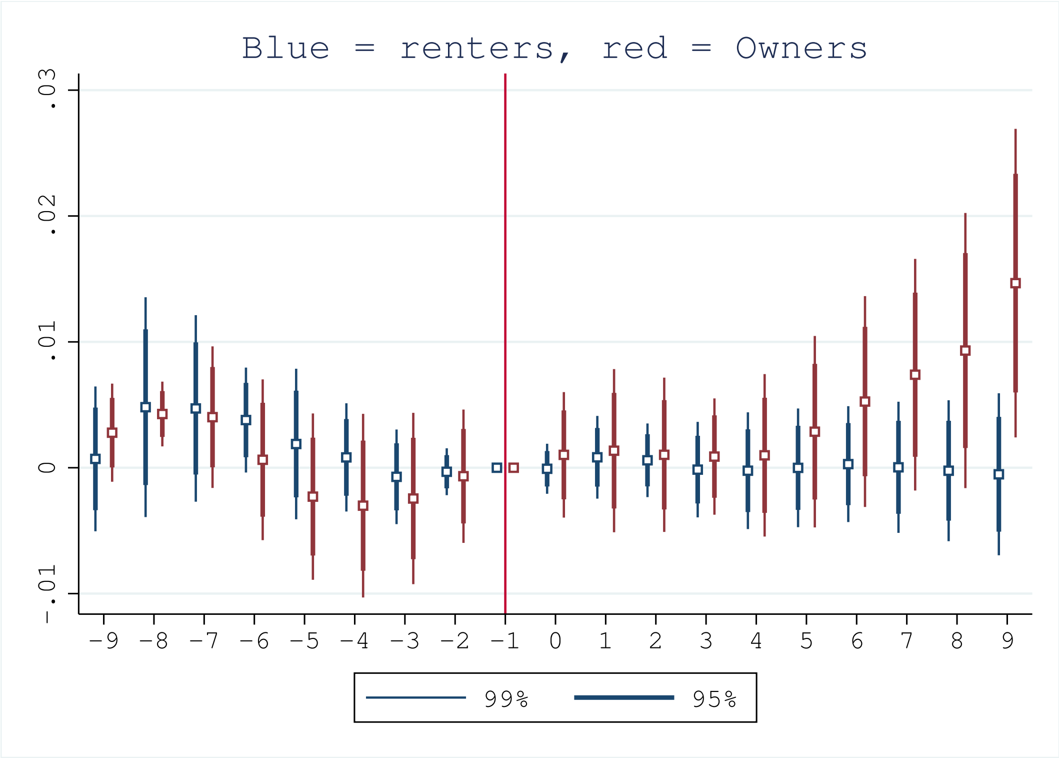

Figure 29: Event study, impact of storm chapter 7, data for the period 2004-2019, all variables are averages computed at the zip code level.

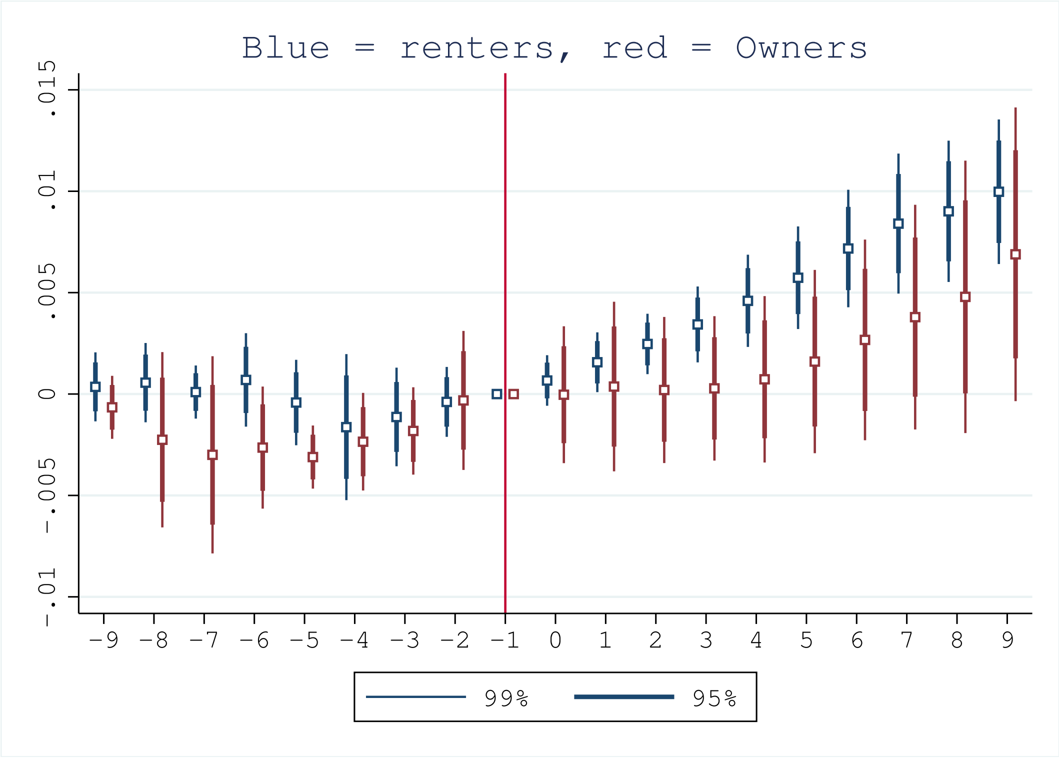

Figure 30: Event study, impact of storm chapter 13, data for the period 2004-2019, all variables are averages computed at the zip code level.

5.3 Credit Score

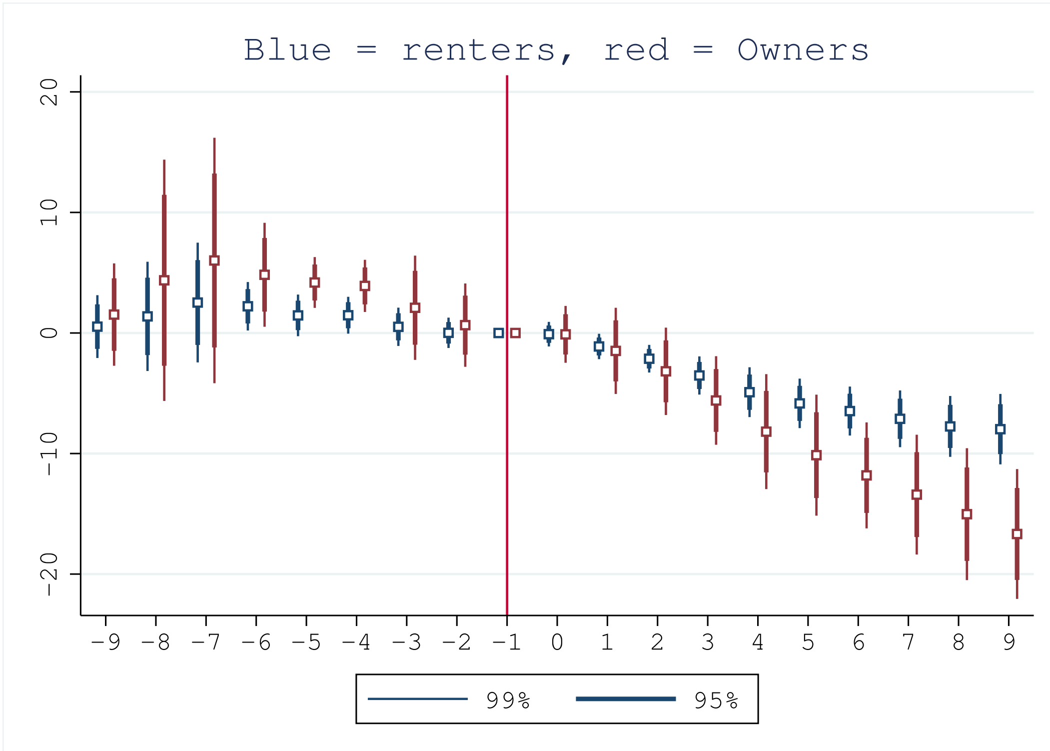

Figure 31: Event study, impact of storm on credit score, data for the period 2004-2019, all variables are averages computed at the zip code level.

5.4 Default on Revolving Credit

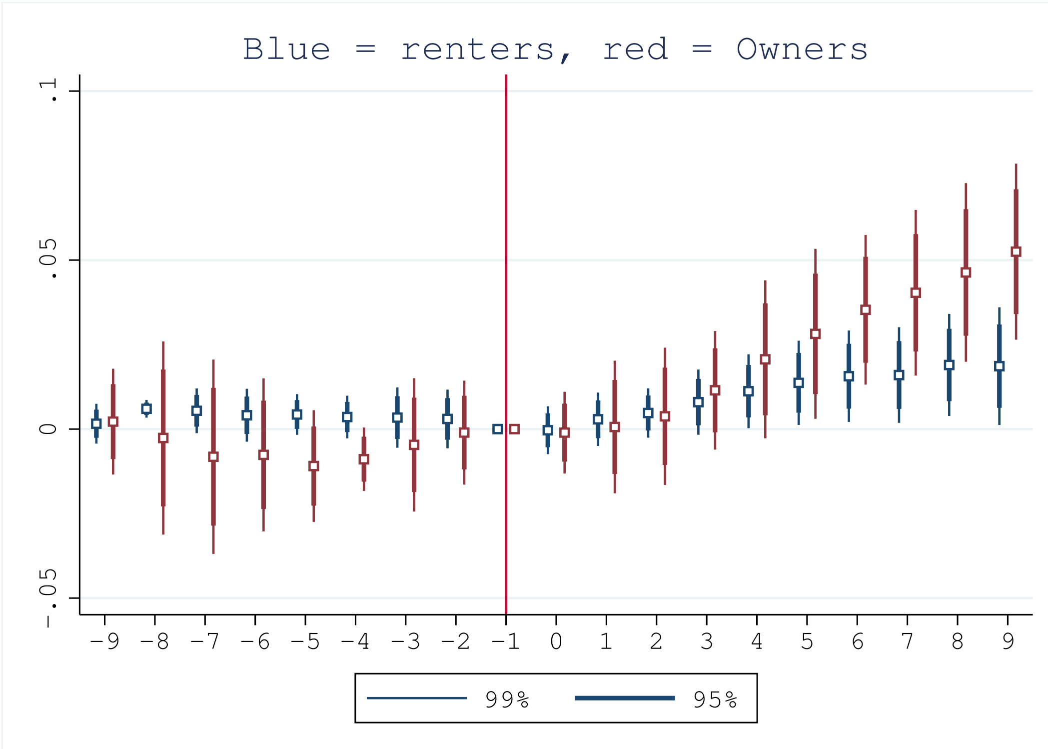

Figure 32: Event study, impact of storm on 90-day default, data for the period 2004-2019, all variables are averages computed at the zip code level.

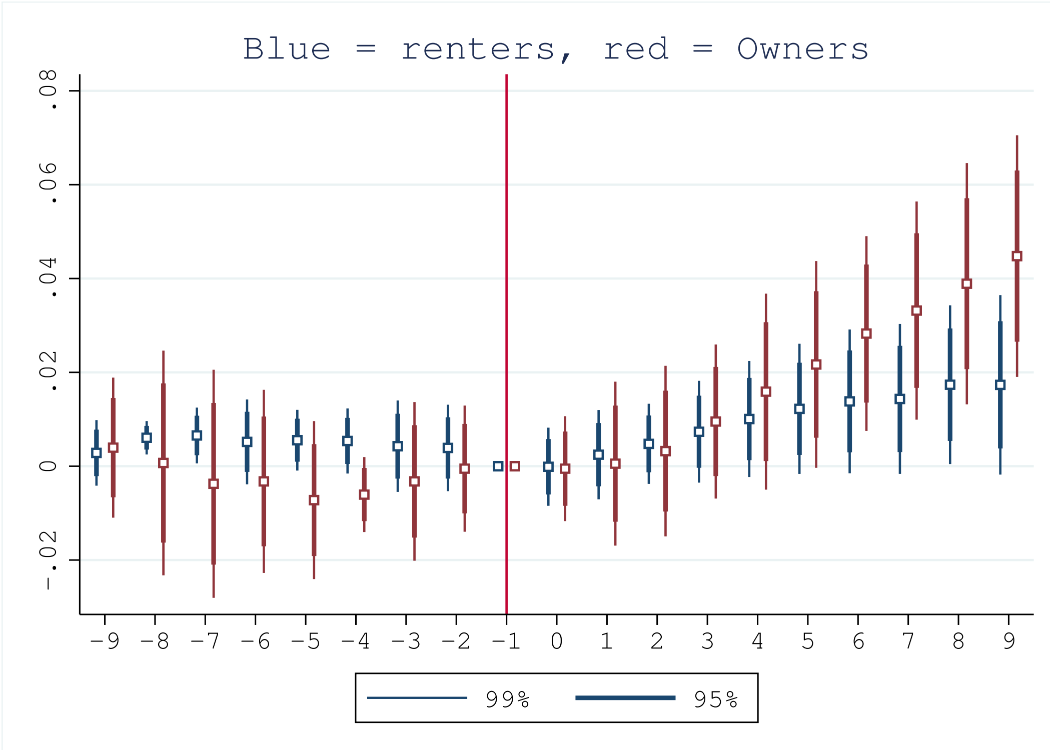

Figure 33: Event study, impact of storm on 120-day delinquencies, data for the period 2004-2019, all variables are averages computed at the zip code level.

5.5 Consumption

5.5.1 Credit Card Balance as Consumption

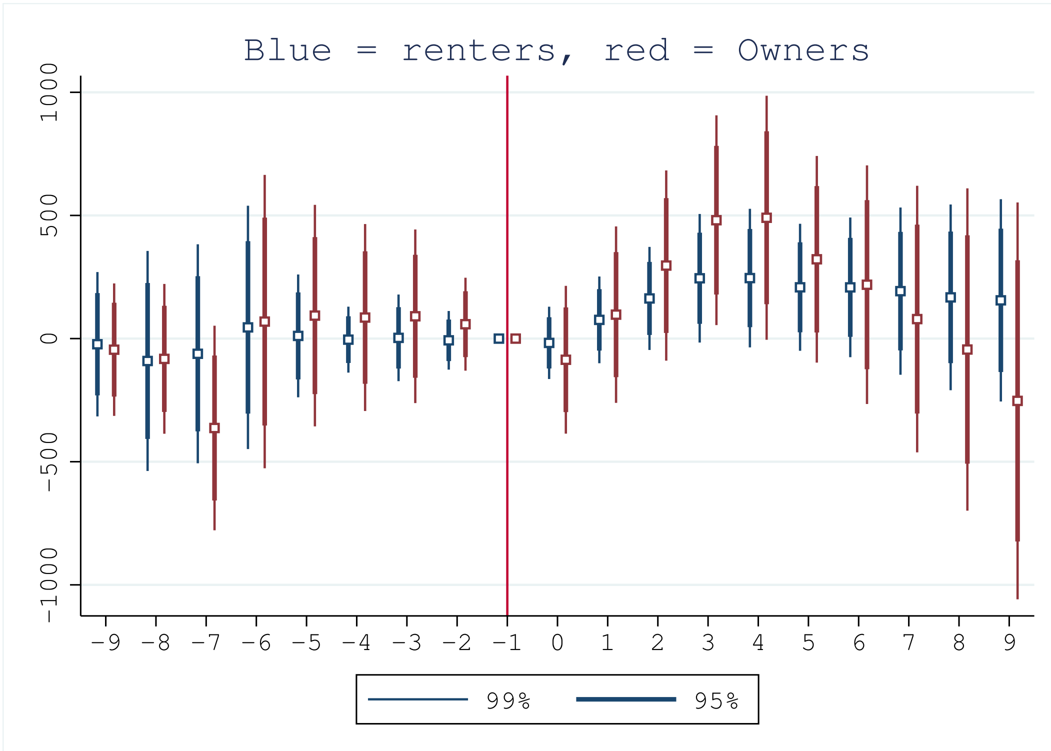

Figure 34: Event study, impact of storm on credit card balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

5.5.2 Auto Loan as Consumption

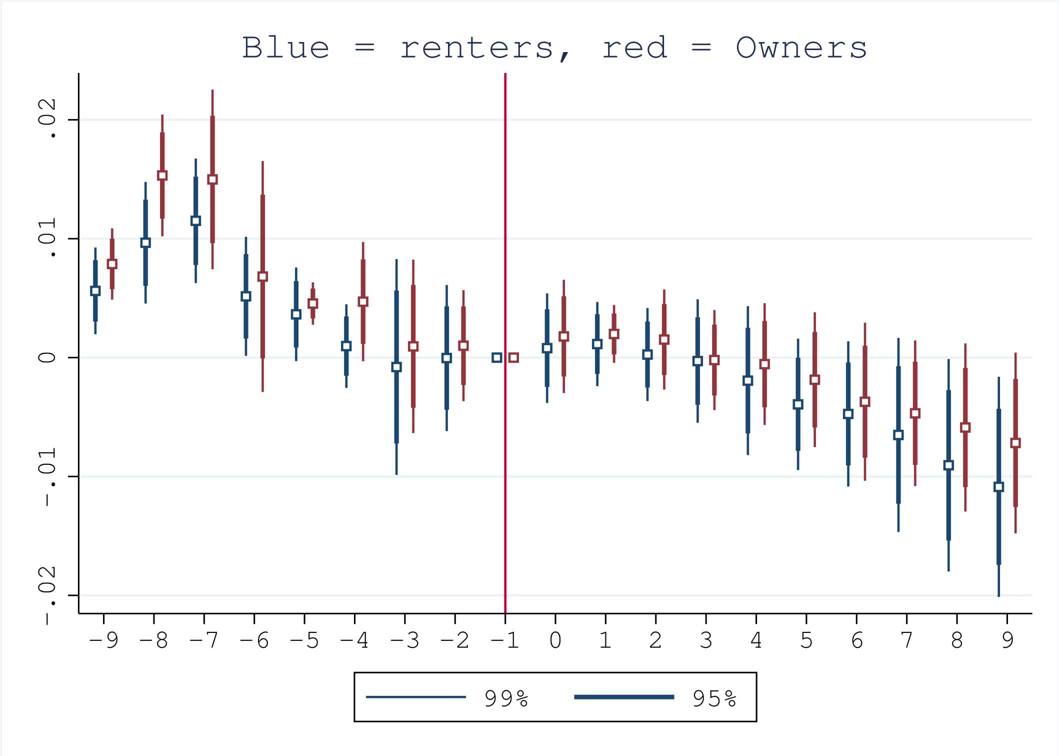

Figure 35: Event study, impact of storm on auto loan origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

5.5.3 Auto Balance as Consumption

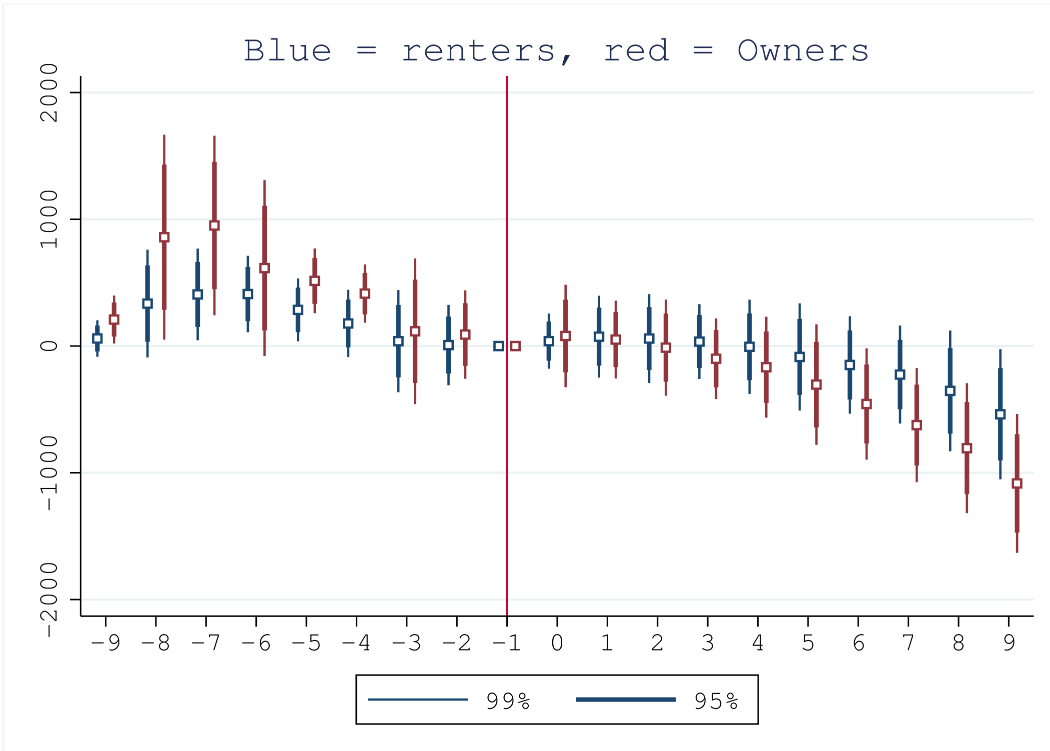

Figure 36: Event study, impact of storm on auto loan, data for the period 2004-2019, all variables are averages computed at the zip code level.

6 Transition mechanisms: the local economy

In this section we investigate the impact of a storm on a series of variables describing the conditions of the local economy. These variables are the House Price Index, the number of establishments, the number of employees, the annual payroll and the first quarter payroll and are all recorded at the level of 5-digit zipcodes. Source for the data on annual and quarter payroll, as well as number of establishments and number of employees is the ZIP Codes Business Patterns dataset[5] from US Census Bureau. Data on the House Price Index are taken from the Federal Housing Finance Agency[6].

From Figure 16 we deduce that a storm has a negative and long-lasting impact on

[5]https://www.census.gov/data/developers/data-sets/cbp-nonemp-zbp/zbp-api.html
[6]https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx

house prices of the affected areas. The impact is around 10-50 points of the index and lasts until 9-10 years after the event. From Figure 17, we find evidence that storms also have a negative and statistically significant impact on the number of establishments in a certain zipcode. The number goes down by 5-30 establishments and the effects becomes more and more negative as time passes, being statistically signficant up to ten years after the event.

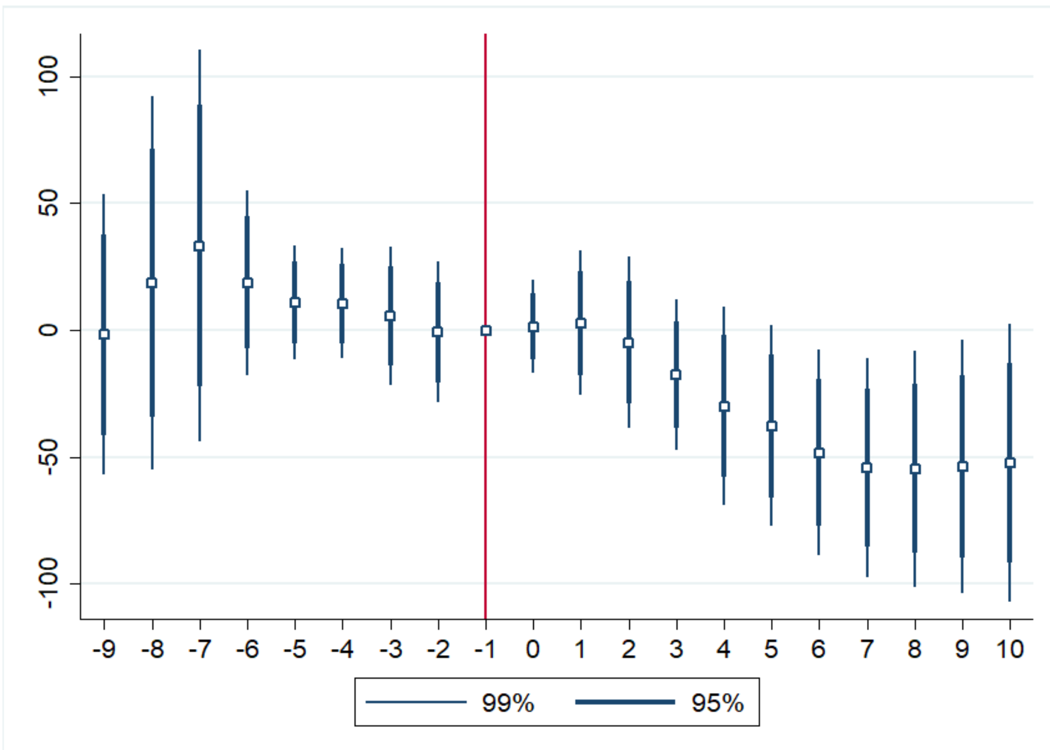

Figure 37: Event study, impact of storm on House Price Index, data for the period 2004-2019, all variables are at the zip code level.

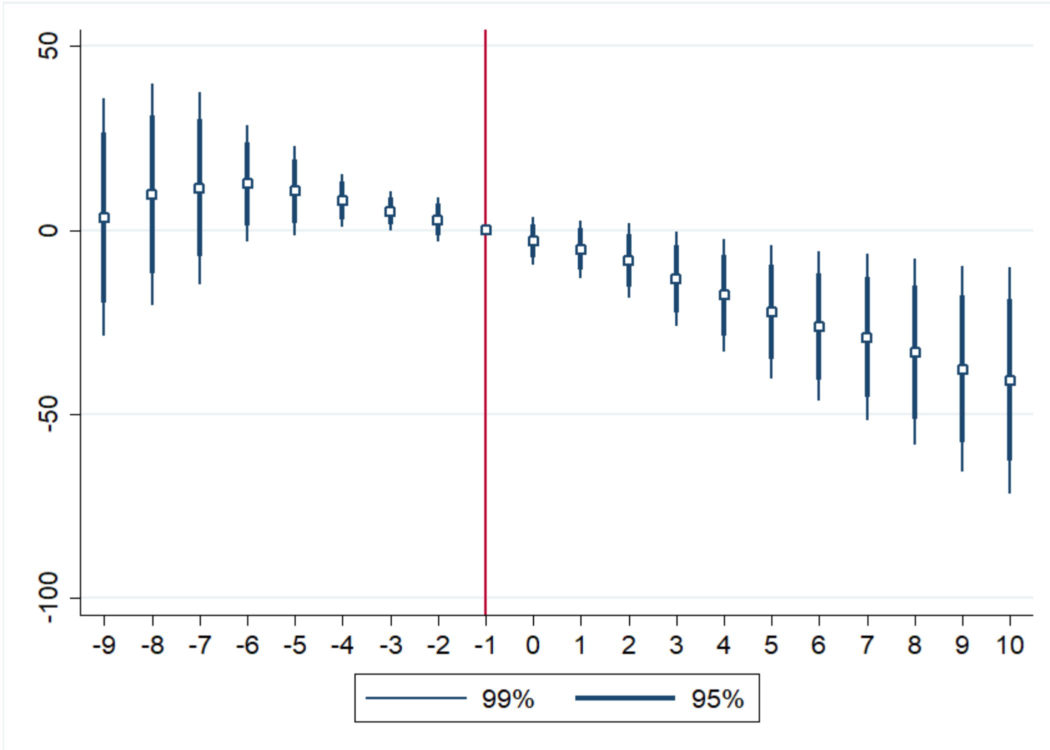

Figure 38: Event study, impact of storm on the number of establishments, data for the period 2004-2019, all variables are at the zip code level.

From Figure 18, we find that storms have a negative and statistically signifcant impact on the number of employees as well. This number indeed goes down by up to 800 units in affected zipcodes. The negative impact becomes larger over time. A storm has long lasting consequences on the local economy, with its aftermath being evident from the graph up to ten years after the event. Finally, Figure 19 and 20 show the impact of a storm on, respectively, annual and first quarter payroll. From these two Figures, we find evidence that a storm has a negative and long-lasting impact on payroll as well. However, the impact is somehow more moderate than that found for local employment and number of establishments, thus suggesting that the negative impact of a storm on the local economy takes place mostly in the form of business closures and subsequent unemployment than in terms of payroll cuts for firms remaining in affected areas.

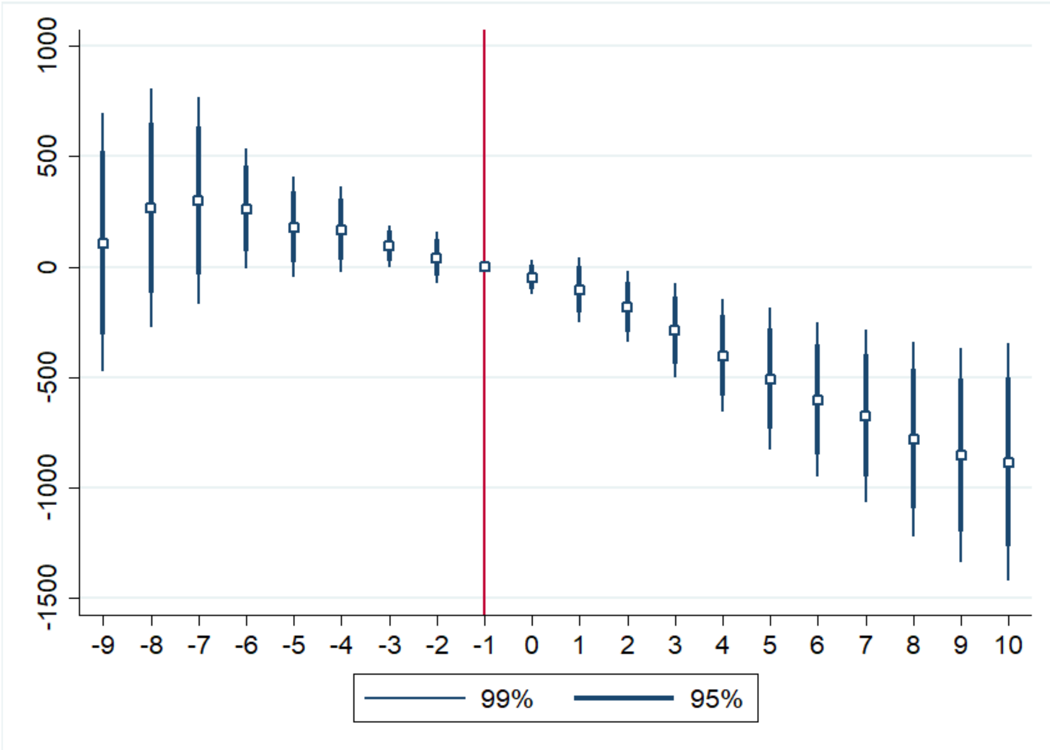

Figure 39: Event study, impact of storm on number of employees, data for the period 2004-2019, all variables are at the zip code level.

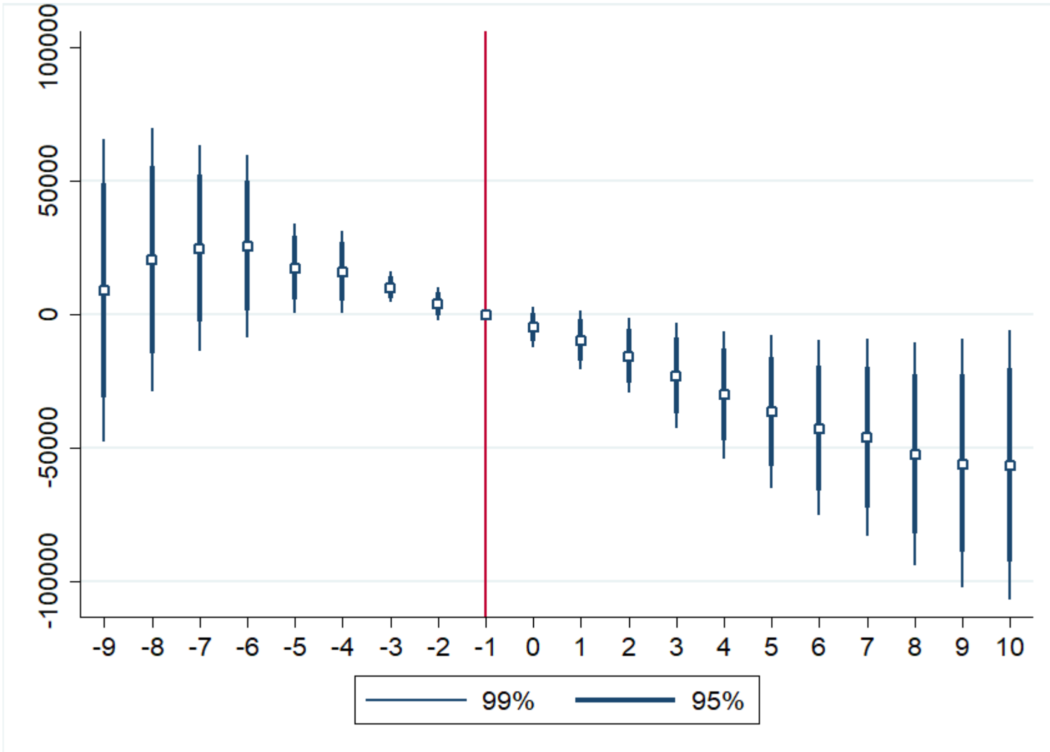

Figure 40: Event study, impact of storm on annual payroll, data for the period 2004-2019, all variables are at the zip code level.

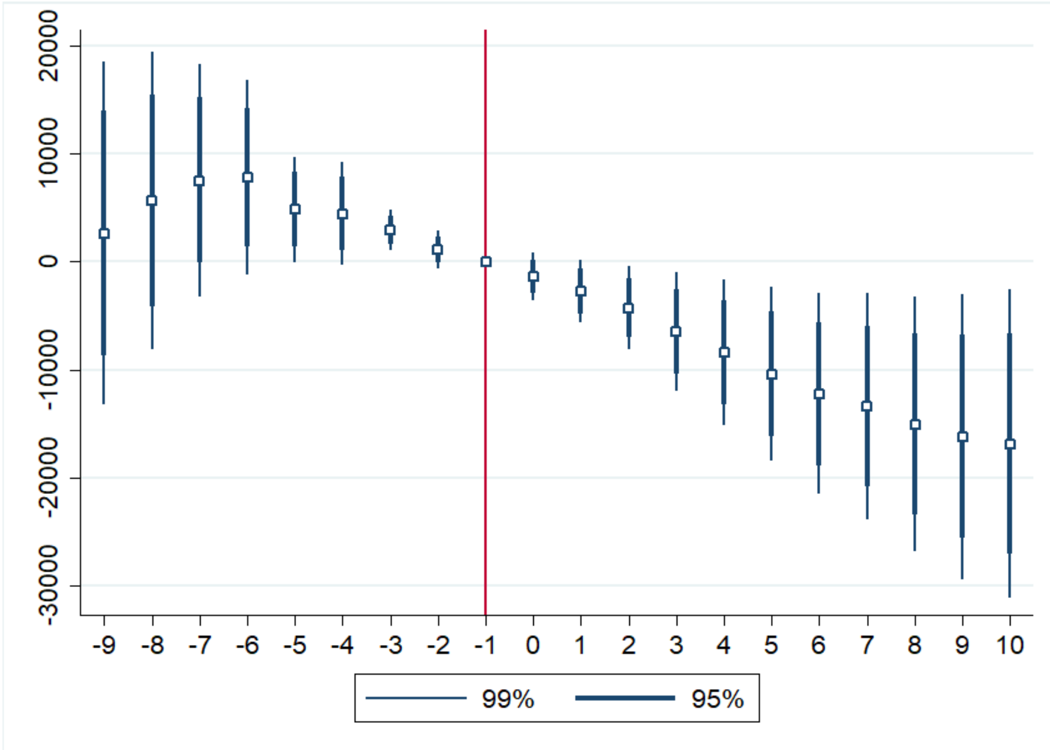

Figure 41: Event study, impact of storm on first quarter payroll, data for the period 2004-2019, all variables are at the zip code level.

To conclude, we claim that the positive impact of storms on defaults, delinquencies and foreclosures, that we have documented in the previous section, is due to the disruptive effect of such storms on the local economy, thus causing business closures and hence a drop in local employment.

7 Conclusion

TO BE DONE

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A Robustness to geographical aggregation: county level instead of zipcode

A.1 Housing Market

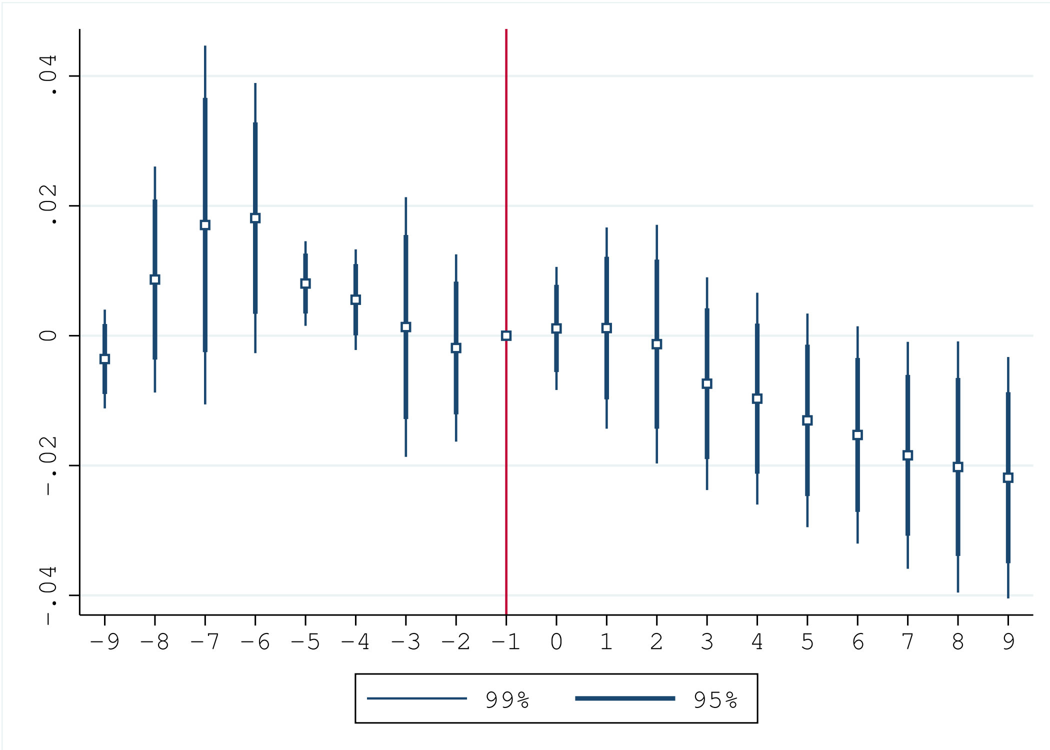

Figure 42: Event study, impact of storm on mortgage origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

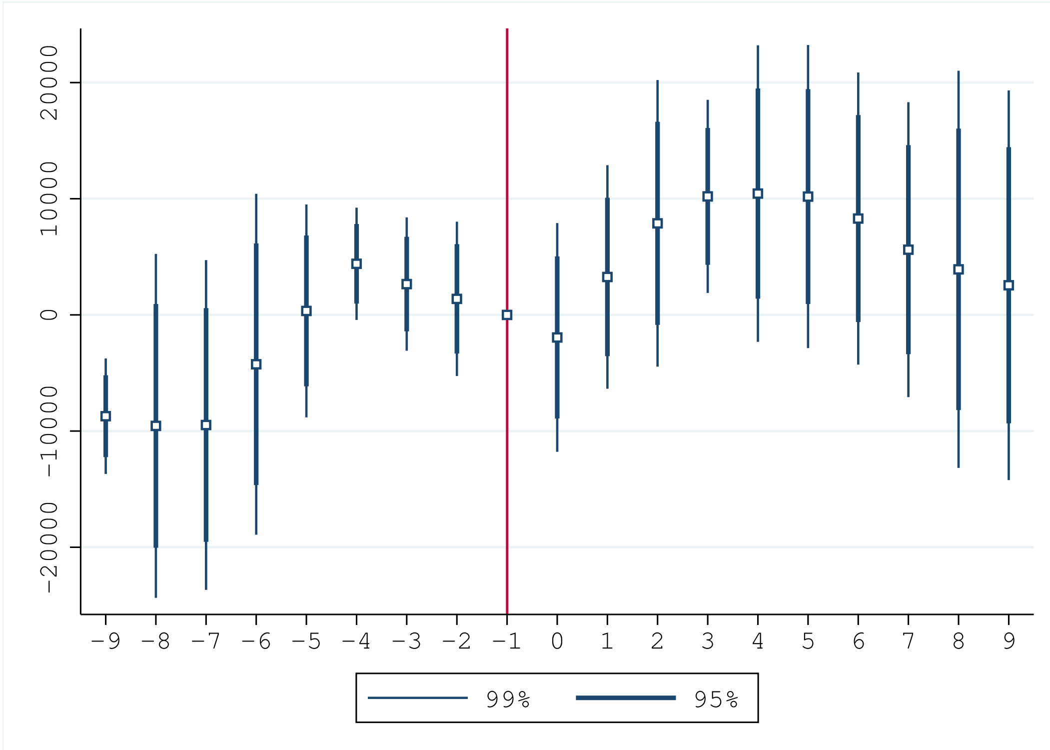

Figure 43: Event study, impact of storm on mortgage balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

A.1.1 Foreclosure

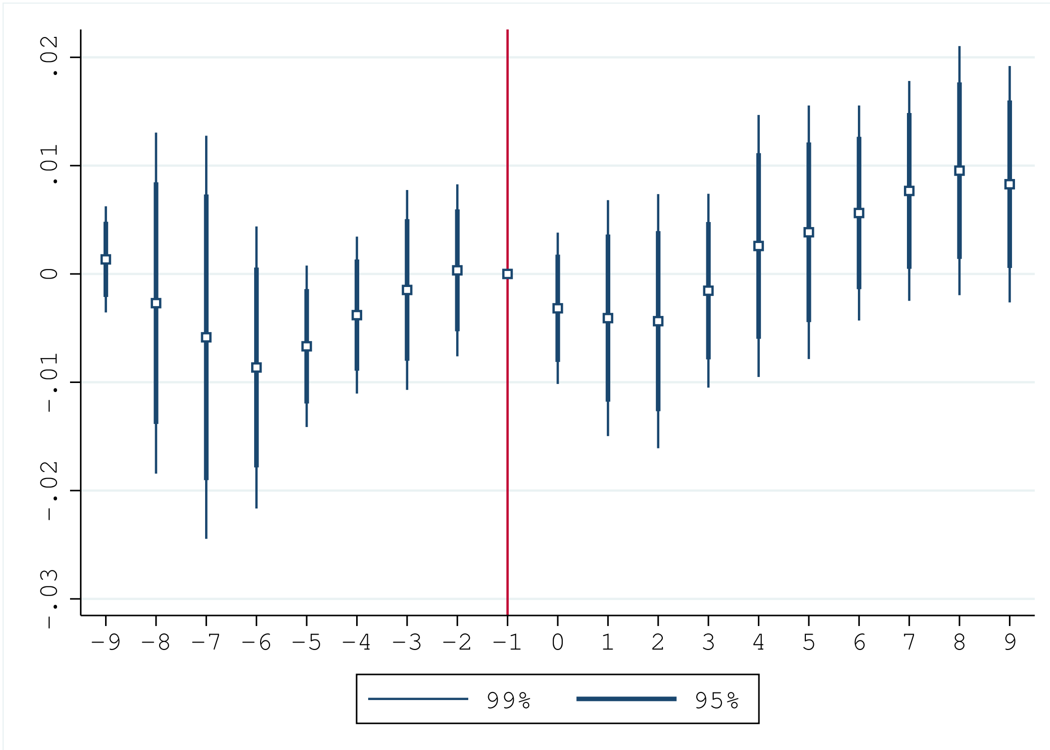

Figure 44: Event study, impact of storm on foreclosures, data for the period 2004-2019, all variables are averages computed at the zip code level.

A.2 Bankruptcy

Chapter 13. prevalence as in Table 1 is 1.6pp. so the effects are massive.[7]

[7] *A chapter 13 bankruptcy is also called a wage earner's plan. It enables individuals with regular income to develop a plan to repay all or part of their debts. Under this chapter, debtors propose a repayment plan to make installments to creditors over three to five years. If the debtor's current monthly income is less than the applicable state median, the plan will be for three years unless the court approves a longer period "for cause." (1) If the debtor's current monthly income is greater than the applicable state median, the plan generally must be for five years. In no case may a plan provide for payments over a period longer than five years. 11 U.S.C. 1322(d). During this time the law forbids creditors from starting or continuing collection efforts. This chapter discusses six aspects of a chapter 13 proceeding: the advantages of choosing chapter 13, the chapter 13 eligibility requirements, how a chapter 13 proceeding works, making the plan work, and the special chapter 13 discharge.* https://www.uscourts.gov/services-forms/bankruptcy/bankruptcy-basics/chapter-13-bankruptcy-basics

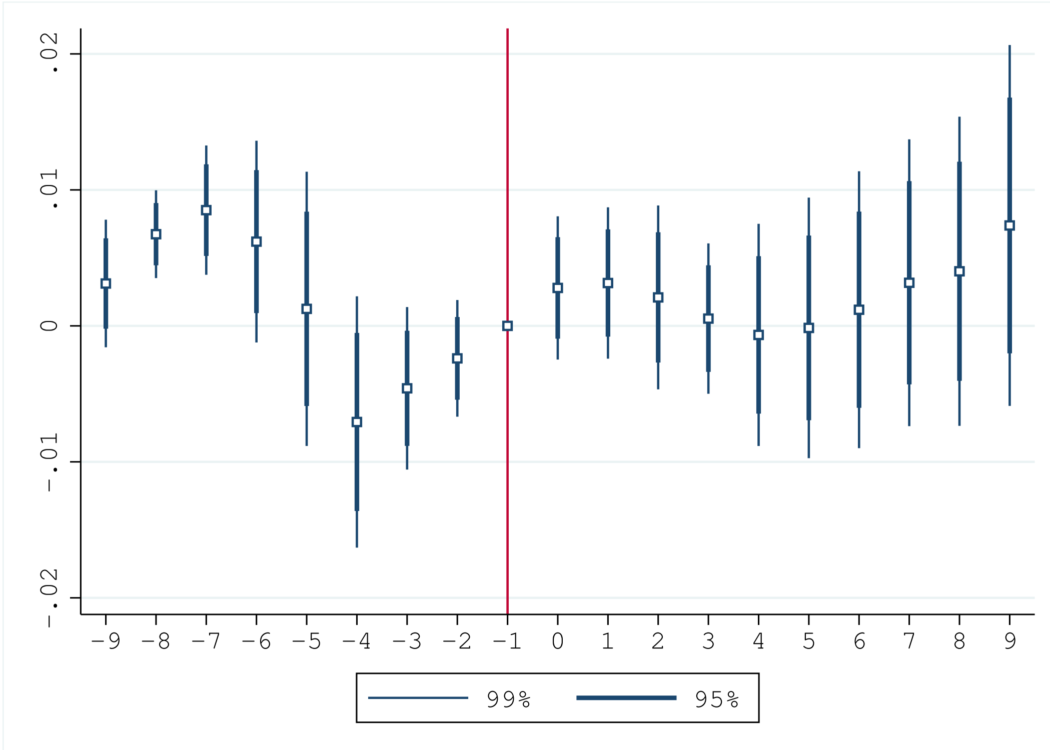

Figure 45: Event study, impact of storm chapter 7, data for the period 2004-2019, all variables are averages computed at the zip code level.

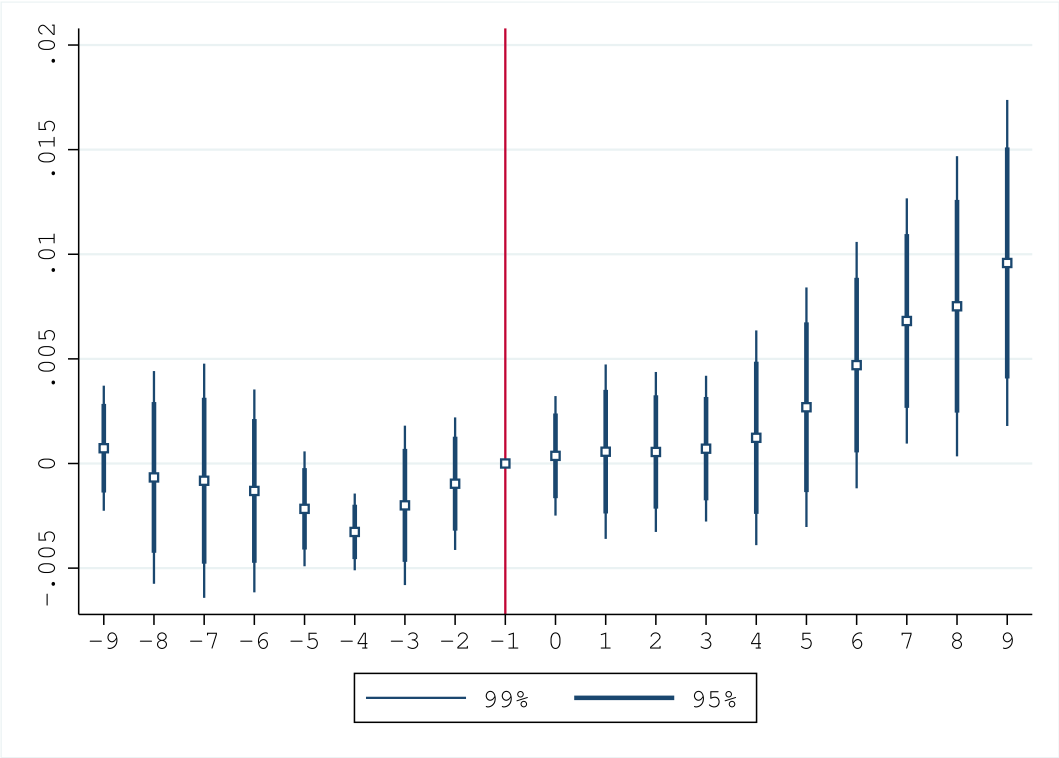

Figure 46: Event study, impact of storm chapter 13, data for the period 2004-2019, all variables are averages computed at the zip code level.

A.3 Credit Score

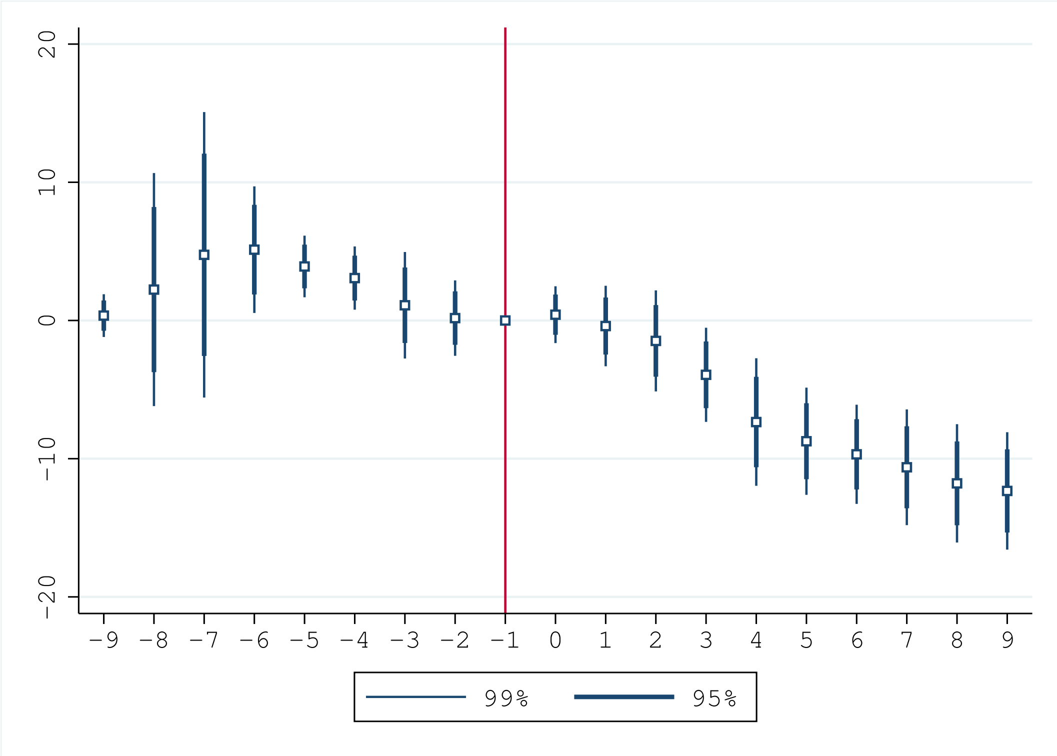

Figure 47: Event study, impact of storm on credit score, data for the period 2004-2019, all variables are averages computed at the zip code level.

A.4 Default on Revolving Credit

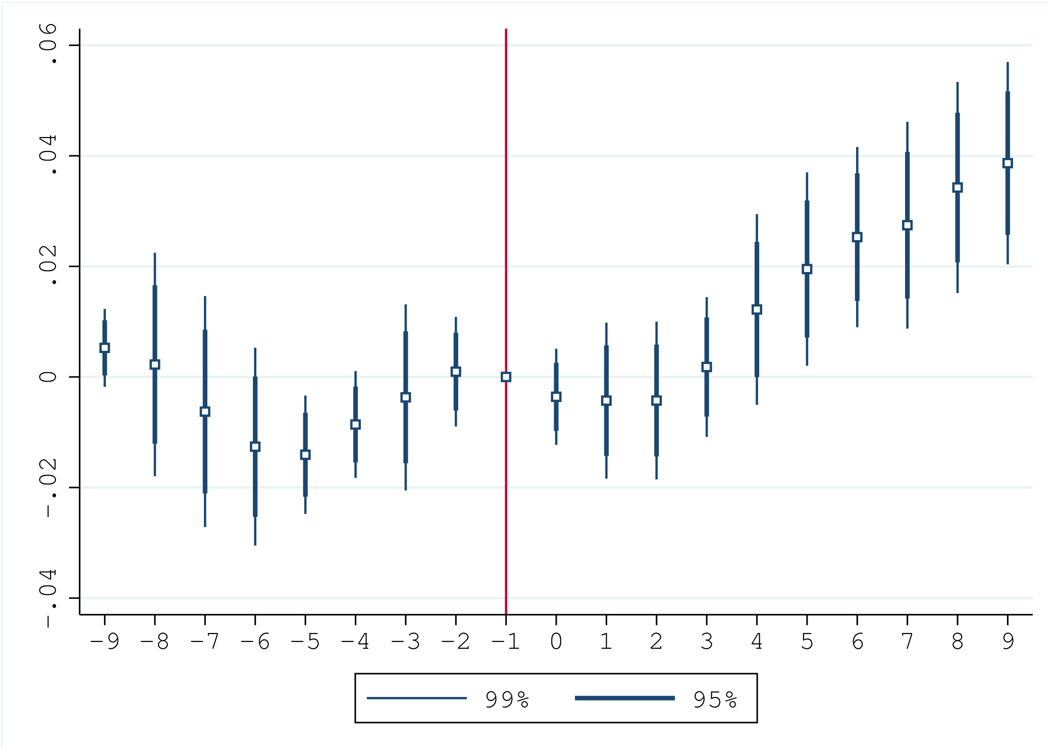

Figure 48: Event study, impact of storm on 90-day default, data for the period 2004-2019, all variables are averages computed at the zip code level.

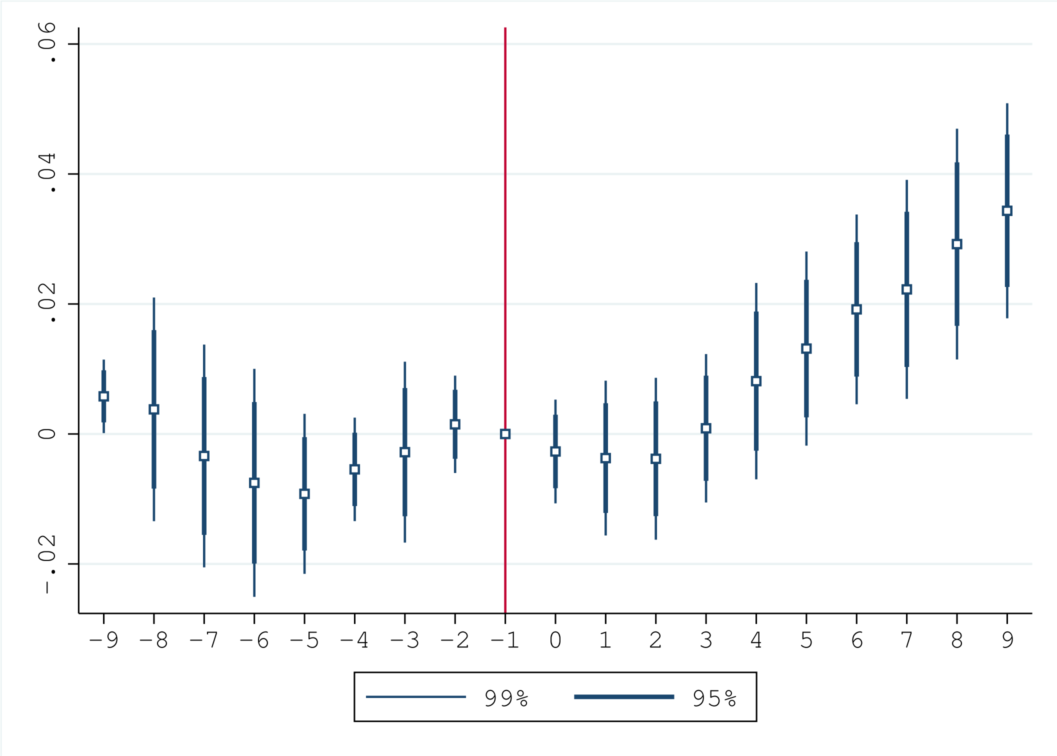

Figure 49: Event study, impact of storm on 120-day delinquencies, data for the period 2004-2019, all variables are averages computed at the zip code level.

A.5 Consumption

A.5.1 Credit Card Balance as Consumption

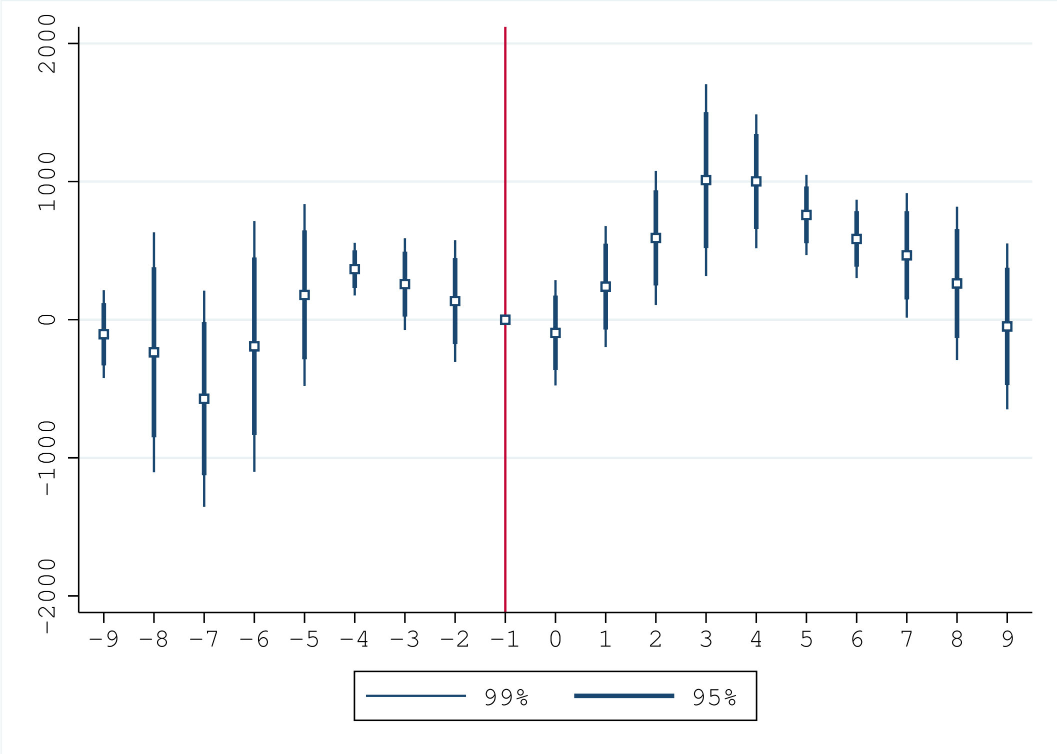

Figure 50: Event study, impact of storm on credit card balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

A.5.2 Auto Loan as Consumption

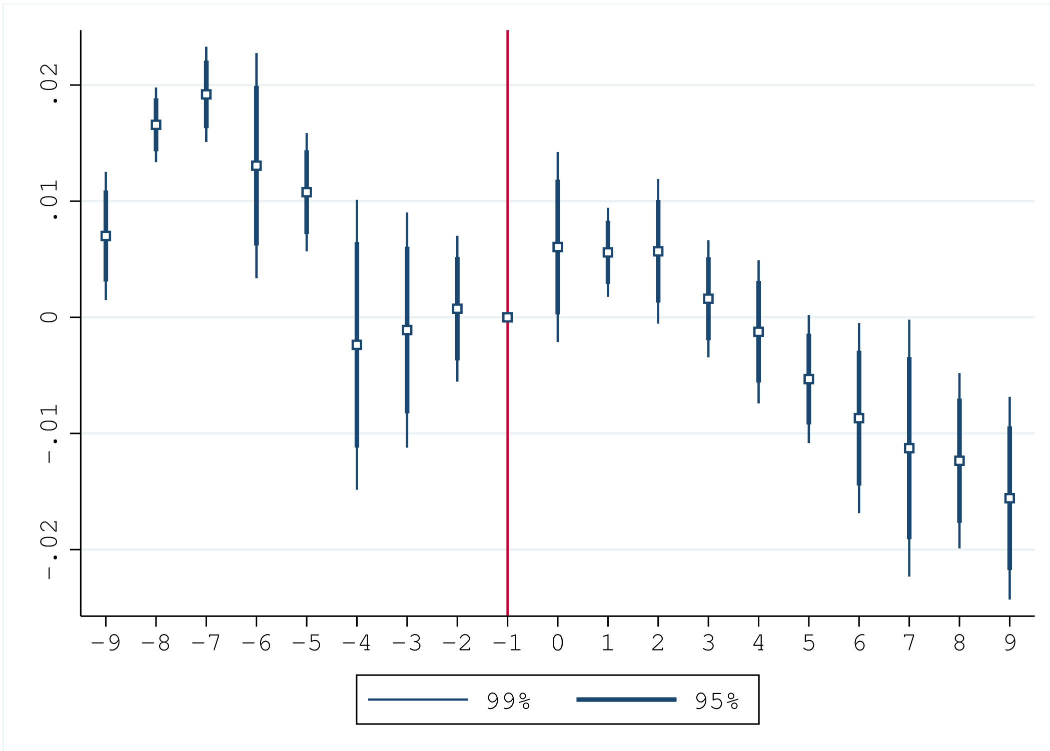

Figure 51: Event study, impact of storm on auto loan origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

A.5.3 Auto Balance as Consumption

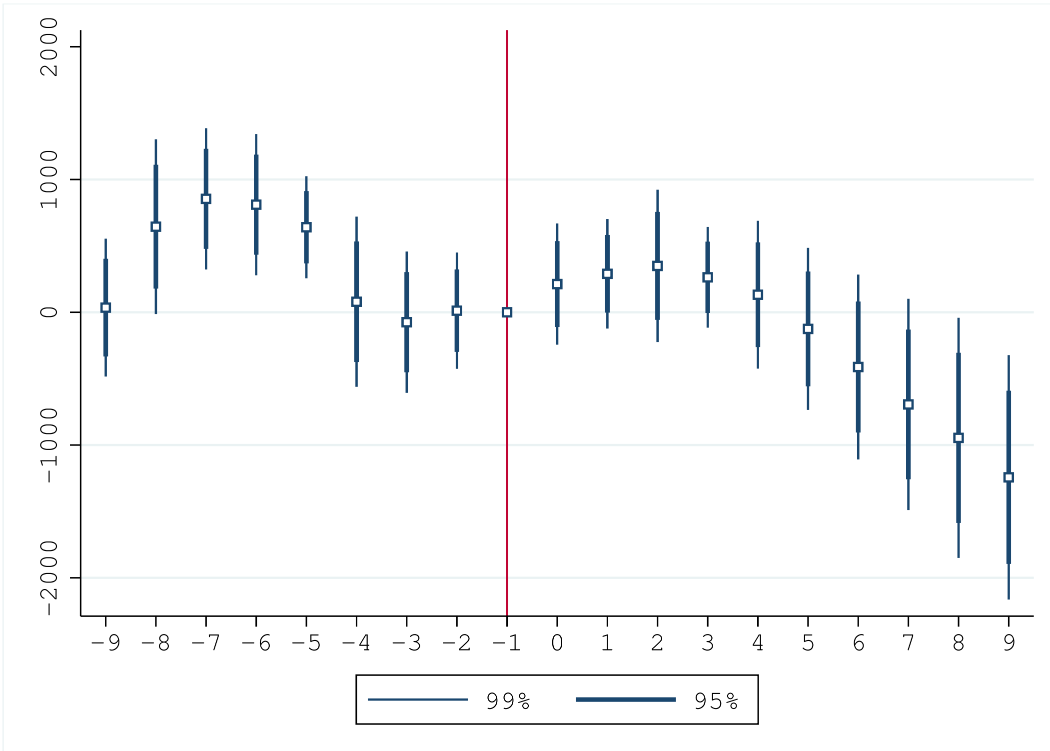

Figure 52: Event study, impact of storm on auto loan, data for the period 2004-2019, all variables are averages computed at the zip code level.

B Robustness to Lags and Leads

B.1 Housing Market

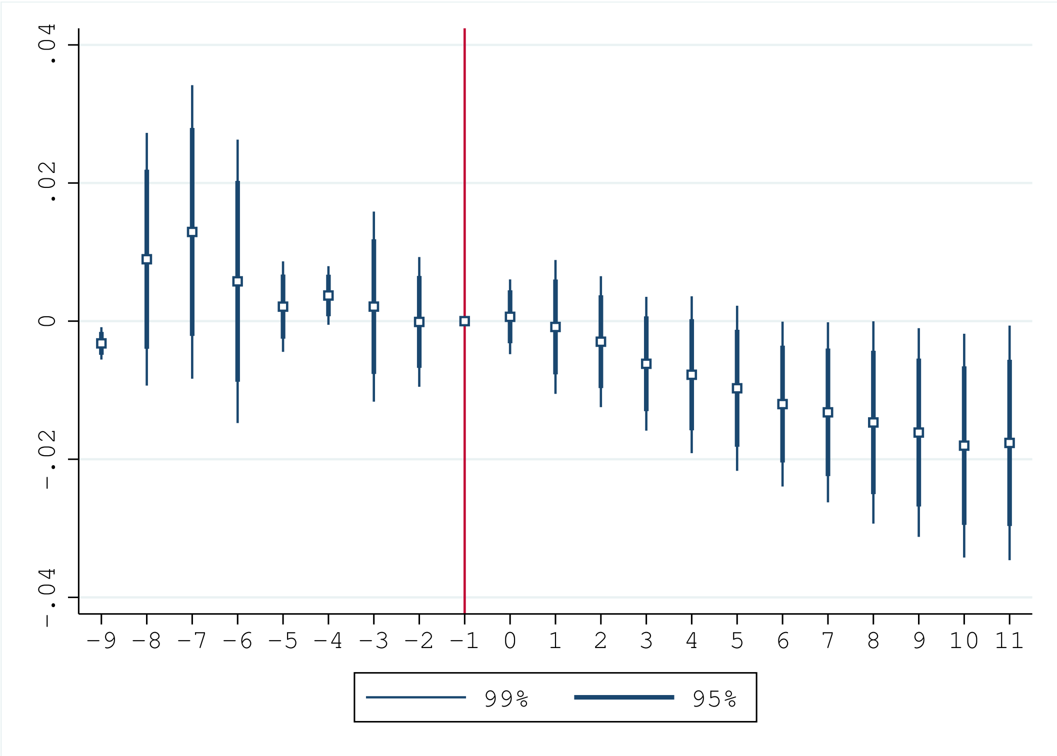

Figure 53: Event study, impact of storm on mortgage origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

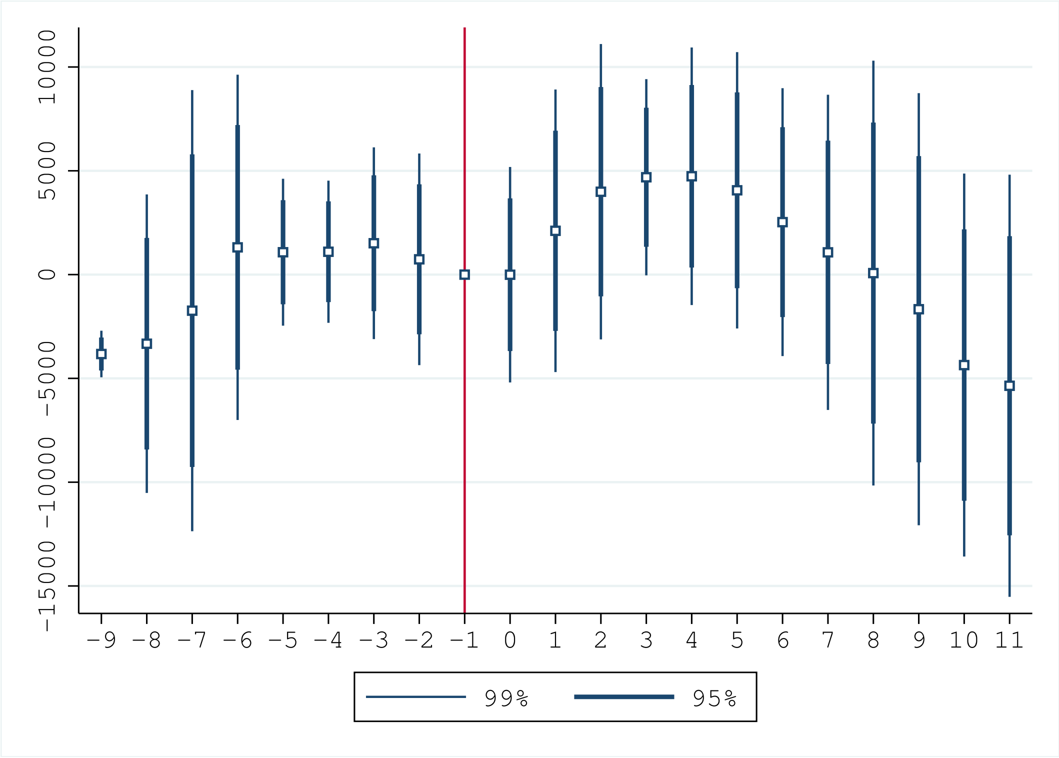

Figure 54: Event study, impact of storm on mortgage balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.1.1 Foreclosure

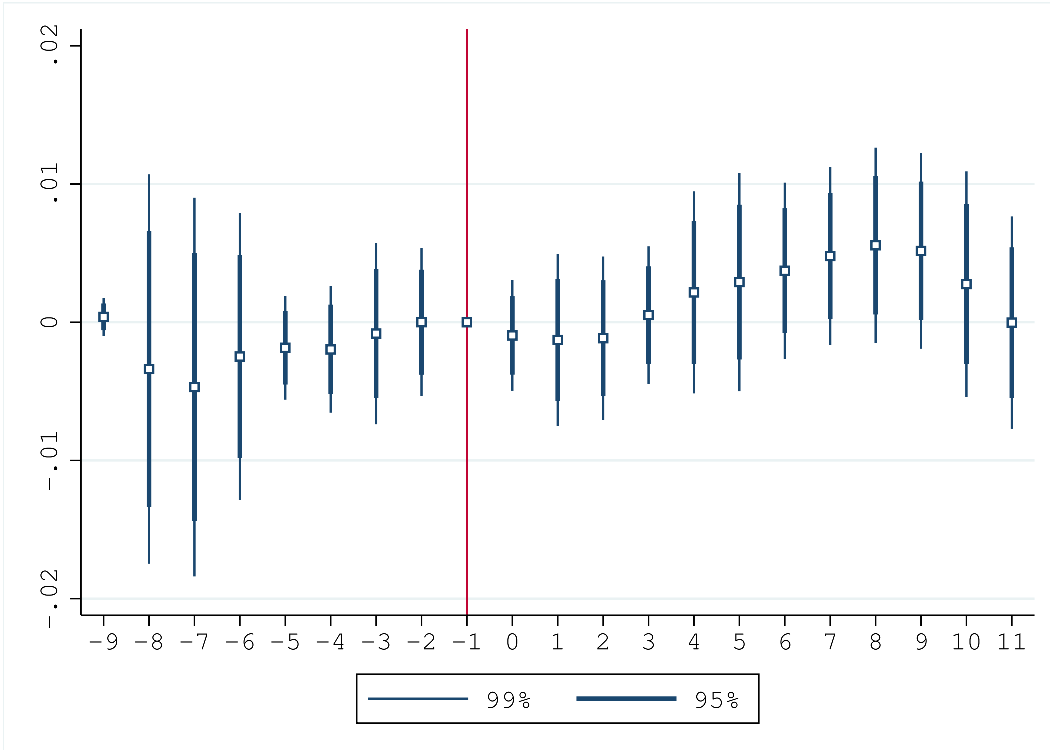

Figure 55: Event study, impact of storm on foreclosures, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.2 Bankruptcy

Chapter 13. prevalence as in Table 1 is 1.6pp. so the effects are massive.[8]

[8] *A chapter 13 bankruptcy is also called a wage earner's plan. It enables individuals with regular income to develop a plan to repay all or part of their debts. Under this chapter, debtors propose a repayment plan to make installments to creditors over three to five years. If the debtor's current monthly income is less than the applicable state median, the plan will be for three years unless the court approves a longer period "for cause." (1) If the debtor's current monthly income is greater than the applicable state median, the plan generally must be for five years. In no case may a plan provide for payments over a period longer than five years. 11 U.S.C. 1322(d). During this time the law forbids creditors from starting or continuing collection efforts. This chapter discusses six aspects of a chapter 13 proceeding: the advantages of choosing chapter 13, the chapter 13 eligibility requirements, how a chapter 13 proceeding works, making the plan work, and the special chapter 13 discharge.* https://www.uscourts.gov/services-forms/bankruptcy/bankruptcy-basics/chapter-13-bankruptcy-basics

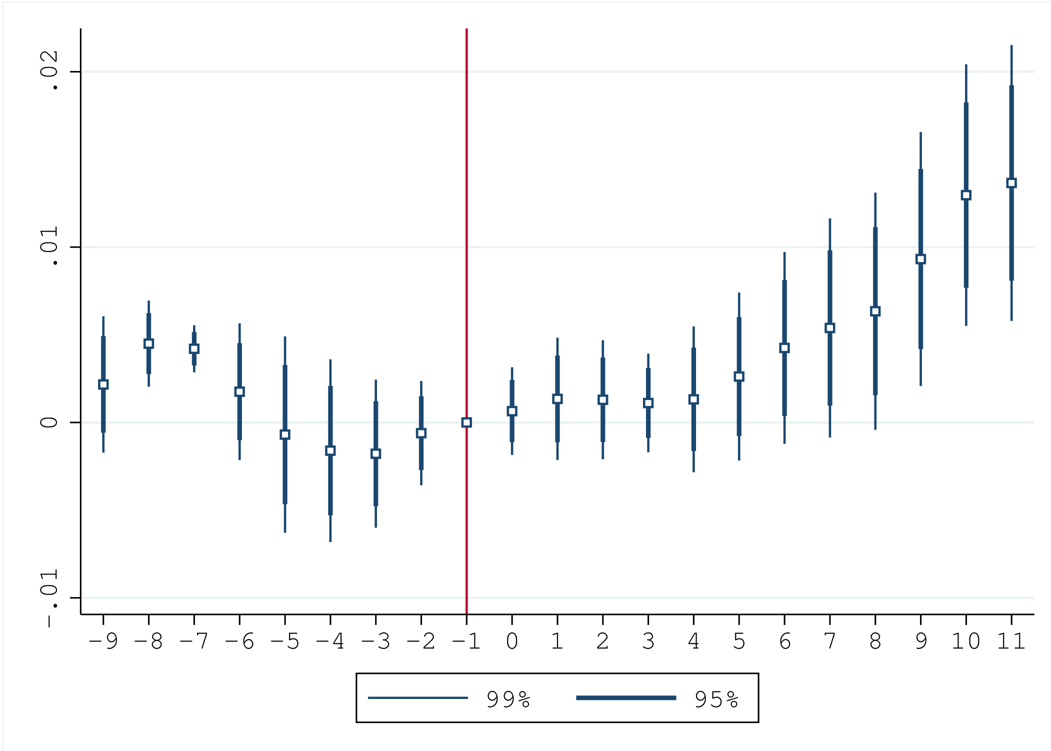

Figure 56: Event study, impact of storm chapter 7, data for the period 2004-2019, all variables are averages computed at the zip code level.

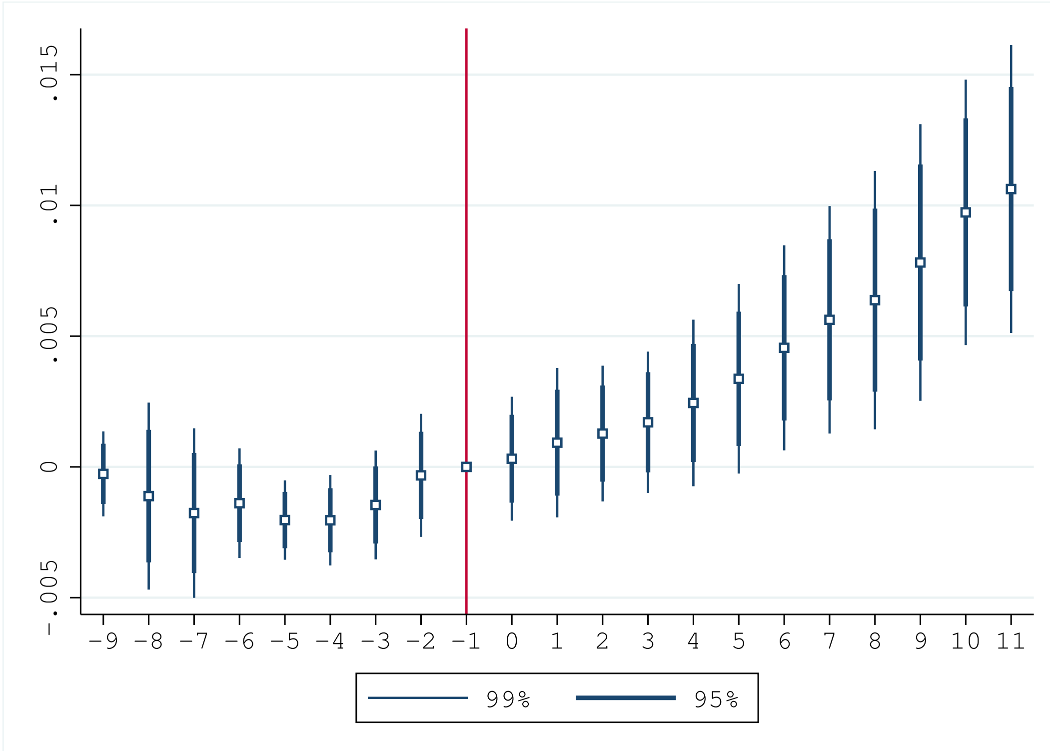

Figure 57: Event study, impact of storm chapter 13, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.3 Credit Score

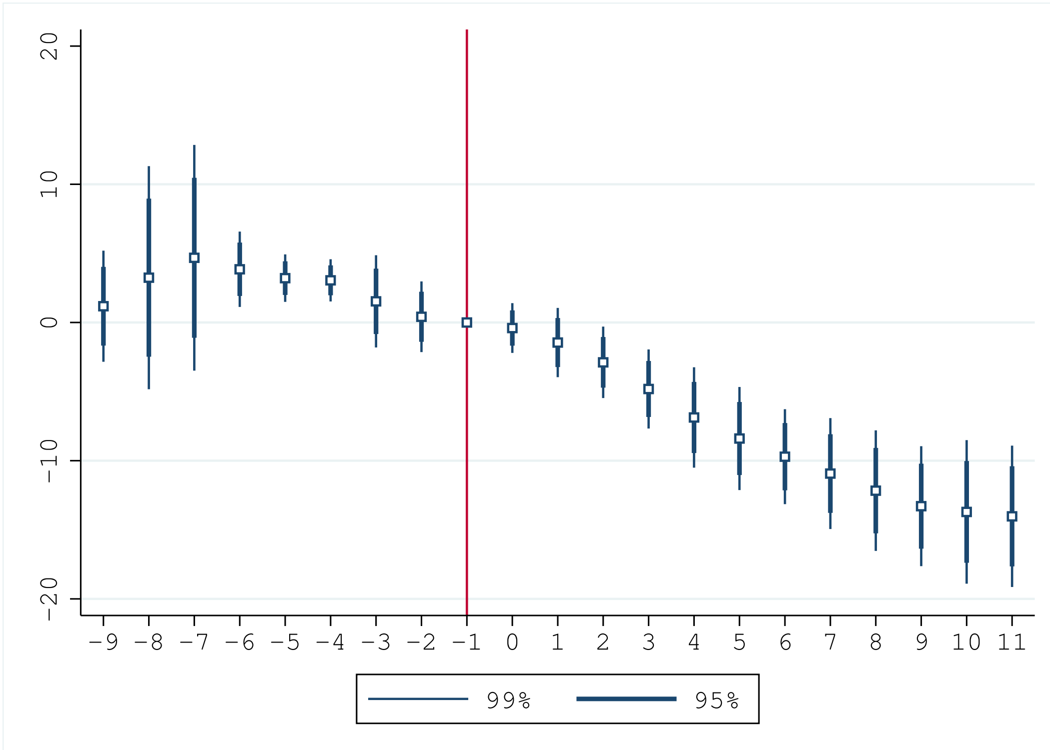

Figure 58: Event study, impact of storm on credit score, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.4 Default on Revolving Credit

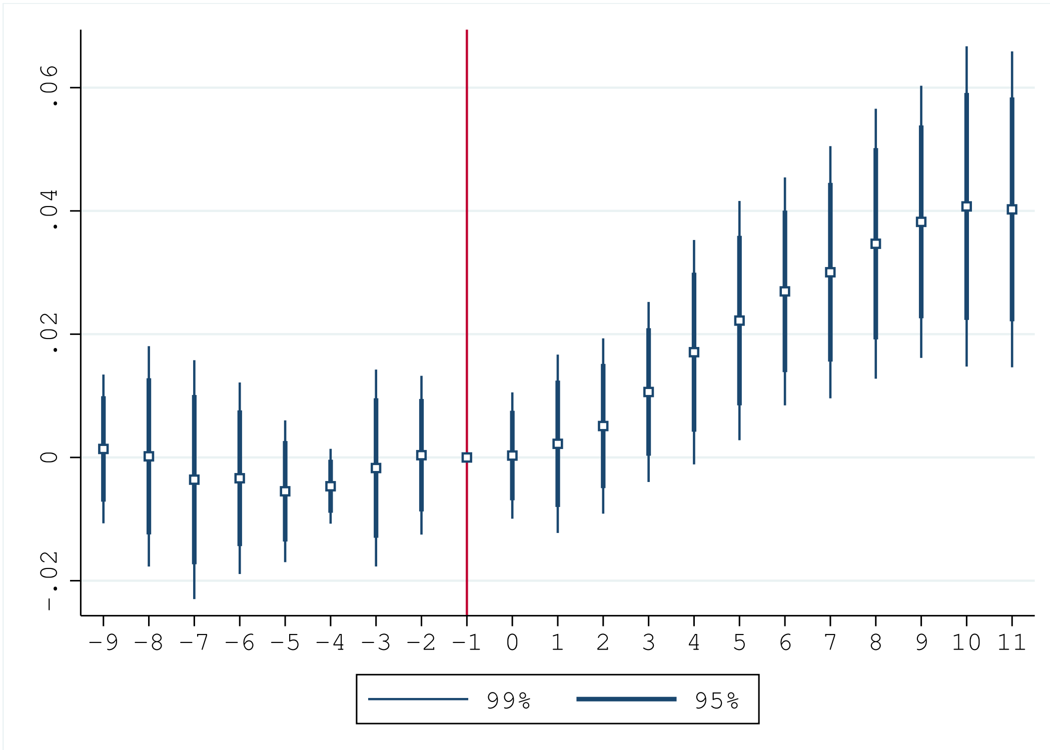

Figure 59: Event study, impact of storm on 90-day default, data for the period 2004-2019, all variables are averages computed at the zip code level.

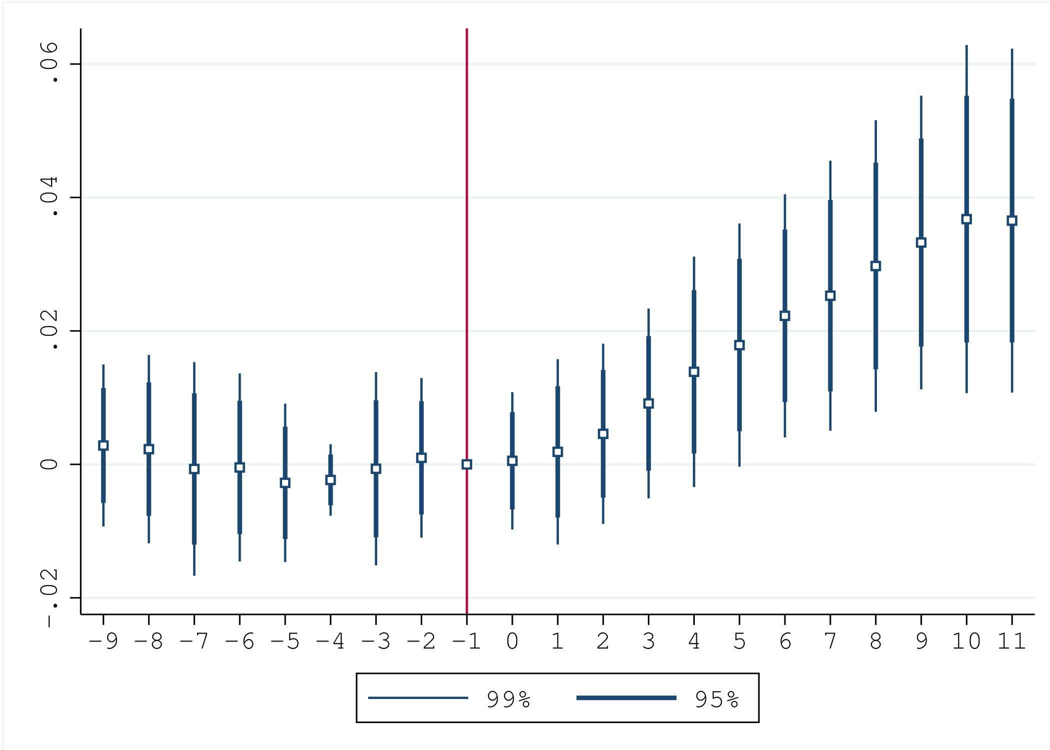

Figure 60: Event study, impact of storm on 120-day delinquencies, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.5 Consumption

B.5.1 Credit Card Balance as Consumption

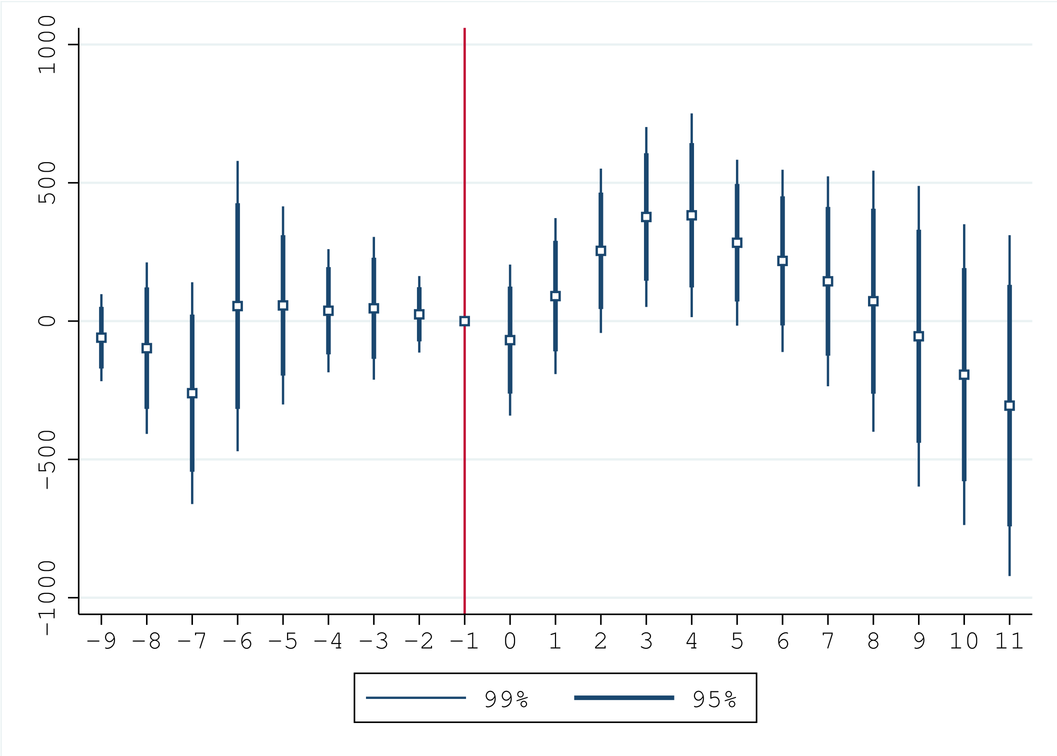

Figure 61: Event study, impact of storm on credit card balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.5.2 Auto Loan as Consumption

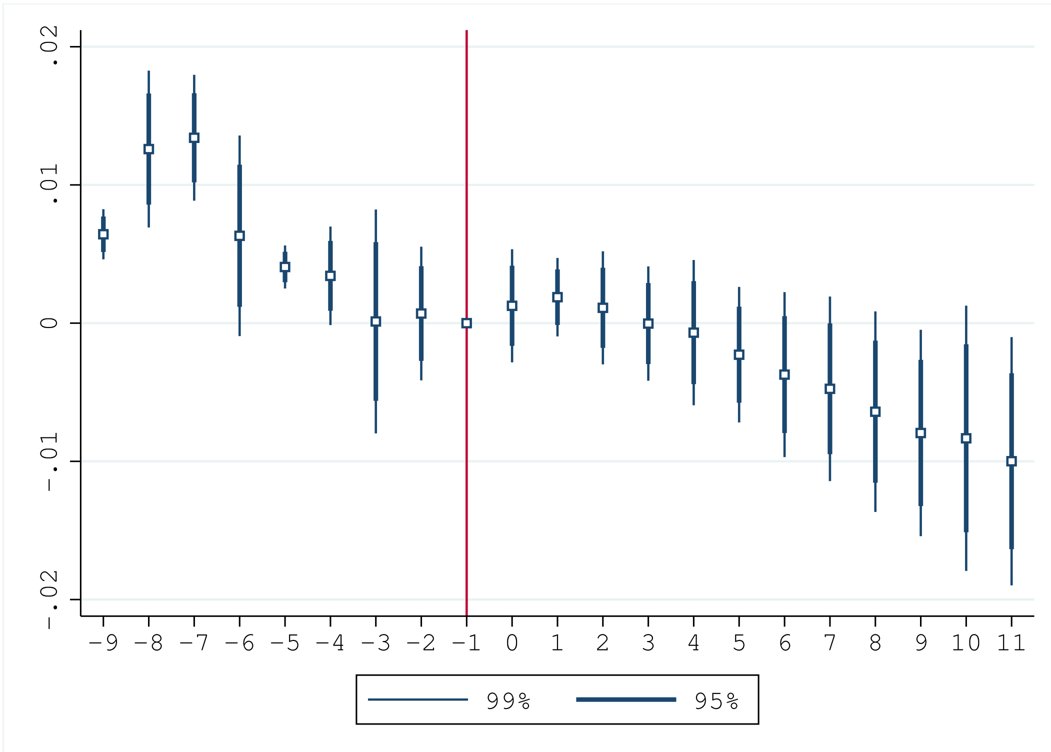

Figure 62: Event study, impact of storm on auto loan origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.5.3 Auto Balance as Consumption

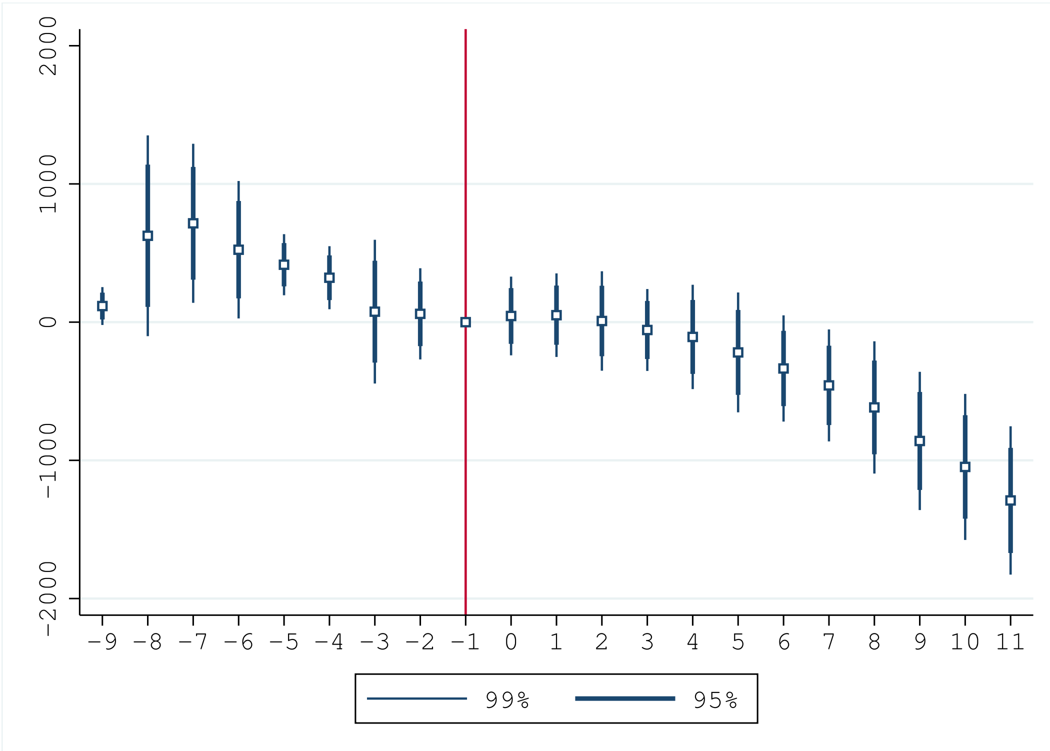

Figure 63: Event study, impact of storm on auto loan, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.6 Housing Market

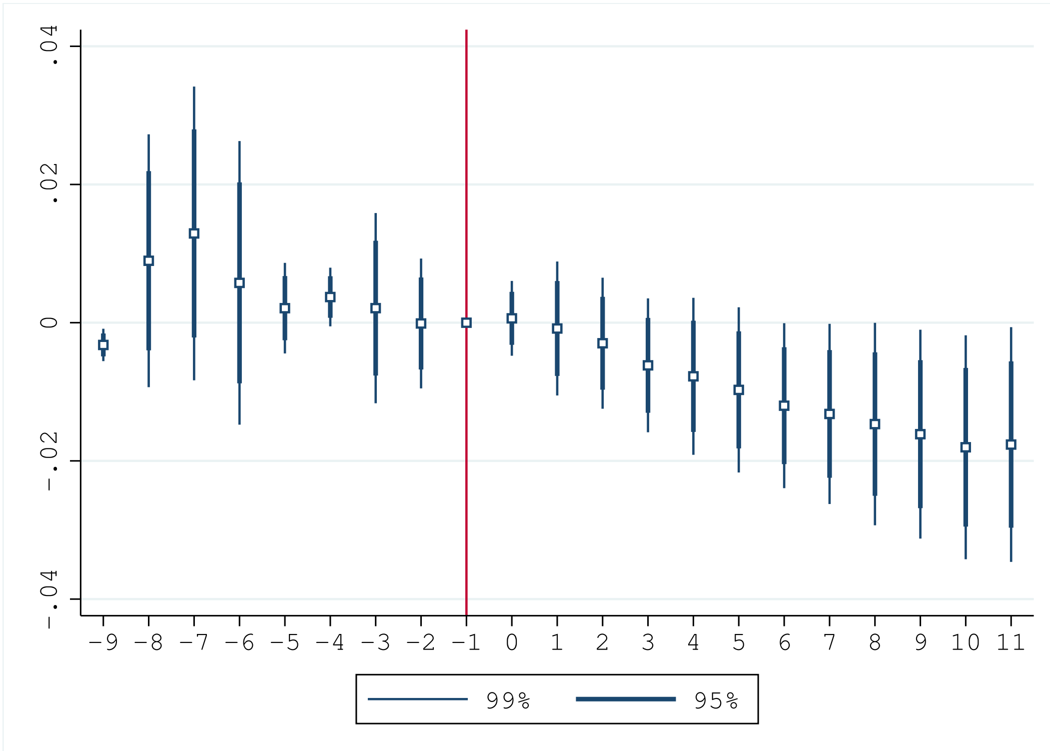

Figure 64: Event study, impact of storm on mortgage origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

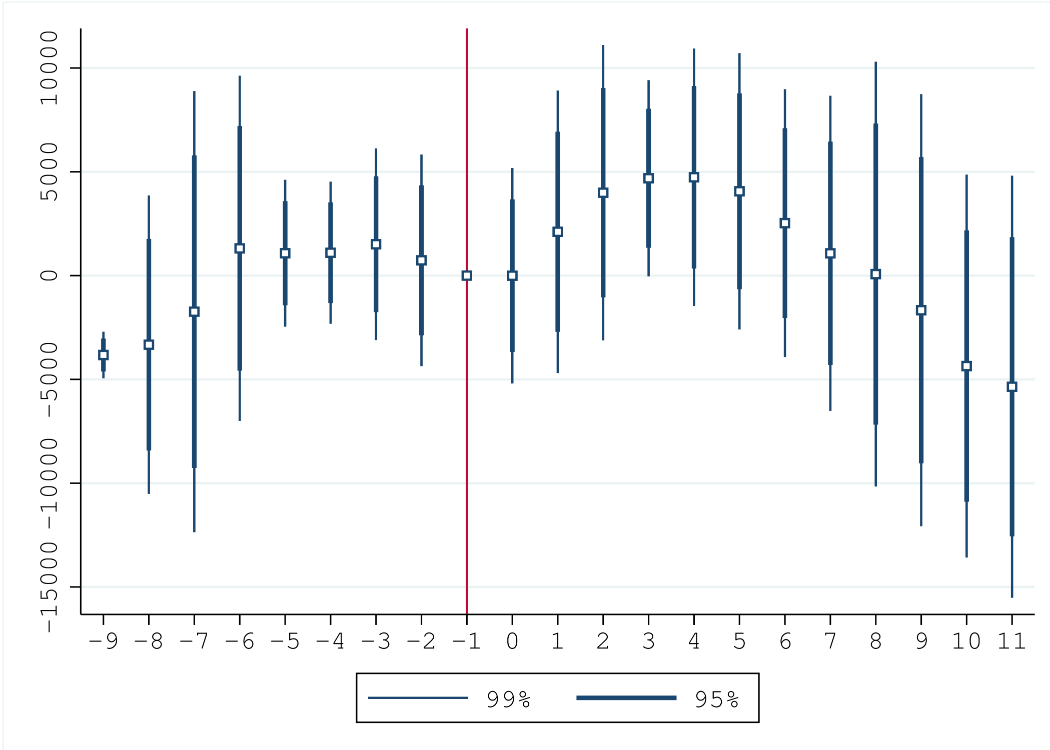

Figure 65: Event study, impact of storm on mortgage balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.6.1 Foreclosure

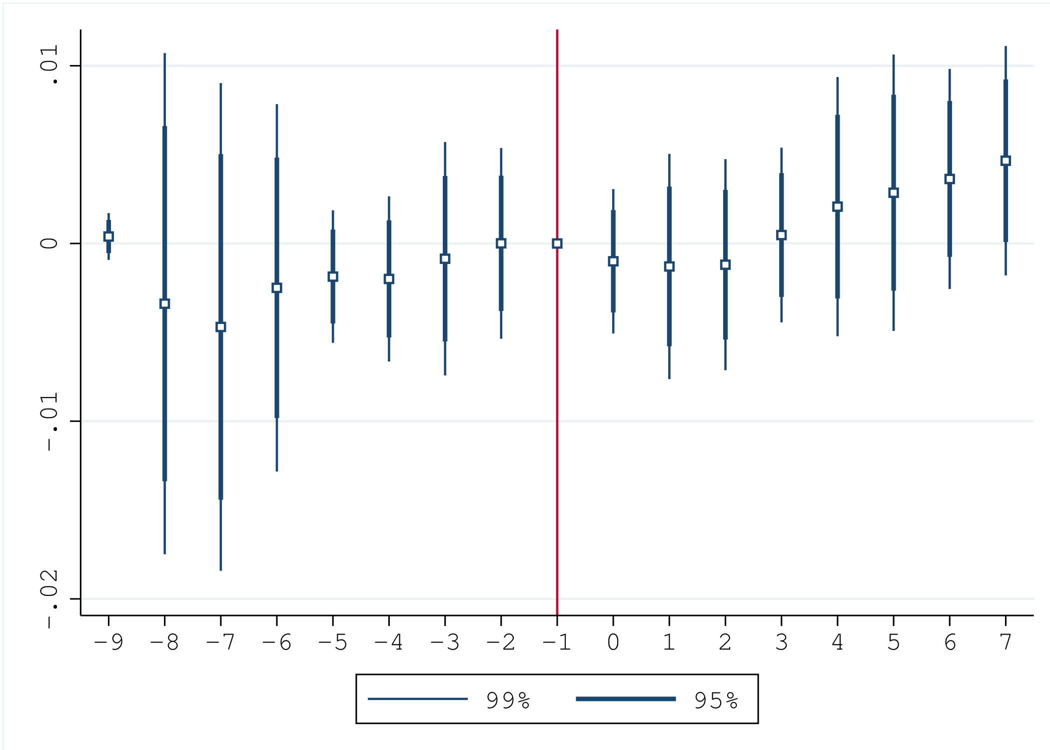

Figure 66: Event study, impact of storm on foreclosures, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.7 Bankruptcy

Chapter 13. prevalence as in Table 1 is 1.6pp. so the effects are massive.[9]

[9] *A chapter 13 bankruptcy is also called a wage earner's plan. It enables individuals with regular income to develop a plan to repay all or part of their debts. Under this chapter, debtors propose a repayment plan to make installments to creditors over three to five years. If the debtor's current monthly income is less than the applicable state median, the plan will be for three years unless the court approves a longer period "for cause." (1) If the debtor's current monthly income is greater than the applicable state median, the plan generally must be for five years. In no case may a plan provide for payments over a period longer than five years. 11 U.S.C. 1322(d). During this time the law forbids creditors from starting or continuing collection efforts. This chapter discusses six aspects of a chapter 13 proceeding: the advantages of choosing chapter 13, the chapter 13 eligibility requirements, how a chapter 13 proceeding works, making the plan work, and the special chapter 13 discharge.* https://www.uscourts.gov/services-forms/bankruptcy/bankruptcy-basics/chapter-13-bankruptcy-basics

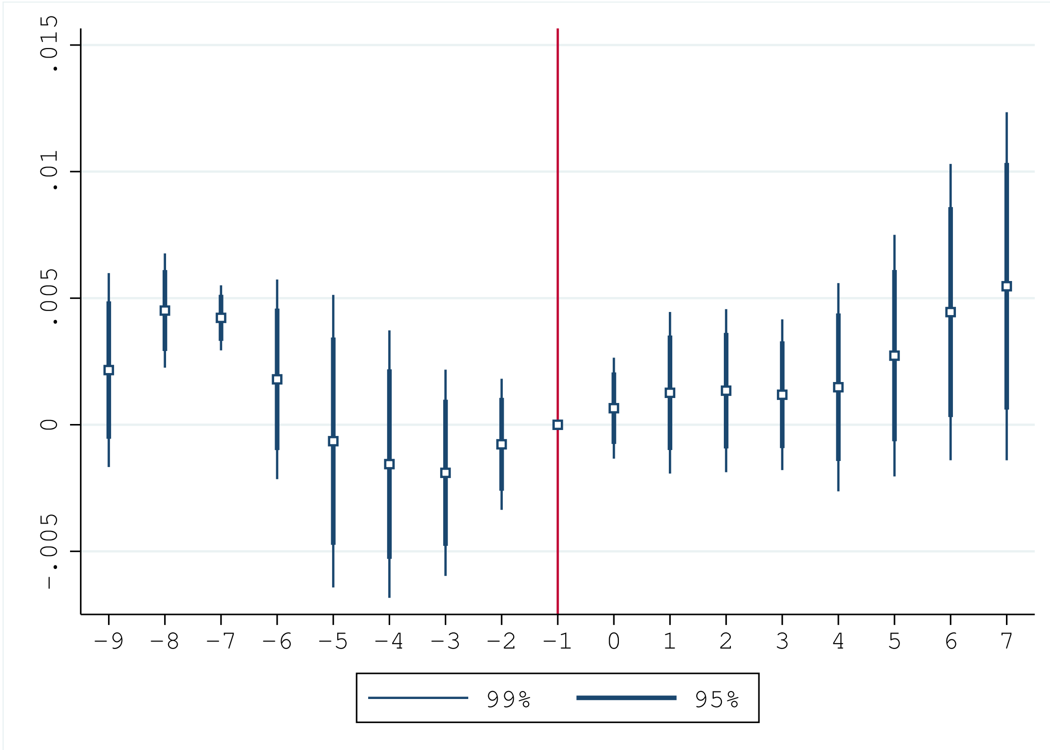

Figure 67: Event study, impact of storm chapter 7, data for the period 2004-2019, all variables are averages computed at the zip code level.

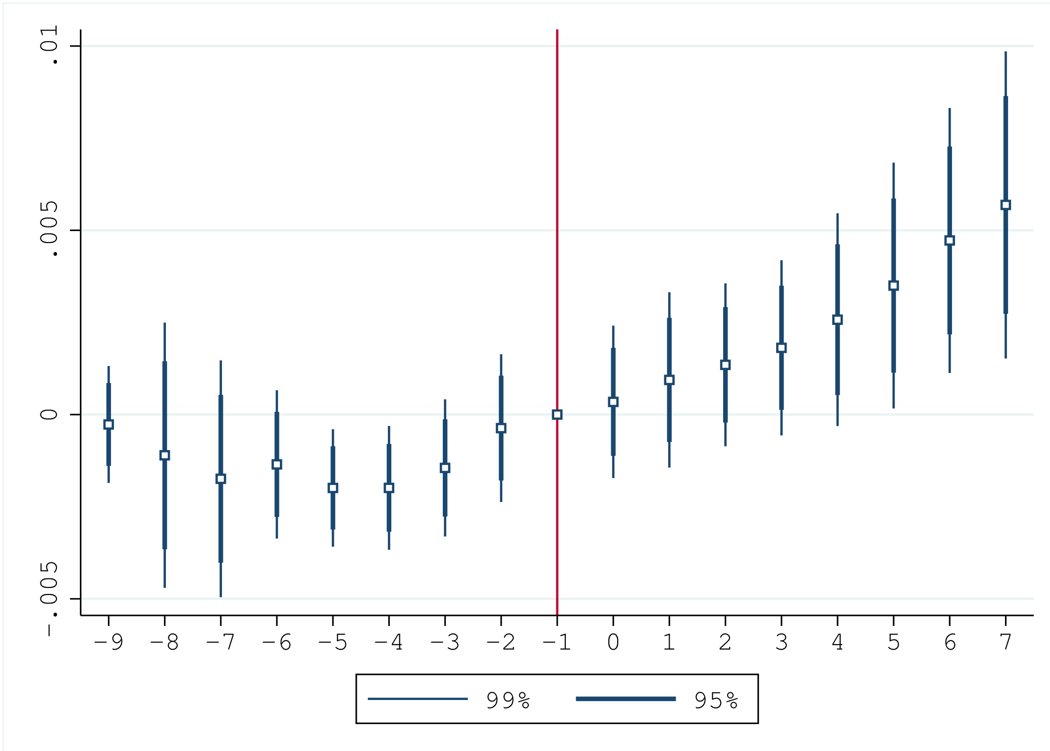

Figure 68: Event study, impact of storm chapter 13, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.8 Credit Score

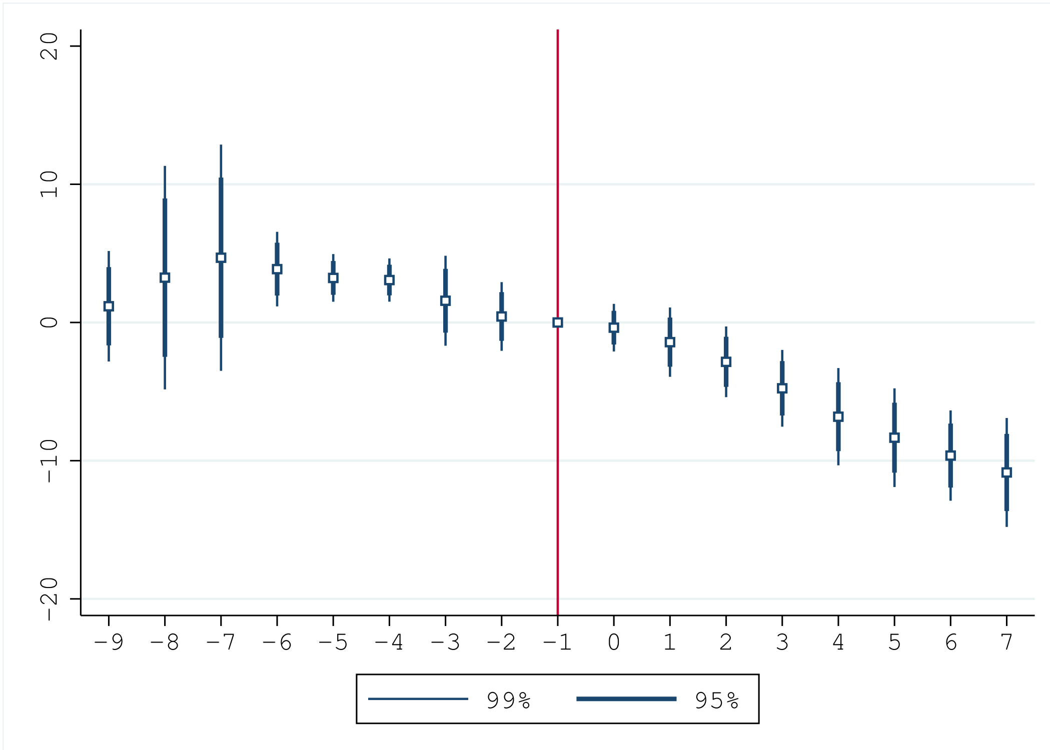

Figure 69: Event study, impact of storm on credit score, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.9 Default on Revolving Credit

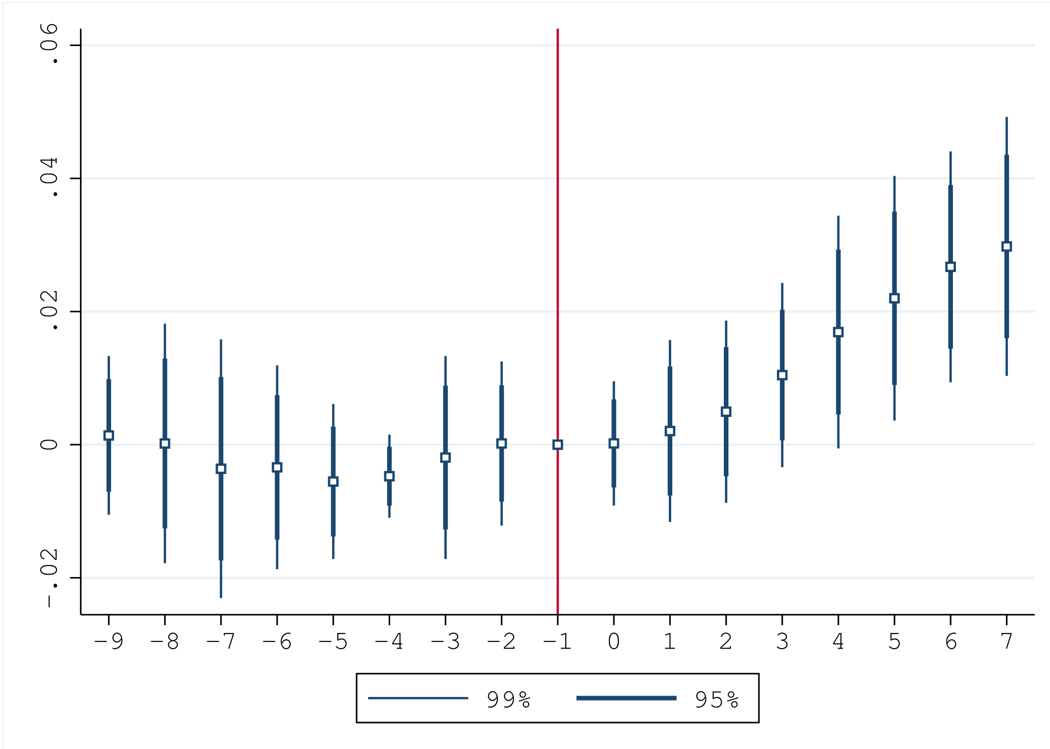

Figure 70: Event study, impact of storm on 90-day default, data for the period 2004-2019, all variables are averages computed at the zip code level.

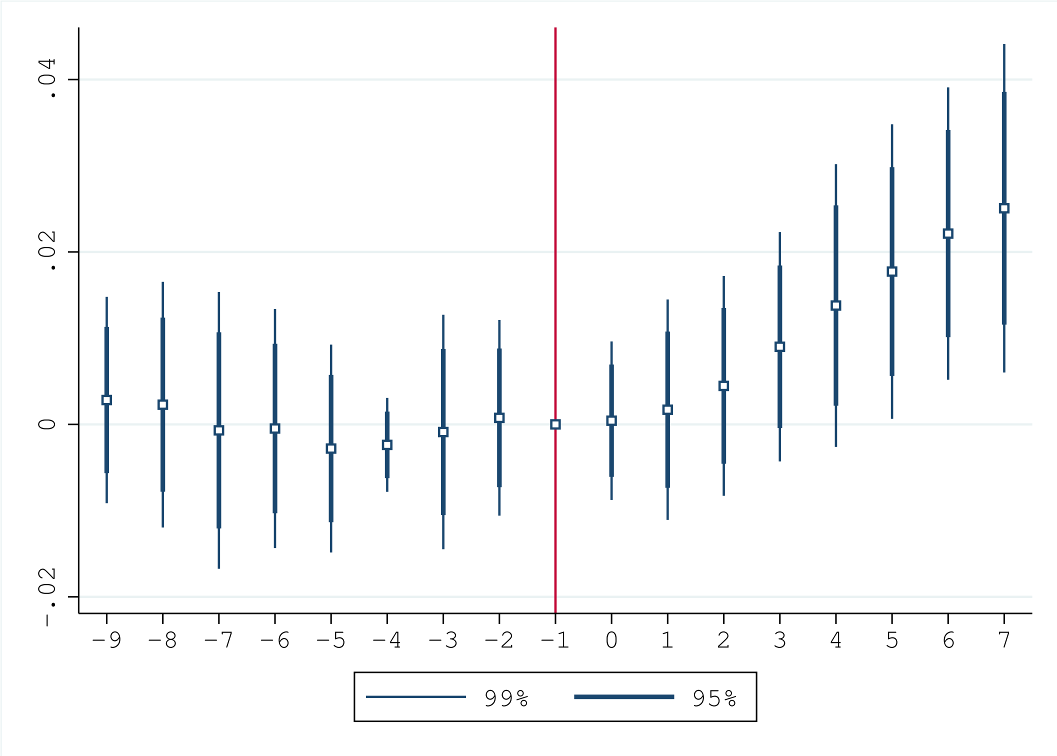

Figure 71: Event study, impact of storm on 120-day delinquencies, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.10 Consumption

B.10.1 Credit Card Balance as Consumption

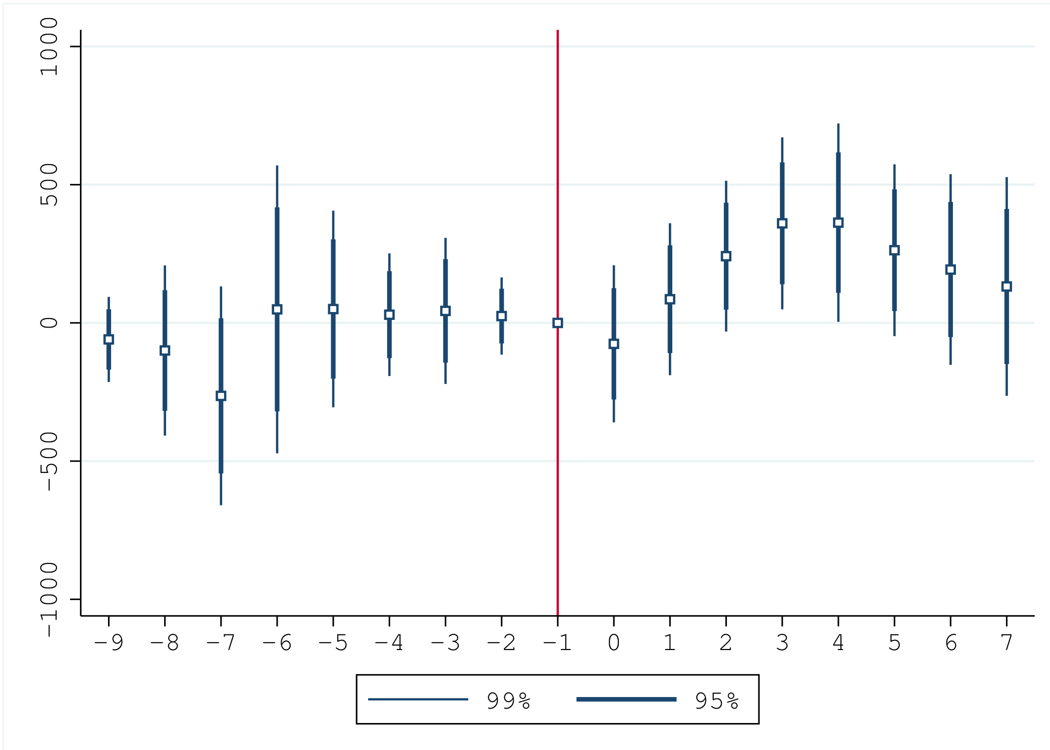

Figure 72: Event study, impact of storm on credit card balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.10.2 Auto Loan as Consumption

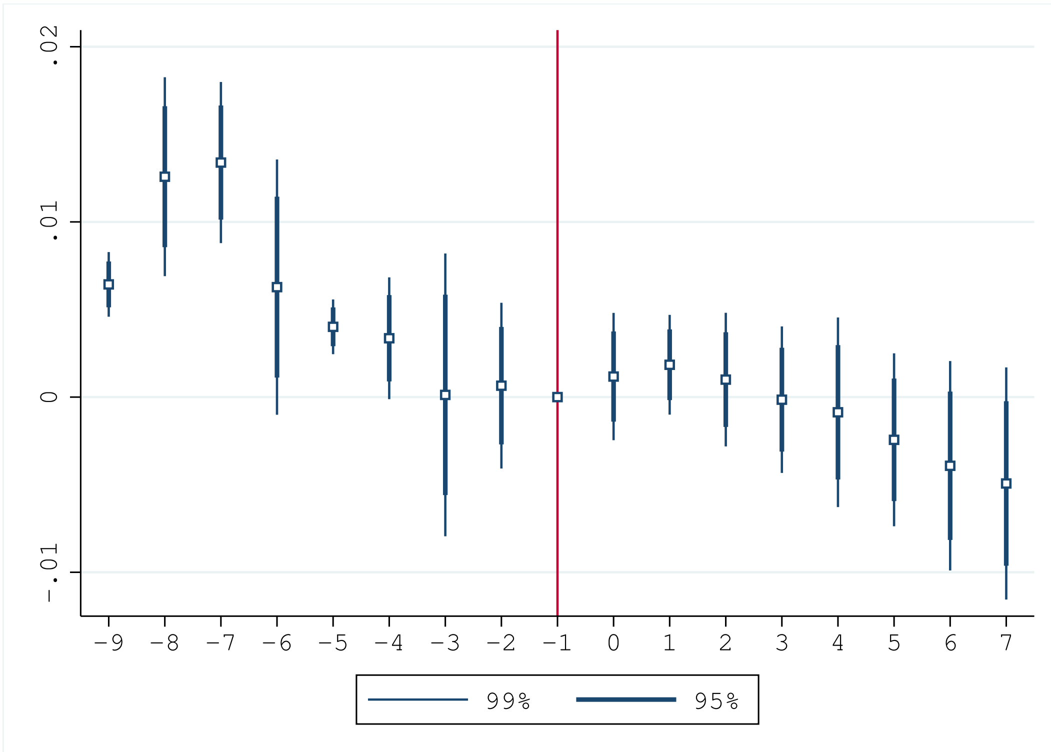

Figure 73: Event study, impact of storm on auto loan origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

B.10.3 Auto Balance as Consumption

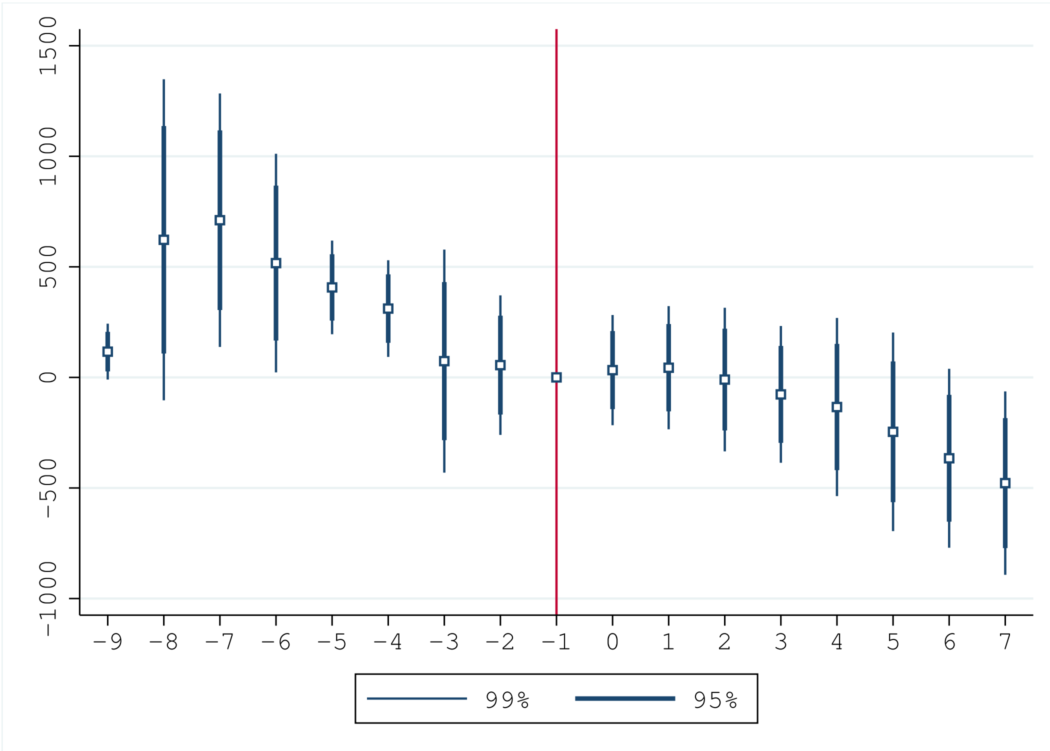

Figure 74: Event study, impact of storm on auto loan, data for the period 2004-2019, all variables are averages computed at the zip code level.

C Analysis on county level data from the National Meteorological service (NOAA)

C.1 Housing Market

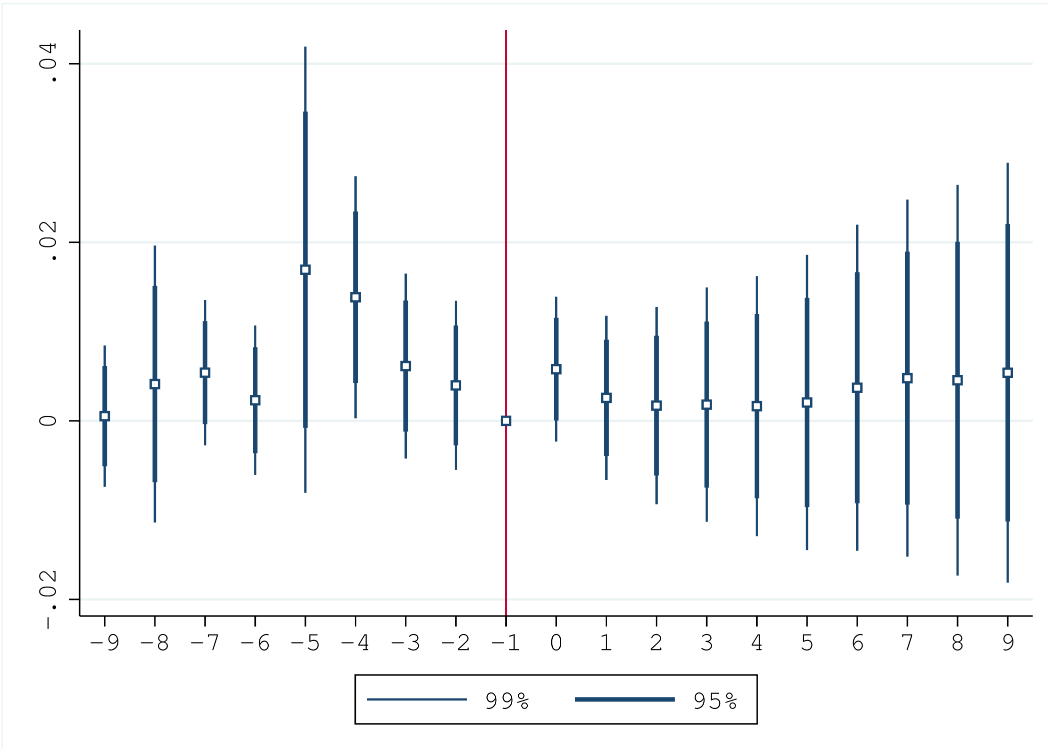

Figure 75: Event study, impact of storm on mortgage origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

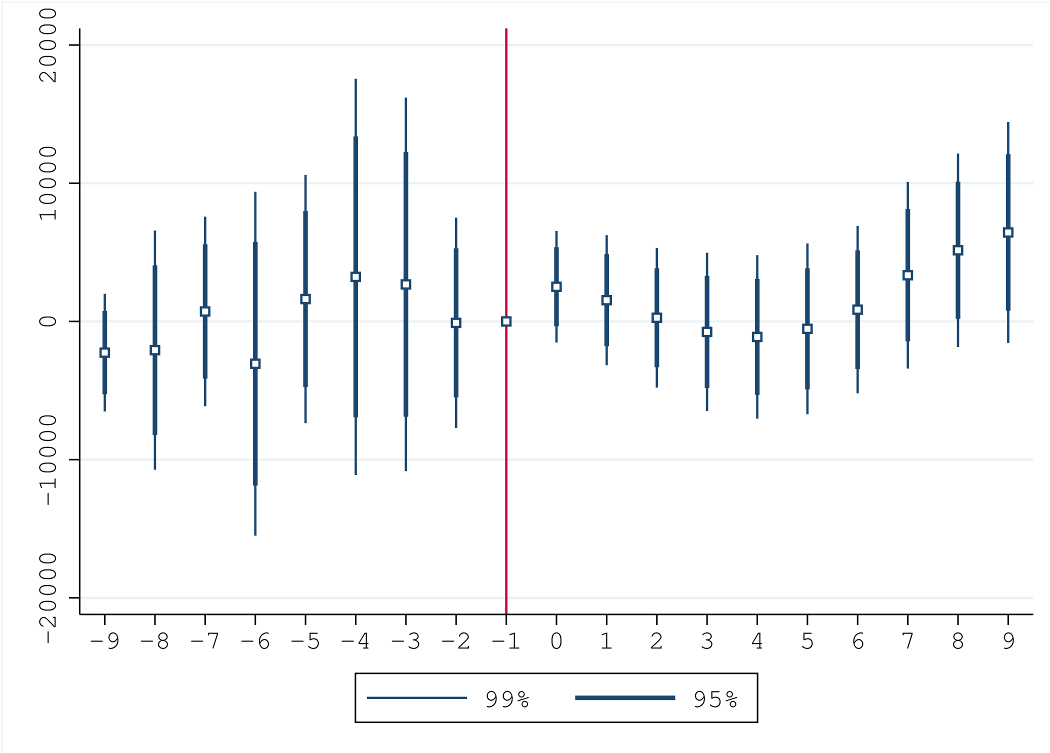

Figure 76: Event study, impact of storm on mortgage balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

C.1.1 Foreclosure

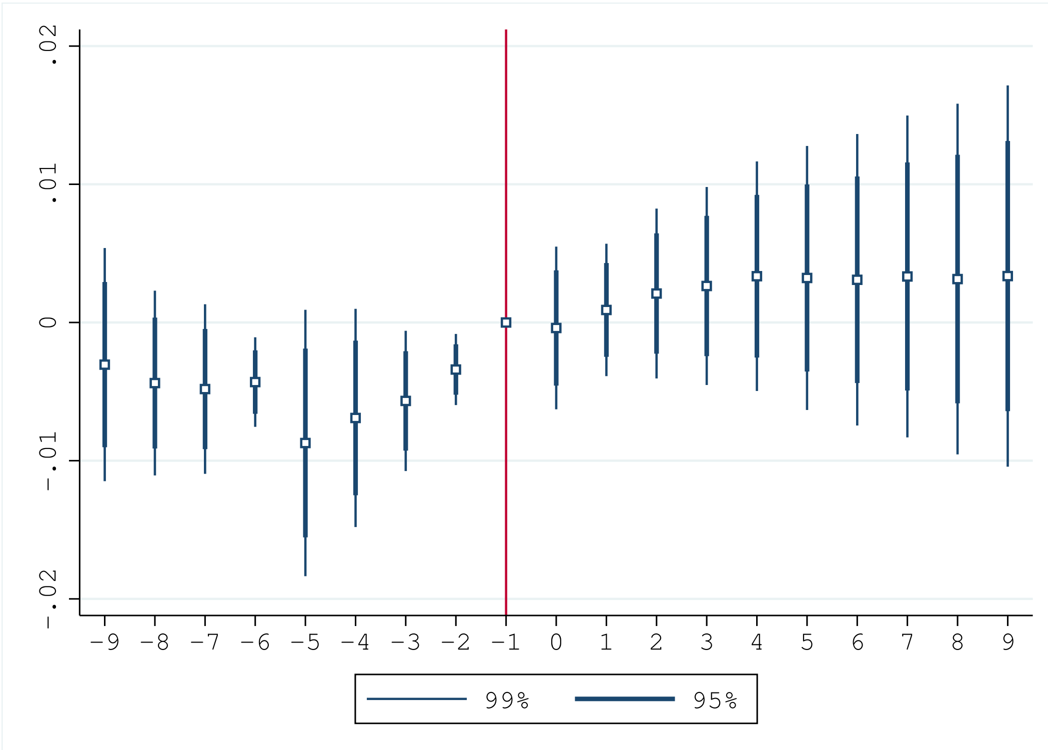

Figure 77: Event study, impact of storm on foreclosures, data for the period 2004-2019, all variables are averages computed at the zip code level.

C.2 Bankruptcy

Chapter 13. prevalence as in Table 1 is 1.6pp. so the effects are massive.

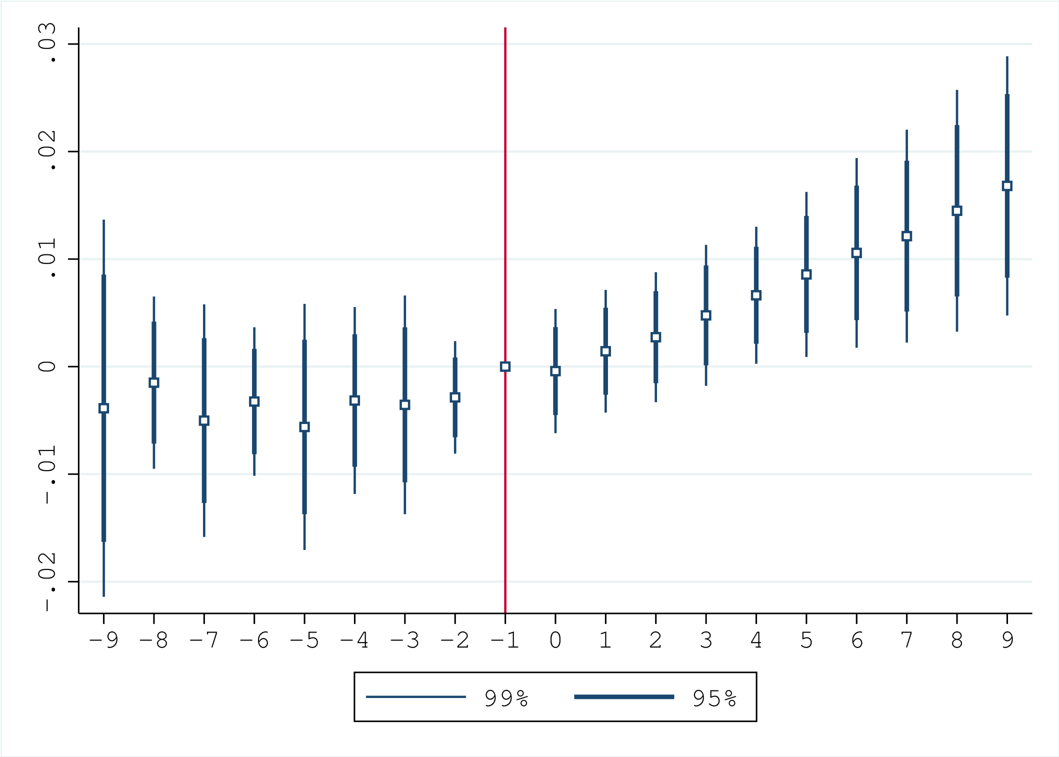

Figure 78: Event study, impact of storm chapter 7, data for the period 2004-2019, all variables are averages computed at the zip code level.

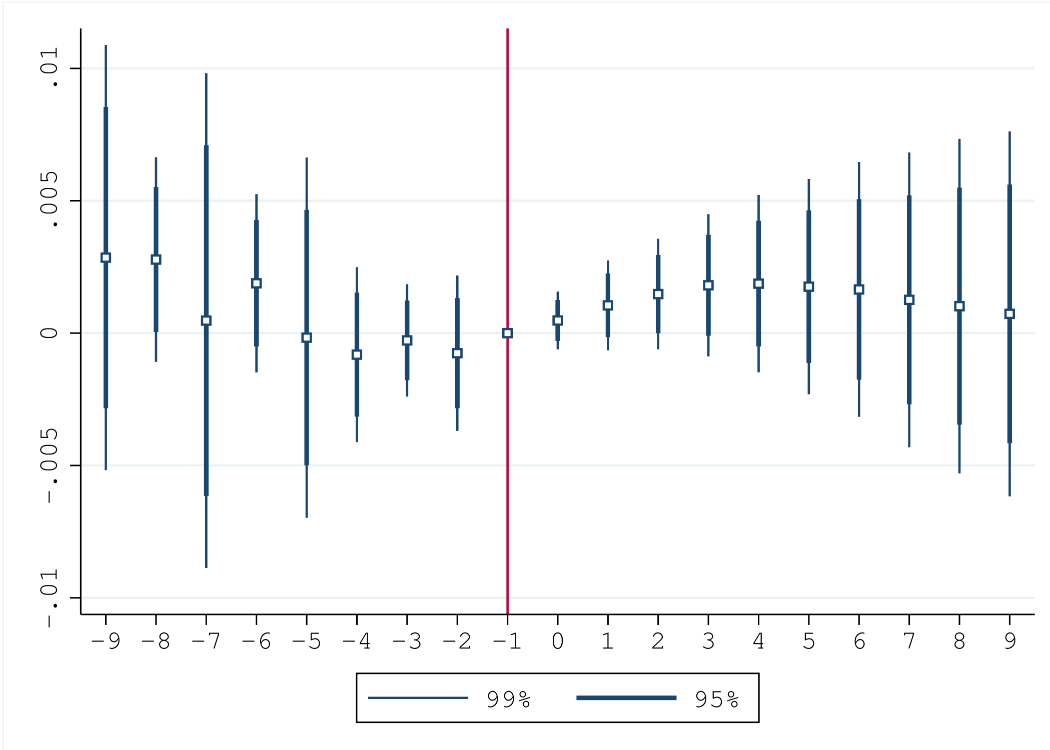

Figure 79: Event study, impact of storm chapter 13, data for the period 2004-2019, all variables are averages computed at the zip code level.

C.3 Credit Score

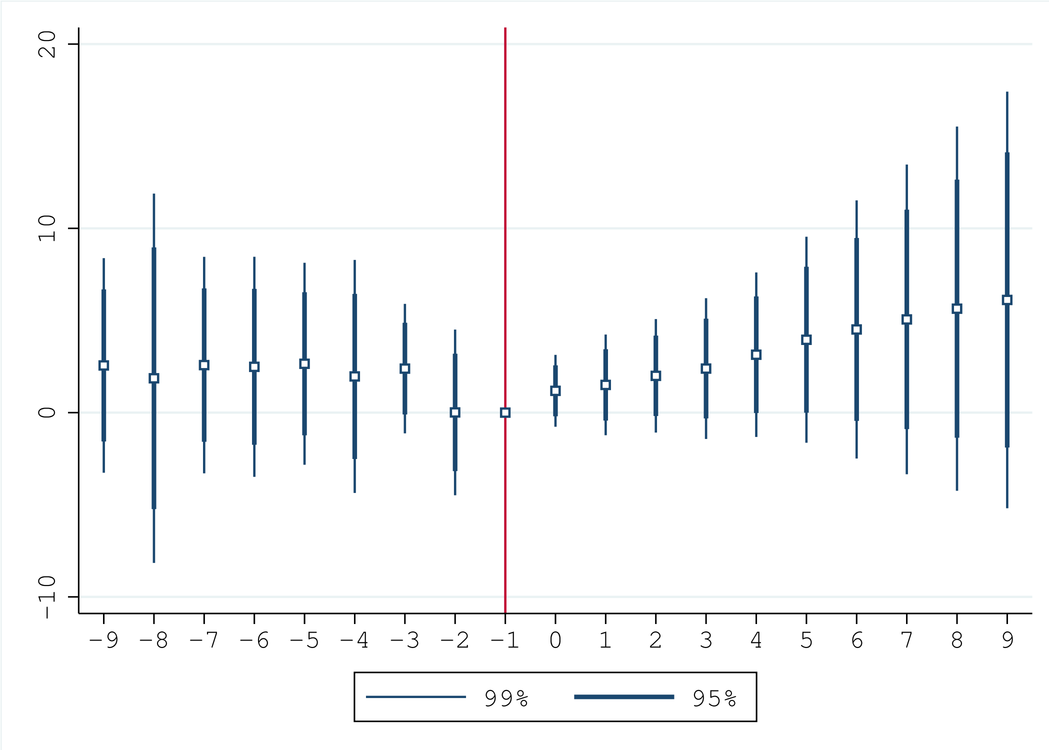

Figure 80: Event study, impact of storm on credit score, data for the period 2004-2019, all variables are averages computed at the zip code level.

C.4 Default on Revolving Credit

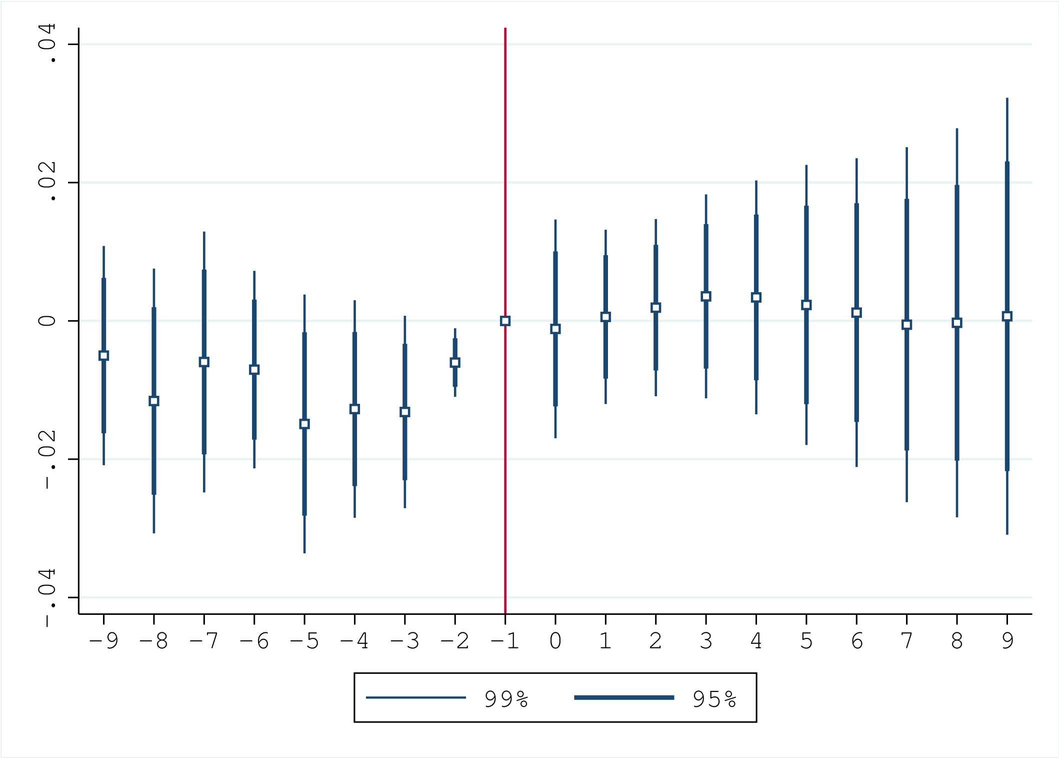

Figure 81: Event study, impact of storm on 90-day default, data for the period 2004-2019, all variables are averages computed at the zip code level.

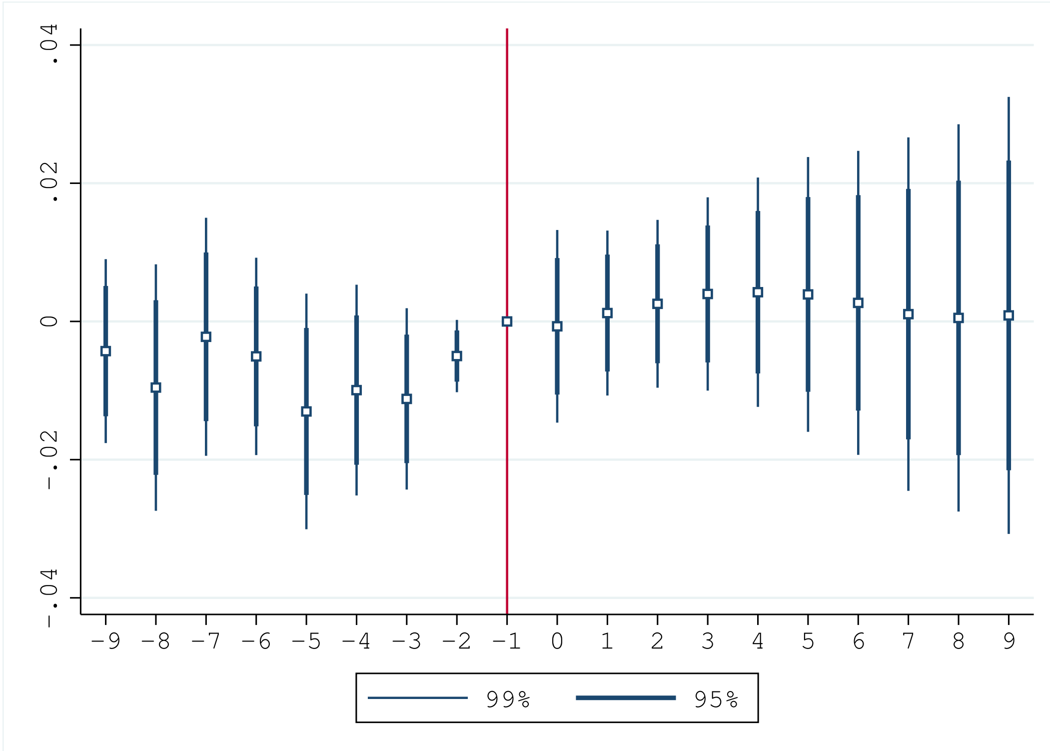

Figure 82: Event study, impact of storm on 120-day delinquencies, data for the period 2004-2019, all variables are averages computed at the zip code level.

C.5 Consumption

C.5.1 Credit Card Balance as Consumption

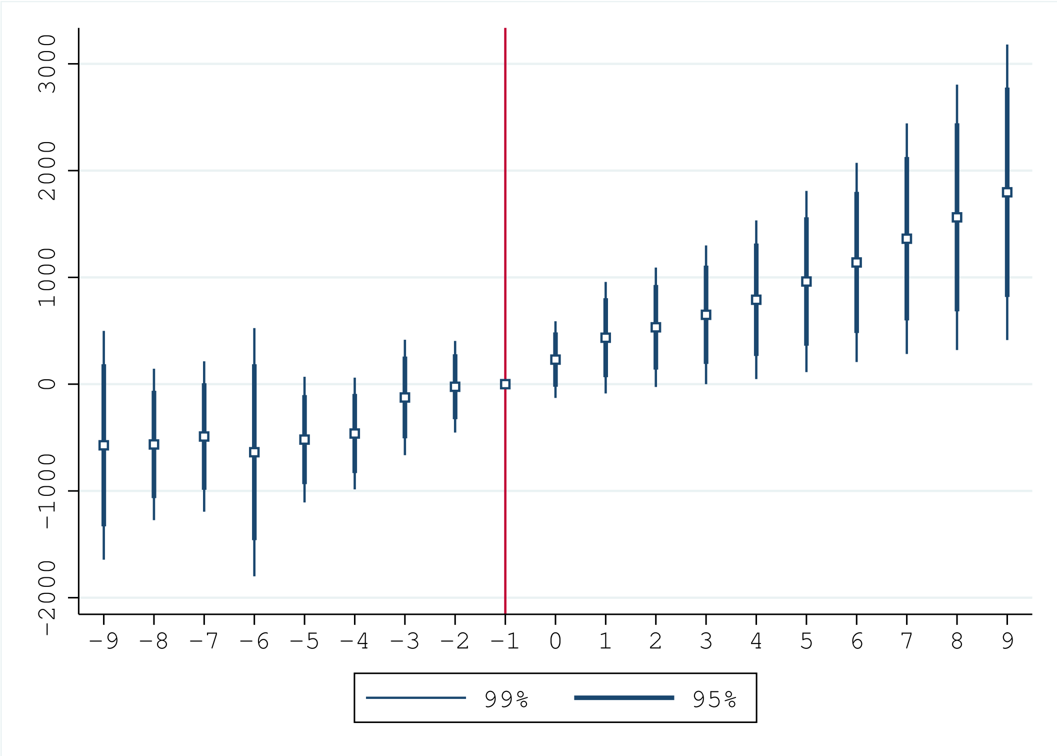

Figure 83: Event study, impact of storm on credit card balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

C.5.2 Auto Loan as Consumption

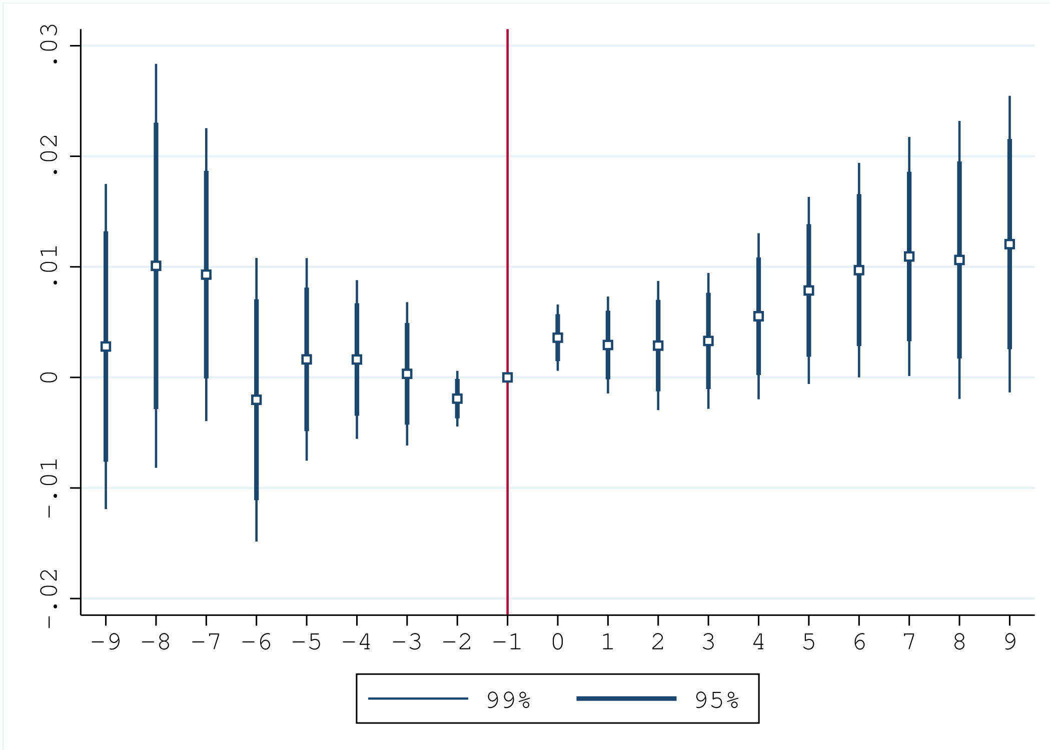

Figure 84: Event study, impact of storm on auto loan origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

C.5.3 Auto Balance as Consumption

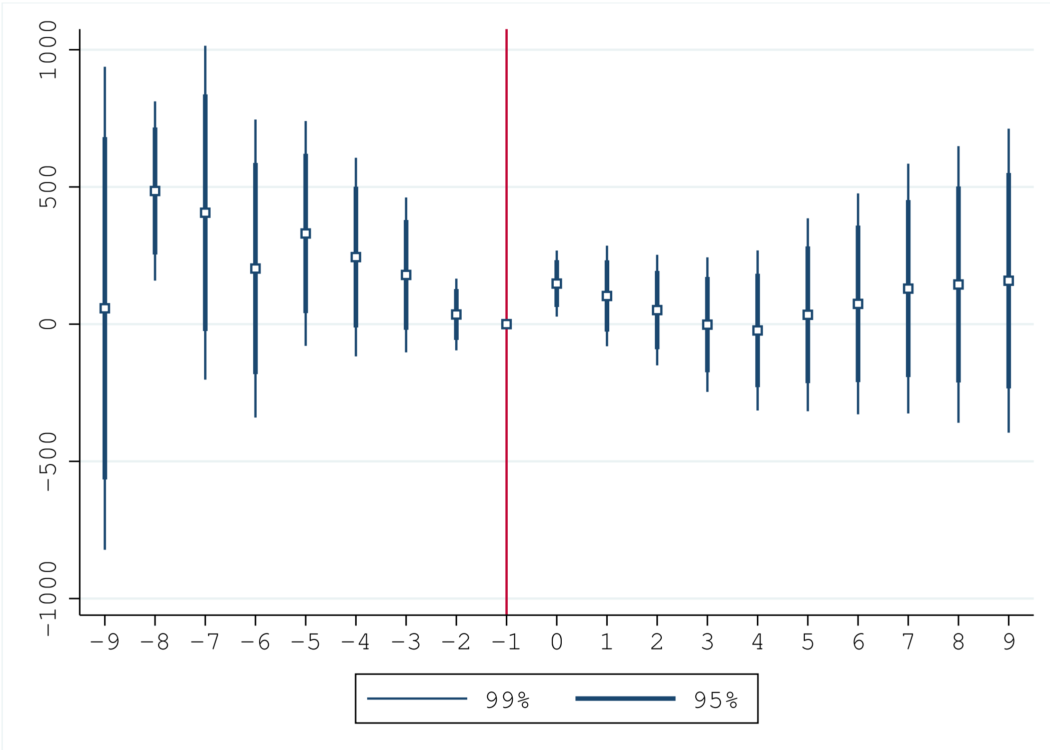

Figure 85: Event study, impact of storm on auto loan, data for the period 2004-2019, all variables are averages computed at the zip code level.

C.6 Housing Market

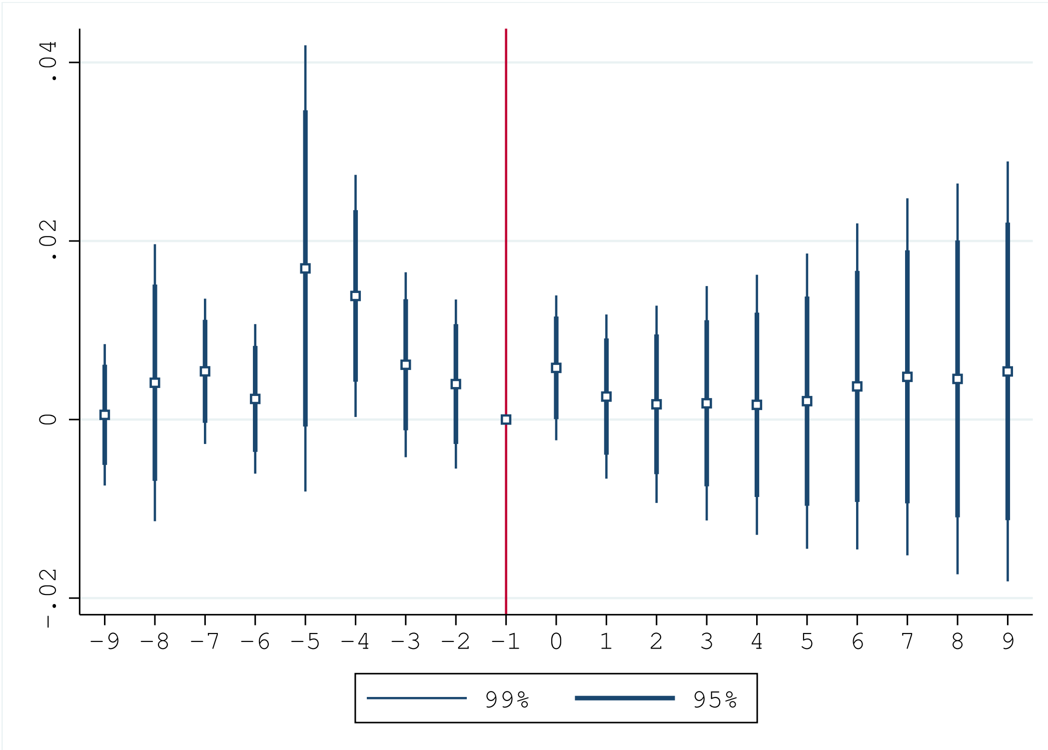

Figure 86: Event study, impact of storm on mortgage origination, data for the period 2004-2019, all variables are averages computed at the zip code level.

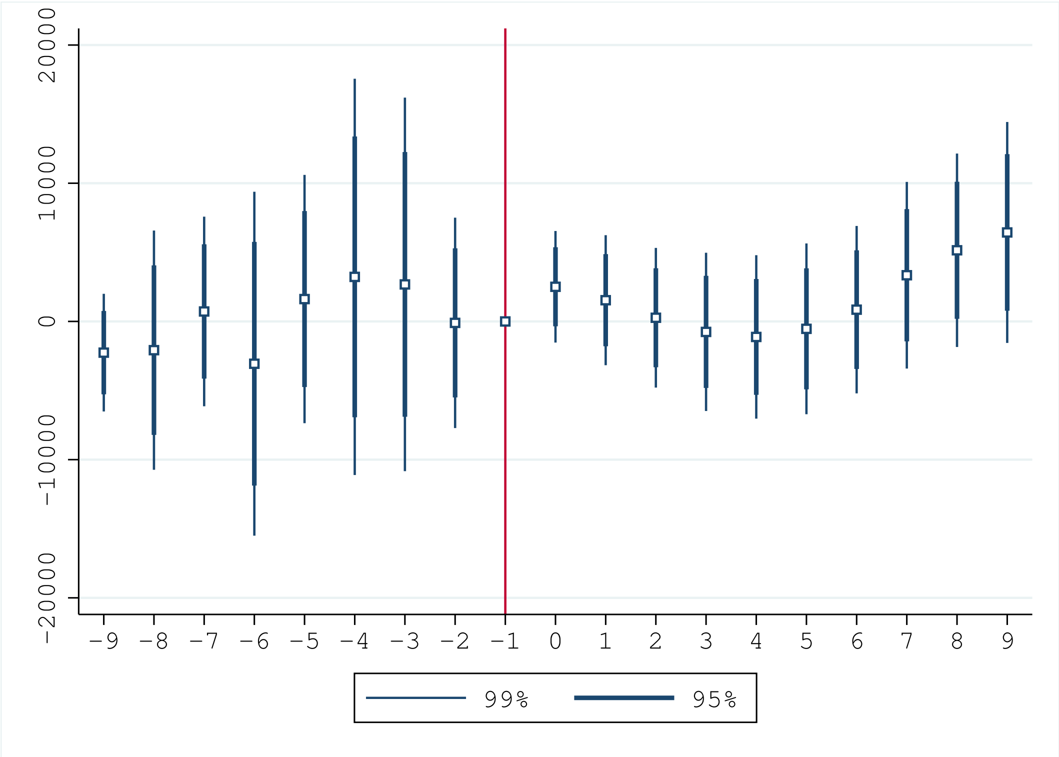

Figure 87: Event study, impact of storm on mortgage balance, data for the period 2004-2019, all variables are averages computed at the zip code level.

D Data Reliability

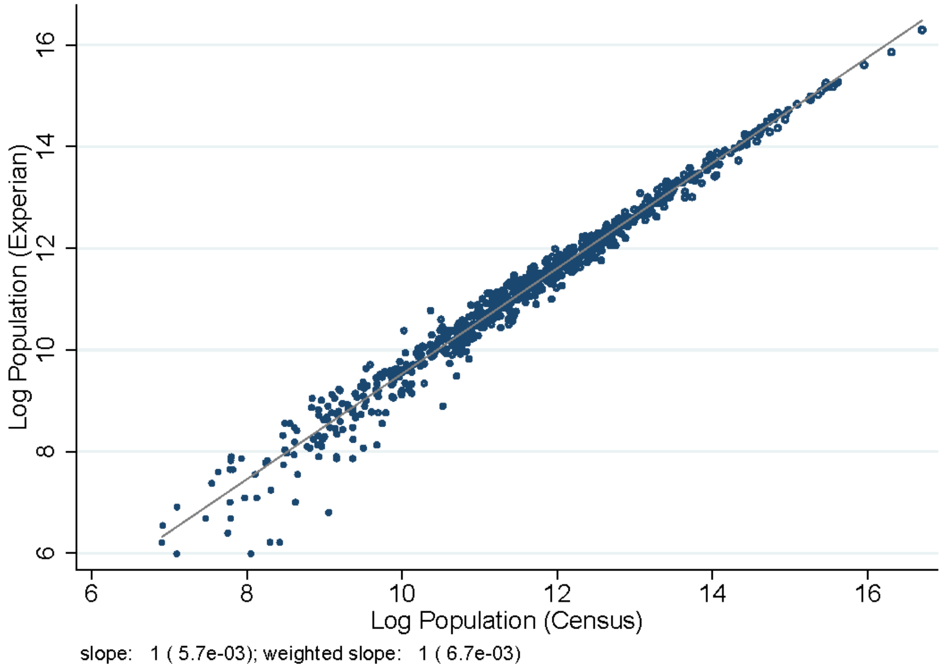

Figure 88: Data representativeness

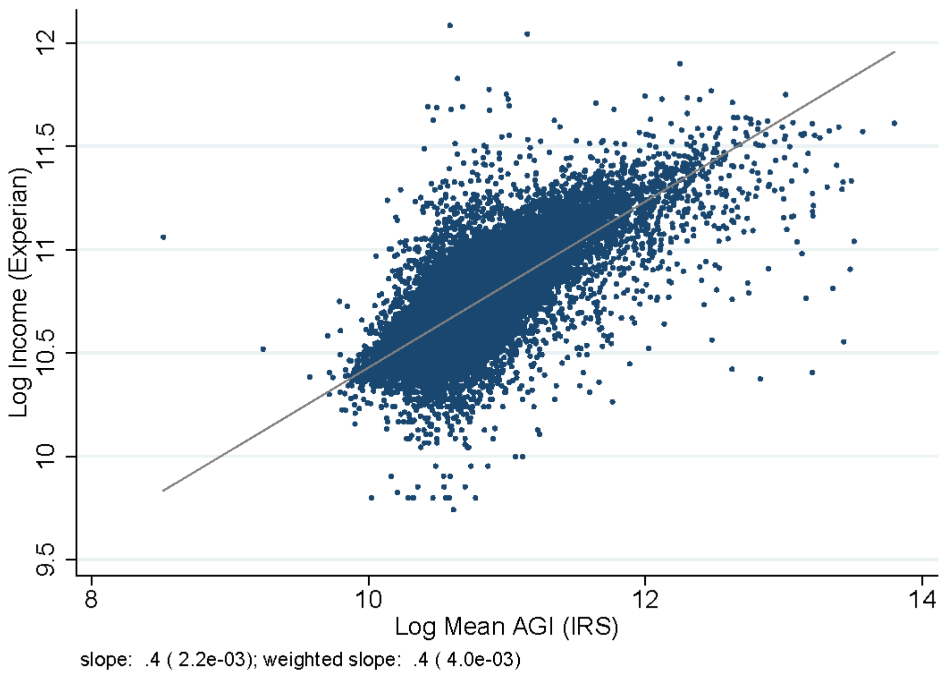

Figure 89: Validity of income imputation

E Methods and results

In the following, we present the estimation results obtained via the following model:

$$y_{izt} = \alpha_0 + \alpha_1 Age_{izt} + \alpha_2 Agesq_{it} + \alpha_3 Shock_{zt} + \delta_t + \gamma_z + \varepsilon_{izt} \quad (2)$$

Where $Shock_{it}$ is alternatively defined in the different model specifications as: (i) a dummy taking value 1 if there was a storm in year t in the ZIP code in which individual i was and zero otherwise, (ii) a dummy taking value 1 if there was a fire in year t in the ZIP code in which individual i was and zero otherwise, (iii) a variable standing for the monetary value of the damage in usd (in case of fire, respectively, storm). y_{it} is one of our dependent variables standing for credit reliability: credit score, 90-day new delinquencies, 90-day current delinquencies, 120-day new delinquencies, 120-day current delinquencies, new foreclosures, current foreclosures, new chapter 13 declarations, current chapter 13 declarations, new chapter 7 declarations, current chapter 7 declarations. All the following model specifications are also estimated for robustness:

$$y_{it} = \alpha_0 + \alpha_1 Age_{it} + \alpha_2 Agesq_{it} + \alpha_3 Shock_{it} + YearFE + \varepsilon_{i,t} \tag{3}$$

$$y_{it} = \alpha_0 + \alpha_1 Age_{it} + \alpha_2 Agesq_{it} + \alpha_3 Shock_{it} + CommutingZoneFE + \varepsilon_{i,t} \tag{4}$$

$$y_{it} = \alpha_0 + \alpha_1 Age_{it} + \alpha_2 Agesq_{it} + \alpha_3 Shock_{it} + YearFE + CommutingZoneFE + \varepsilon_{i,t} \tag{5}$$

$$\begin{aligned} y_{it} &= \alpha_0 + \alpha_1 Age_{it} + \alpha_2 Agesq_{it} + \alpha_3 Shock_{it} + \alpha_4 Shock_{it-1} + \alpha_5 Shock_{it-2} \\ &+ YearFE + CommutingZoneFE + \varepsilon_{i,t} \end{aligned} \tag{6}$$

$$\begin{aligned} y_{it} &= \alpha_0 + \alpha_1 Age_{it} + \alpha_2 Agesq_{it} + \alpha_3 Shock_{it} + \alpha_4 Shock_{it-1} + \alpha_5 Shock_{it-2} \\ &+ \alpha_6 Shock_{it-3} + \alpha_7 Shock_{it-4} + YearFE + CommutingZoneFE + \varepsilon_{i,t} \end{aligned} \tag{7}$$

$$\begin{aligned} y_{it} &= \alpha_0 + \alpha_1 Age_{it} + \alpha_2 Agesq_{it} + \alpha_3 Shock_{it} + \alpha_4 Shock_{it-1} + \alpha_5 Shock_{it-2} \\ &+ \alpha_6 Shock_{it-3} + \alpha_7 Shock_{it-4} + YearFE + CommutingZoneFE \\ &+ \gamma FemaleDummy + OccupationDummies + EducationDummies + \varepsilon_{i,t} \end{aligned} \tag{8}$$

In the following we present and comment the estimation results. All the standard errors in the Tables have been clustered at the commuting zone level.

E.1 Results with fire (dummy) as a shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00861***	0.00872***	0.00869***	0.00880***	0.00817***	0.00740***	0.00769***
	(31.94)	(32.74)	(33.05)	(33.61)	(33.52)	(29.40)	(26.81)
agesq	-0.0000942***	-0.0000950***	-0.0000952***	-0.0000960***	-0.0000893***	-0.0000812***	-0.0000839***
	(-32.77)	(-33.67)	(-34.96)	(-35.77)	(-35.90)	(-32.44)	(-30.10)
Fire	0.00212	0.00231	-0.00498	-0.00498*	-0.00340	-0.00613	-0.00884**
	(0.62)	(0.66)	(-1.76)	(-2.32)	(-1.43)	(-1.84)	(-2.82)
L.Fire					-0.00283	-0.00540**	-0.00765***
					(-1.72)	(-2.68)	(-3.69)
L2.Fire					0.0000584	-0.000107	-0.00183
					(0.04)	(-0.06)	(-0.94)
L3.Fire						0.00288**	0.00131
						(2.67)	(1.14)
L4.Fire						0.00690***	0.00575***
						(5.07)	(4.74)
Female dummy							0.00700***
							(12.43)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.116***	-0.119***	-0.118***	-0.121***	-0.107***	-0.0903***	-0.103***
	(-22.65)	(-22.66)	(-18.50)	(-18.82)	(-17.53)	(-13.97)	(-12.85)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Impact of fire (dummy) on Chapter 7 current declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000824***	0.00149***	0.000835***	0.00151***	0.000308***	0.000342***	0.000327***
	(12.83)	(20.77)	(12.85)	(20.74)	(8.47)	(7.09)	(5.95)
agesq	-0.0000108***	-0.0000165***	-0.0000109***	-0.0000166***	-0.00000408***	-0.00000439***	-0.00000422***
	(-17.82)	(-24.01)	(-18.35)	(-24.57)	(-12.12)	(-9.66)	(-8.20)
Fire	-0.00454***	0.00118***	-0.00706***	-0.00114	-0.000000198	-0.000883***	-0.000867***
	(-8.04)	(3.69)	(-7.13)	(-1.82)	(-0.00)	(-3.40)	(-3.35)
L.Fire					0.00138***	0.00153***	0.00151***
					(7.17)	(9.04)	(8.45)
L2.Fire					0.00390***	0.00310***	0.00320***
					(6.37)	(6.88)	(6.43)
L3.Fire						0.00388***	0.00390***
						(8.26)	(7.40)
L4.Fire						0.00197***	0.00203***
						(3.63)	(3.77)
Female dummy							0.000540***
							(10.23)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00244	-0.0207***	-0.00264	-0.0209***	0.000916	0.0000931	-0.000253
	(-1.55)	(-12.39)	(-1.56)	(-11.30)	(0.97)	(0.07)	(-0.18)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Impact of fire (dummy) on Chapter 7 new declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00295***	0.00293***	0.00297***	0.00295***	0.00310***	0.00326***	0.00356***
	(20.88)	(20.20)	(21.16)	(20.44)	(20.80)	(21.91)	(22.28)
agesq	-0.0000307***	-0.0000305***	-0.0000308***	-0.0000307***	-0.0000319***	-0.0000333***	-0.0000362***
	(-19.69)	(-19.21)	(-20.28)	(-19.77)	(-20.22)	(-21.39)	(-21.80)
Fire	-0.00791***	-0.00779***	-0.00303***	-0.00278***	-0.00266***	-0.00405***	-0.00463***
	(-5.28)	(-5.11)	(-4.84)	(-4.90)	(-4.39)	(-5.67)	(-6.34)
L.Fire					-0.00190***	-0.00295***	-0.00339***
					(-4.02)	(-3.82)	(-4.32)
L2.Fire					-0.000513	-0.000998	-0.00138*
					(-0.99)	(-1.78)	(-2.51)
L3.Fire						0.000376	0.000139
						(0.71)	(0.30)
L4.Fire						0.00220*	0.00187
						(2.07)	(1.91)
Female dummy							0.000442
							(1.69)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.0506***	-0.0501***	-0.0511***	-0.0507***	-0.0545***	-0.0588***	-0.0654***
	(-22.89)	(-21.56)	(-16.87)	(-16.11)	(-16.50)	(-17.52)	(-17.00)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Impact of fire (dummy) on current Chapter 13 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000538***	0.000680***	0.000541***	0.000684***	0.000400***	0.000441***	0.000468***
	(26.39)	(23.92)	(27.15)	(24.31)	(25.54)	(24.98)	(24.89)
agesq	-0.00000602***	-0.00000721***	-0.00000604***	-0.00000724***	-0.00000430***	-0.00000468***	-0.00000494***
	(-24.47)	(-22.69)	(-25.48)	(-23.40)	(-25.10)	(-25.54)	(-25.63)
Fire	-0.00174***	-0.000790***	-0.000807***	0.000204	-0.000203	-0.000325**	-0.000411*
	(-9.09)	(-4.52)	(-4.69)	(1.28)	(-1.95)	(-2.95)	(-2.53)
L.Fire					0.000232*	0.000233	0.000208
					(2.00)	(1.82)	(1.93)
L2.Fire					0.000944***	0.000769***	0.000793***
					(4.44)	(4.50)	(4.63)
L3.Fire						0.000861***	0.000909***
						(5.13)	(5.03)
L4.Fire						0.000744***	0.000638**
						(3.94)	(3.09)
Female dummy							0.0000424
							(1.03)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00776***	-0.0116***	-0.00786***	-0.0118***	-0.00640***	-0.00737***	-0.00789***
	(-26.18)	(-25.96)	(-20.11)	(-19.74)	(-18.82)	(-17.93)	(-16.15)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Impact of Fire (dummy) on new Chapter 13 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	1.928***	2.305***	1.794***	2.164***	1.962***	1.452***	-0.223*
	(18.15)	(21.59)	(17.82)	(21.50)	(17.24)	(11.21)	(-2.26)
agesq	0.00980***	0.00671***	0.0112***	0.00820***	0.0101***	0.0149***	0.0300***
	(8.74)	(6.13)	(10.46)	(7.87)	(9.10)	(12.39)	(30.04)
Fire	-12.58**	-14.95***	-9.365**	-11.86***	-11.70***	-14.14***	-10.67***
	(-3.29)	(-4.03)	(-3.01)	(-4.06)	(-5.28)	(-5.59)	(-5.67)
L.Fire					-11.99***	-14.23***	-11.51***
					(-10.02)	(-9.48)	(-10.15)
L2.Fire					-13.38***	-13.62***	-10.70***
					(-6.21)	(-8.87)	(-9.41)
L3.Fire						-11.34***	-8.454***
						(-8.99)	(-9.01)
L4.Fire						-12.20***	-8.539***
						(-6.38)	(-7.15)
Female dummy							-1.525***
							(-4.55)
Edu dummies							YES
Occupation dummies							YES
Constant	568.0***	557.4***	570.9***	560.5***	564.7***	575.9***	616.4***
	(196.15)	(181.93)	(213.91)	(202.09)	(175.35)	(154.02)	(179.91)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: impact of fire (dummy) on credit score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00155***	-0.000409	0.00212***	0.000195	-0.00149***	-0.00134**	0.00539***
	(3.48)	(-0.94)	(5.08)	(0.48)	(-3.57)	(-2.93)	(13.47)
agesq	-0.0000923***	-0.0000762***	-0.0000987***	-0.0000828***	-0.0000667***	-0.0000686***	-0.000130***
	(-19.12)	(-16.14)	(-21.51)	(-18.52)	(-14.76)	(-14.40)	(-28.44)
Fire	0.0258	0.0377*	0.0217*	0.0345***	0.0331***	0.0374***	0.0224***
	(1.62)	(2.43)	(2.35)	(3.71)	(4.82)	(4.07)	(3.65)
L.Fire					0.0433***	0.0482***	0.0367***
					(10.11)	(7.24)	(7.25)
L2.Fire					0.0540***	0.0520***	0.0407***
					(6.48)	(9.35)	(11.51)
L3.Fire						0.0472***	0.0360***
						(8.48)	(8.65)
L4.Fire						0.0503***	0.0357***
						(6.67)	(7.97)
Female dummy							0.0133***
							(9.00)
Edu dummies							YES
Occupation dummies							YES
Constant	0.503***	0.557***	0.491***	0.544***	0.593***	0.597***	0.431***
	(38.56)	(42.06)	(46.66)	(52.06)	(54.58)	(48.58)	(37.66)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Impact of fire (dummy) on 90-day current delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00618***	-0.00316***	-0.00612***	-0.00309***	0.000162***	0.00112***	0.00118***
	(-41.91)	(-29.59)	(-41.57)	(-29.66)	(3.35)	(18.12)	(16.68)
agesq	0.0000460***	0.0000202***	0.0000454***	0.0000196***	-0.00000626***	-0.0000155***	-0.0000158***
	(34.18)	(20.46)	(33.70)	(20.22)	(-12.86)	(-25.47)	(-22.92)
Fire	-0.0104**	0.0155***	-0.0159***	0.0111***	0.0111***	0.0113***	0.0108***
	(-3.27)	(5.97)	(-5.59)	(4.39)	(11.05)	(12.16)	(10.87)
L.Fire					0.0136***	0.0156***	0.0161***
					(6.61)	(10.59)	(9.90)
L2.Fire					0.00596***	0.00554***	0.00566**
					(4.52)	(3.69)	(3.30)
L3.Fire						0.00261*	0.00227
						(2.38)	(1.69)
L4.Fire						0.000863	0.000254
						(1.51)	(0.39)
Female dummy							-0.00193***
							(-14.16)
Edu dummies							YES
Occupation dummies							YES
Constant	0.246***	0.164***	0.244***	0.162***	0.0439***	0.0202***	0.0179***
	(60.68)	(58.51)	(64.24)	(60.57)	(36.92)	(12.94)	(9.73)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Impact of fire (dummy) on 90-day new delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00110*	-0.000695	0.00167***	-0.0000930	-0.00199***	-0.00212***	0.00466***
	(2.54)	(-1.62)	(4.12)	(-0.23)	(-4.90)	(-4.81)	(11.37)
agesq	-0.0000862***	-0.0000714***	-0.0000925***	-0.0000781***	-0.0000597***	-0.0000588***	-0.000121***
	(-17.94)	(-15.19)	(-20.35)	(-17.57)	(-13.20)	(-12.37)	(-24.87)
Fire	0.0192	0.0316*	0.0181*	0.0315***	0.0307***	0.0353***	0.0206***
	(1.20)	(2.02)	(2.15)	(3.54)	(4.49)	(3.88)	(3.39)
L.Fire					0.0368***	0.0411***	0.0293***
					(10.28)	(7.12)	(7.05)
L2.Fire					0.0453***	0.0441***	0.0327***
					(5.80)	(8.06)	(9.31)
L3.Fire						0.0423***	0.0307***
						(8.27)	(8.80)
L4.Fire						0.0479***	0.0332***
						(6.29)	(7.08)
Female dummy							0.0136***
							(9.41)
Edu dummies							YES
Occupation dummies							YES
Constant	0.497***	0.547***	0.485***	0.534***	0.587***	0.597***	0.431***
	(38.38)	(41.17)	(47.76)	(52.34)	(56.12)	(51.50)	(39.26)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Impact of fire (dummy) on 120-day current delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00612***	-0.00315***	-0.00606***	-0.00308***	0.00000430	0.000941***	0.00105***
	(-42.00)	(-29.80)	(-41.67)	(-29.91)	(0.10)	(17.39)	(18.21)
agesq	0.0000457***	0.0000204***	0.0000451***	0.0000197***	-0.00000461***	-0.0000136***	-0.0000144***
	(34.78)	(20.91)	(34.21)	(20.63)	(-10.51)	(-25.54)	(-25.55)
Fire	-0.0145***	0.0122***	-0.0192***	0.00857***	0.00893***	0.00926***	0.00895***
	(-6.19)	(5.91)	(-9.58)	(4.01)	(12.06)	(12.33)	(11.02)
L.Fire					0.0107***	0.0125***	0.0125***
					(7.03)	(11.33)	(11.00)
L2.Fire					0.00529***	0.00492***	0.00510***
					(5.77)	(5.42)	(5.16)
L3.Fire						0.00384***	0.00352**
						(3.36)	(3.00)
L4.Fire						0.00102**	0.000326
						(2.68)	(0.93)
Female dummy							-0.00208***
							(-16.33)
Edu dummies							YES
Occupation dummies							YES
Constant	0.240***	0.160***	0.239***	0.158***	0.0443***	0.0209***	0.0177***
	(58.46)	(56.08)	(63.04)	(59.56)	(42.25)	(15.42)	(11.53)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Impact of fire (dummy) on 120-day new delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00274***	0.00229***	0.00277***	0.00233***	0.00237***	0.00250***	0.00255***
	(23.56)	(26.52)	(23.15)	(26.05)	(22.95)	(17.86)	(17.14)
agesq	-0.0000305***	-0.0000268***	-0.0000308***	-0.0000271***	-0.0000278***	-0.0000294***	-0.0000298***
	(-24.01)	(-26.31)	(-23.80)	(-26.10)	(-23.76)	(-19.48)	(-18.78)
Fire	0.00676***	0.00847***	0.00240*	0.00413***	0.00272***	0.00109	-0.00000744
	(4.40)	(5.70)	(2.53)	(5.47)	(6.52)	(1.63)	(-0.01)
L.Fire					0.00959***	0.00941***	0.00901***
					(12.26)	(10.54)	(13.10)
L2.Fire					0.0102***	0.00830***	0.00767***
					(12.74)	(15.21)	(12.35)
L3.Fire						0.00800***	0.00723***
						(13.19)	(12.66)
L4.Fire						0.00992***	0.00911***
						(7.46)	(7.44)
Female dummy							-0.00587***
							(-17.47)
Edu dummies							YES
							YES
Constant	-0.0388***	-0.0265***	-0.0396***	-0.0275***	-0.0261***	-0.0260***	-0.0258***
	(-21.19)	(-22.45)	(-15.13)	(-15.18)	(-11.94)	(-8.26)	(-7.01)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Impact of fire (dummy) on current foreclosures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000710***	0.000709***	0.000718***	0.000718***	0.000589***	0.000632***	0.000591***
	(23.58)	(25.80)	(23.27)	(25.54)	(17.62)	(12.86)	(11.51)
agesq	-0.00000835***	-0.00000828***	-0.00000842***	-0.00000836***	-0.00000705***	-0.00000753***	-0.00000712***
	(-26.35)	(-28.49)	(-25.94)	(-28.13)	(-20.42)	(-15.28)	(-13.94)
Fire	0.0103***	0.00913***	0.00963***	0.00835***	0.00762***	0.00801***	0.00777***
	(5.80)	(7.18)	(6.09)	(8.24)	(10.11)	(11.80)	(10.79)
L.Fire					0.00699***	0.00752***	0.00785***
					(12.30)	(17.67)	(16.11)
L2.Fire					0.00269***	0.00233***	0.00223***
					(6.02)	(4.15)	(4.35)
L3.Fire						0.00190***	0.00172***
						(3.39)	(3.66)
L4.Fire						0.00121**	0.00118*
						(2.60)	(2.51)
Female dummy							-0.00132***
							(-17.12)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00830***	-0.00842***	-0.00850***	-0.00866***	-0.00570***	-0.00607***	-0.00513***
	(-13.59)	(-15.34)	(-11.86)	(-13.33)	(-7.24)	(-5.12)	(-3.90)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Impact of fire (dummy) on new foreclosures

E.2 Results with storm (dummy) as a shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00861***	0.00872***	0.00870***	0.00880***	0.00817***	0.00740***	0.00770***
	(31.76)	(32.75)	(32.86)	(33.58)	(33.45)	(29.29)	(26.70)
agesq	-0.0000942***	-0.0000950***	-0.0000952***	-0.0000960***	-0.0000893***	-0.0000813***	-0.0000840***
	(-32.66)	(-33.67)	(-34.85)	(-35.75)	(-35.86)	(-32.34)	(-30.01)
Storm	0.00252	0.00174	0.00178	0.000948	0.000689	0.000462	0.000843
	(1.05)	(0.72)	(1.95)	(1.08)	(0.88)	(0.44)	(0.74)
L.Storm					0.00136	0.00182	0.00228**
					(1.89)	(1.92)	(2.74)
L2.Storm					0.00157*	0.00236**	0.00280***
					(2.26)	(3.00)	(4.04)
L3.Storm						0.00130	0.00161
						(1.17)	(1.29)
L4.Storm						0.000922	0.000909
						(0.72)	(0.59)
Female dummy							0.00700***
							(12.44)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.116***	-0.120***	-0.118***	-0.121***	-0.107***	-0.0909***	-0.104***
	(-22.35)	(-22.53)	(-18.27)	(-18.69)	(-17.45)	(-14.21)	(-13.08)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Impact of storm (dummy) on current Chapter 7 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000820***	0.00149***	0.000830***	0.00151***	0.000308***	0.000342***	0.000326***
	(13.20)	(20.78)	(13.21)	(20.73)	(8.48)	(7.10)	(5.93)
agesq	-0.0000108***	-0.0000165***	-0.0000109***	-0.0000166***	-0.00000408***	-0.00000439***	-0.00000422***
	(-18.41)	(-24.01)	(-18.95)	(-24.57)	(-12.11)	(-9.65)	(-8.16)
Storm	-0.00508***	-0.000135	-0.00547***	-0.000273	0.000147	0.000310	0.000458**
	(-13.26)	(-0.41)	(-13.94)	(-0.84)	(0.88)	(1.62)	(2.62)
L.Storm					0.000112	0.000479*	0.000553**
					(0.29)	(2.44)	(2.69)
L2.Storm					-0.000188	0.0000823	-0.0000403
					(-0.52)	(0.36)	(-0.18)
L3.Storm						-0.000214	-0.000226
						(-0.73)	(-0.68)
L4.Storm						0.0000122	0.00000380
						(0.07)	(0.02)
Female dummy							0.000540***
							(10.30)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00199	-0.0207***	-0.00214	-0.0209***	0.000951	0.000138	-0.000211
	(-1.30)	(-12.52)	(-1.31)	(-11.38)	(1.06)	(0.12)	(-0.16)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Impact of storm (dummy) on new Chapter 7 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00295***	0.00293***	0.00297***	0.00295***	0.00310***	0.00326***	0.00357***
	(20.94)	(20.25)	(21.16)	(20.45)	(20.82)	(21.94)	(22.33)
agesq	-0.0000307***	-0.0000305***	-0.0000308***	-0.0000307***	-0.0000319***	-0.0000333***	-0.0000362***
	(-19.72)	(-19.24)	(-20.28)	(-19.78)	(-20.24)	(-21.43)	(-21.85)
Storm	0.00158	0.00179	0.000236	0.000388	0.000745*	0.000890	0.000924
	(1.52)	(1.71)	(0.85)	(1.55)	(2.22)	(1.90)	(1.80)
L.Storm					0.000556	0.00148***	0.00151***
					(1.87)	(3.60)	(3.68)
L2.Storm					0.000674	0.00140***	0.00163***
					(1.88)	(3.82)	(4.28)
L3.Storm						0.000631	0.000745
						(1.24)	(1.28)
L4.Storm						0.000708	0.000828
						(1.25)	(1.28)
Female dummy							0.000438
							(1.68)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.0508***	-0.0503***	-0.0512***	-0.0508***	-0.0547***	-0.0593***	-0.0659***
	(-22.82)	(-21.57)	(-16.84)	(-16.11)	(-16.42)	(-17.28)	(-16.80)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Impact of storm (dummy) on current Chapter 13 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000537***	0.000680***	0.000540***	0.000684***	0.000400***	0.000441***	0.000468***
	(26.16)	(23.94)	(26.83)	(24.31)	(25.52)	(24.95)	(24.88)
agesq	-0.00000602***	-0.00000721***	-0.00000604***	-0.00000724***	-0.00000430***	-0.00000468***	-0.00000494***
	(-24.28)	(-22.71)	(-25.23)	(-23.40)	(-25.10)	(-25.52)	(-25.64)
Storm	-0.000767***	0.000202	-0.00107***	-0.0000641	0.000108	0.000152	0.000190
	(-4.92)	(1.22)	(-8.09)	(-0.54)	(1.35)	(1.42)	(1.84)
L.Storm					0.0000866	0.000193*	0.000242*
					(0.82)	(1.97)	(2.27)
L2.Storm					-0.0000428	0.0000188	0.0000551
					(-0.45)	(0.22)	(0.65)
L3.Storm						-0.000103	-0.0000802
						(-0.89)	(-0.60)
L4.Storm						0.0000823	0.0000398
						(0.79)	(0.34)
Female dummy							0.0000423
							(1.03)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00771***	-0.0117***	-0.00776***	-0.0118***	-0.00641***	-0.00738***	-0.00790***
	(-25.81)	(-25.83)	(-19.73)	(-19.68)	(-18.59)	(-17.83)	(-16.09)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Impact of storm (dummy) on new Chapter 13 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	1.930***	2.307***	1.797***	2.165***	1.964***	1.457***	-0.220*
	(18.27)	(21.67)	(17.98)	(21.55)	(17.36)	(11.37)	(-2.23)
agesq	0.00979***	0.00670***	0.0112***	0.00819***	0.0101***	0.0149***	0.0299***
	(8.72)	(6.11)	(10.47)	(7.87)	(9.09)	(12.40)	(29.88)
Storm	0.176	-1.587	0.837	-0.965*	-1.508**	-2.240**	-2.084***
	(0.11)	(-1.09)	(0.92)	(-2.02)	(-2.90)	(-3.01)	(-3.69)
L.Storm					-0.932	-1.855**	-1.798***
					(-1.66)	(-2.95)	(-3.38)
L2.Storm					-1.060	-1.810*	-1.685**
					(-1.68)	(-2.57)	(-2.69)
L3.Storm						-1.714**	-1.743**
						(-2.87)	(-3.27)
L4.Storm						-2.192***	-2.490***
						(-3.63)	(-4.34)
Female dummy							-1.523***
							(-4.59)
Edu dummies							YES
Occupation dummies							YES
Constant	567.8***	557.4***	570.7***	560.5***	564.7***	576.0***	616.6***
	(201.21)	(184.70)	(218.95)	(203.71)	(179.04)	(157.56)	(181.04)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Impact of storm (dummy) on credit score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00155***	-0.000414	0.00211***	0.000193	-0.00149***	-0.00136**	0.00539***
	(3.49)	(-0.95)	(5.10)	(0.48)	(-3.61)	(-2.98)	(13.41)
agesq	-0.0000923***	-0.0000761***	-0.0000986***	-0.0000828***	-0.0000666***	-0.0000685***	-0.000130***
	(-19.11)	(-16.12)	(-21.56)	(-18.53)	(-14.76)	(-14.38)	(-28.37)
Storm	0.00375	0.00985	-0.00216	0.00390	0.00638**	0.0104***	0.00949***
	(0.46)	(1.36)	(-0.49)	(1.84)	(2.86)	(3.62)	(4.31)
L.Storm					0.00283	0.00850***	0.00853***
					(1.05)	(3.42)	(4.04)
L2.Storm					0.00250	0.00653*	0.00643*
					(0.80)	(2.21)	(2.48)
L3.Storm						0.00516	0.00499
						(1.77)	(1.76)
L4.Storm						0.00696**	0.00788***
						(2.94)	(3.79)
Female dummy							0.0133***
							(9.07)
Edu dummies							YES
Occupation dummies							YES
Constant	0.503***	0.557***	0.492***	0.544***	0.593***	0.597***	0.430***
	(39.43)	(42.52)	(47.97)	(52.49)	(55.74)	(49.37)	(37.63)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 18: Impact of storm (dummy) on current 90-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00620***	-0.00316***	-0.00615***	-0.00309***	0.000159***	0.00112***	0.00117***
	(-44.49)	(-29.79)	(-44.29)	(-29.77)	(3.35)	(18.63)	(16.99)
agesq	0.0000461***	0.0000203***	0.0000456***	0.0000196***	-0.00000624***	-0.0000154***	-0.0000157***
	(36.23)	(20.52)	(35.79)	(20.28)	(-12.97)	(-26.08)	(-23.27)
Storm	-0.0256***	-0.000132	-0.0276***	-0.000778	0.000179	-0.0000932	0.000288
	(-24.91)	(-0.21)	(-24.39)	(-0.95)	(0.39)	(-0.15)	(0.50)
L.Storm					-0.000478	-0.000473	-0.000571
					(-0.75)	(-0.91)	(-1.11)
L2.Storm					-0.000617	-0.000282	-0.000373
					(-1.26)	(-0.63)	(-0.96)
L3.Storm						0.00112**	0.00109*
						(2.60)	(2.23)
L4.Storm						0.00192	0.00246
						(1.65)	(1.83)
Female dummy							-0.00193***
							(-14.27)
Edu dummies							YES
Occupation dummies							YES
Constant	0.248***	0.164***	0.247***	0.162***	0.0443***	0.0204***	0.0181***
	(63.87)	(59.96)	(68.73)	(61.35)	(38.70)	(13.02)	(9.69)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 19: Impact of storm (dummy) new 90-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00111*	-0.000700	0.00167***	-0.0000944	-0.00200***	-0.00214***	0.00465***
	(2.54)	(-1.63)	(4.14)	(-0.24)	(-4.93)	(-4.85)	(11.32)
agesq	-0.0000862***	-0.0000713***	-0.0000925***	-0.0000780***	-0.0000596***	-0.0000587***	-0.000121***
	(-17.92)	(-15.17)	(-20.38)	(-17.57)	(-13.19)	(-12.33)	(-24.82)
Storm	0.00423	0.0105	-0.00188	0.00437*	0.00652**	0.0106***	0.00953***
	(0.52)	(1.45)	(-0.49)	(2.22)	(3.02)	(3.94)	(4.52)
L.Storm					0.00312	0.00845***	0.00853***
					(1.31)	(3.66)	(4.35)
L2.Storm					0.00311	0.00675*	0.00694**
					(1.12)	(2.31)	(2.73)
L3.Storm						0.00536	0.00524*
						(1.91)	(1.97)
L4.Storm						0.00627**	0.00716***
						(2.61)	(3.36)
Female dummy							0.0135***
							(9.47)
Edu dummies							YES
Occupation dummy							YES
Constant	0.497***	0.546***	0.486***	0.534***	0.587***	0.596***	0.430***
	(39.03)	(41.52)	(48.84)	(52.68)	(56.94)	(51.92)	(39.05)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: Impact of storm (dummy) on 120-day current delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00614***	-0.00315***	-0.00609***	-0.00308***	0.00000212	0.000937***	0.00105***
	(-44.32)	(-29.94)	(-44.15)	(-29.99)	(0.05)	(17.72)	(18.43)
agesq	0.0000458***	0.0000204***	0.0000453***	0.0000197***	-0.00000459***	-0.0000136***	-0.0000144***
	(36.70)	(20.94)	(36.17)	(20.67)	(-10.52)	(-25.95)	(-25.80)
Storm	-0.0249***	0.000237	-0.0269***	-0.000543	0.000428	0.000234	0.000531
	(-27.64)	(0.40)	(-26.78)	(-0.69)	(1.14)	(0.44)	(1.20)
L.Storm					-0.000375	-0.000447	-0.000424
					(-0.72)	(-0.99)	(-1.02)
L2.Storm					-0.000462	-0.000300	-0.000358
					(-1.27)	(-0.78)	(-1.04)
L3.Storm						0.000937**	0.000755*
						(2.73)	(2.04)
L4.Storm						0.00162*	0.00214*
						(2.01)	(2.32)
Female dummy							-0.00208***
							(-16.44)
Edu dummies							YES
Occupation dummies							YES
Constant	0.242***	0.160***	0.241***	0.158***	0.0445***	0.0211***	0.0178***
	(61.08)	(57.09)	(66.85)	(60.09)	(42.63)	(15.54)	(11.54)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 21: Impact of storm (dummy) on 120-day new delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00273***	0.00229***	0.00277***	0.00233***	0.00237***	0.00250***	0.00255***
	(23.82)	(26.59)	(23.31)	(26.08)	(23.05)	(17.93)	(17.13)
agesq	-0.0000305***	-0.0000268***	-0.0000308***	-0.0000271***	-0.0000278***	-0.0000294***	-0.0000298***
	(-24.15)	(-26.33)	(-23.90)	(-26.11)	(-23.82)	(-19.51)	(-18.76)
Storm	-0.00295*	-0.00130	-0.00159	0.000183	0.000985*	0.00112**	0.00121**
	(-2.17)	(-1.60)	(-1.23)	(0.28)	(2.51)	(2.80)	(2.59)
L.Storm					-0.000697	0.000479	0.000737
					(-0.68)	(1.12)	(1.65)
L2.Storm					-0.00143	-0.000487	-0.000324
					(-1.22)	(-0.88)	(-0.56)
L3.Storm						-0.000535	-0.000436
						(-0.70)	(-0.51)
L4.Storm						0.000234	0.000420
						(0.60)	(0.94)
Female dummy							-0.00587***
							(-17.52)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.0384***	-0.0263***	-0.0394***	-0.0275***	-0.0258***	-0.0257***	-0.0256***
	(-22.33)	(-23.13)	(-15.47)	(-15.35)	(-12.32)	(-8.39)	(-7.03)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 22: Impact of storm (dummy) on current foreclosures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000708***	0.000708***	0.000716***	0.000718***	0.000587***	0.000629***	0.000589***
	(24.43)	(26.23)	(23.89)	(25.77)	(17.99)	(13.14)	(11.68)
agesq	-0.00000834***	-0.00000828***	-0.00000841***	-0.00000836***	-0.00000704***	-0.00000751***	-0.00000710***
	(-26.77)	(-28.65)	(-26.31)	(-28.29)	(-20.73)	(-15.54)	(-14.09)
Storm	-0.000583	-0.000550	-0.000287	-0.000243	-0.0000594	0.0000408	0.000107
	(-1.00)	(-1.42)	(-0.50)	(-0.67)	(-0.23)	(0.14)	(0.39)
L.Storm					-0.000678	-0.000511	-0.000295
					(-1.57)	(-1.67)	(-1.02)
L2.Storm					-0.000586	-0.000409	-0.000274
					(-1.52)	(-1.33)	(-0.87)
L3.Storm						0.000678	0.000706
						(1.91)	(1.81)
L4.Storm						0.00101	0.00112
						(1.67)	(1.61)
Female dummy							-0.00132***
							(-17.24)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00813***	-0.00830***	-0.00838***	-0.00858***	-0.00545***	-0.00592***	-0.00501***
	(-15.35)	(-16.77)	(-12.58)	(-13.75)	(-7.53)	(-5.03)	(-3.75)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: Impact of storm (dummy) on new foreclosures

E.3 Results with share of affected individuals

In this Section, we measure the intensity of the weather shock, by the share of individuals who have been affected by it (i.e. either fire or storm) in each commuting zone in each year. In all the estimation results reported in this section this is the definition of the shock variable.

E.3.1 Shock is defined as share of individuals affected by a storm in each commuting zone in each year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00861***	0.00872***	0.00870***	0.00880***	0.00817***	0.00740***	0.00769***
	(31.74)	(32.77)	(32.85)	(33.59)	(33.47)	(29.31)	(26.71)
agesq	-0.0000942***	-0.0000950***	-0.0000952***	-0.0000960***	-0.0000893***	-0.0000812***	-0.0000840***
	(-32.65)	(-33.69)	(-34.84)	(-35.76)	(-35.88)	(-32.36)	(-30.02)
ShareStorm	0.00246	0.00131	0.00137	0.0000877	-0.000508	-0.00132	-0.000303
	(0.74)	(0.39)	(1.15)	(0.07)	(-0.52)	(-0.97)	(-0.19)
L.ShareStorm					0.000413	0.000414	0.00167
					(0.48)	(0.39)	(1.59)
L2.ShareStorm					0.000620	0.00119	0.00242**
					(0.78)	(1.29)	(2.84)
L3.ShareStorm						-0.000107	0.000530
						(-0.07)	(0.29)
L4.ShareStorm						-0.000815	-0.000694
						(-0.48)	(-0.32)
Female dummy							0.00700***
							(12.42)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.116***	-0.120***	-0.118***	-0.121***	-0.107***	-0.0903***	-0.103***
	(-22.24)	(-22.44)	(-18.20)	(-18.62)	(-17.34)	(-14.16)	(-13.15)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 24: Impact of shock on chapter 7 current declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000818***	0.00149***	0.000827***	0.00151***	0.000308***	0.000342***	0.000326***
	(13.39)	(20.78)	(13.40)	(20.74)	(8.48)	(7.08)	(5.93)
agesq	-0.0000108***	-0.0000165***	-0.0000109***	-0.0000166***	-0.00000408***	-0.00000439***	-0.00000422***
	(-18.70)	(-24.01)	(-19.26)	(-24.57)	(-12.11)	(-9.64)	(-8.16)
ShareStorm	-0.00742***	-0.000313	-0.00819***	-0.000536	0.0000238	0.000121	0.000366
	(-15.37)	(-0.67)	(-14.57)	(-1.09)	(0.09)	(0.40)	(1.24)
L.ShareStorm					-0.0000518	0.000371	0.000502
					(-0.09)	(1.23)	(1.54)
L2.ShareStorm					-0.000494	-0.000166	-0.000259
					(-0.93)	(-0.48)	(-0.70)
L3.ShareStorm						-0.000579	-0.000550
						(-1.34)	(-1.11)
L4.ShareStorm						-0.000288	-0.000260
						(-1.21)	(-0.94)
Female dummy							0.000540***
							(10.28)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00178	-0.0206***	-0.00188	-0.0209***	0.000996	0.000239	-0.000136
	(-1.17)	(-12.56)	(-1.16)	(-11.41)	(1.13)	(0.21)	(-0.10)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 25: Impact of shock on chapter 7 new declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00295***	0.00293***	0.00297***	0.00295***	0.00310***	0.00326***	0.00356***
	(20.92)	(20.25)	(21.13)	(20.44)	(20.81)	(21.95)	(22.33)
agesq	-0.0000307***	-0.0000305***	-0.0000308***	-0.0000307***	-0.0000319***	-0.0000333***	-0.0000362***
	(-19.71)	(-19.25)	(-20.25)	(-19.77)	(-20.23)	(-21.43)	(-21.84)
ShareStorm	0.00129	0.00158	-0.000718**	-0.000548*	-0.000405	-0.000650	-0.000629
	(0.95)	(1.14)	(-3.02)	(-2.26)	(-1.23)	(-1.42)	(-1.23)
L.ShareStorm					-0.000475	0.000190	0.000368
					(-1.80)	(0.55)	(0.94)
L2.ShareStorm					-0.000318	0.000129	0.000524
					(-0.85)	(0.42)	(1.49)
L3.ShareStorm						-0.000528	-0.000381
						(-0.89)	(-0.52)
L4.ShareStorm						-0.000523	-0.000407
						(-0.77)	(-0.50)
Female dummy							0.000441
							(1.69)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.0508***	-0.0502***	-0.0511***	-0.0507***	-0.0544***	-0.0587***	-0.0654***
	(-22.75)	(-21.54)	(-16.82)	(-16.13)	(-16.44)	(-17.33)	(-16.79)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 26: Impact of shock on chapter 13 current declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000537***	0.000680***	0.000539***	0.000684***	0.000400***	0.000440***	0.000468***
	(26.03)	(23.95)	(26.65)	(24.30)	(25.52)	(24.96)	(24.87)
agesq	-0.00000602***	-0.00000721***	-0.00000603***	-0.00000724***	-0.00000430***	-0.00000468***	-0.00000494***
	(-24.17)	(-22.72)	(-25.08)	(-23.39)	(-25.09)	(-25.52)	(-25.63)
ShareStorm	-0.00124***	0.000151	-0.00173***	-0.000255	-0.0000361	-0.0000682	0.0000361
	(-6.40)	(0.67)	(-8.85)	(-1.57)	(-0.37)	(-0.51)	(0.24)
L.ShareStorm					-0.0000551	-0.00000535	0.0000762
					(-0.40)	(-0.05)	(0.55)
L2.ShareStorm					-0.000207	-0.000225*	-0.000145
					(-1.66)	(-2.06)	(-1.19)
L3.ShareStorm						-0.000369*	-0.000326
						(-2.42)	(-1.78)
L4.ShareStorm						-0.000188	-0.000197
						(-1.40)	(-1.23)
Female dummy							0.0000426
							(1.04)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00766***	-0.0117***	-0.00769***	-0.0118***	-0.00637***	-0.00728***	-0.00782***
	(-25.69)	(-25.79)	(-19.57)	(-19.69)	(-18.55)	(-17.80)	(-16.10)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 27: Impact of shock on chapter 13 new declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	1.932***	2.307***	1.799***	2.165***	1.964***	1.458***	-0.219*
	(18.35)	(21.69)	(18.09)	(21.56)	(17.39)	(11.41)	(-2.23)
agesq	0.00978***	0.00670***	0.0112***	0.00819***	0.0101***	0.0149***	0.0299***
	(8.73)	(6.12)	(10.46)	(7.87)	(9.10)	(12.42)	(29.94)
ShareStorm	2.203	-0.277	3.339***	0.769*	0.656*	0.764**	0.744*
	(1.09)	(-0.14)	(3.78)	(2.14)	(2.21)	(2.78)	(2.54)
L.ShareStorm					1.025*	0.775*	0.536
					(2.32)	(2.24)	(1.60)
L2.ShareStorm					0.937	0.908*	0.703
					(1.88)	(2.37)	(1.91)
L3.ShareStorm						0.349	0.113
						(1.39)	(0.45)
L4.ShareStorm						-0.306	-0.790
						(-0.65)	(-1.37)
Female dummy							-1.528***
							(-4.60)
Edu dummies							YES
Occupation dummies							YES
Constant	567.6***	557.3***	570.4***	560.4***	564.2***	575.1***	615.8***
	(201.98)	(184.36)	(220.64)	(203.74)	(179.58)	(157.64)	(181.13)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 28: Impact of shock on credit score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00154***	-0.000414	0.00210***	0.000193	-0.00150***	-0.00136**	0.00538***
	(3.49)	(-0.95)	(5.10)	(0.47)	(-3.61)	(-3.00)	(13.43)
agesq	-0.0000923***	-0.0000761***	-0.0000986***	-0.0000828***	-0.0000666***	-0.0000684***	-0.000130***
	(-19.13)	(-16.13)	(-21.59)	(-18.53)	(-14.77)	(-14.41)	(-28.40)
ShareStorm	-0.00216	0.00650	-0.0114*	-0.00274	-0.00214	-0.00106	-0.00172
	(-0.21)	(0.69)	(-2.37)	(-1.62)	(-1.40)	(-0.75)	(-1.04)
L.ShareStorm					-0.00515*	-0.00174	-0.000922
					(-1.99)	(-1.08)	(-0.53)
L2.ShareStorm					-0.00591	-0.00425*	-0.00309
					(-1.91)	(-2.57)	(-1.78)
L3.ShareStorm						-0.00367	-0.00340
						(-1.71)	(-1.36)
L4.ShareStorm						-0.000987	0.000261
						(-1.02)	(0.24)
Female dummy							0.0133***
							(9.07)
Edu dummies							YES
Occupation dummies							YES
Constant	0.504***	0.557***	0.493***	0.545***	0.595***	0.600***	0.434***
	(39.71)	(42.49)	(48.50)	(52.51)	(56.06)	(49.77)	(37.88)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 29: Impact of shock on current 90-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00621***	-0.00316***	-0.00616***	-0.00309***	0.000159***	0.00112***	0.00117***
	(-45.67)	(-29.78)	(-45.64)	(-29.78)	(3.35)	(18.63)	(16.97)
agesq	0.0000462***	0.0000203***	0.0000457***	0.0000196***	-0.00000624***	-0.0000154***	-0.0000157***
	(37.16)	(20.51)	(36.82)	(20.29)	(-12.98)	(-26.06)	(-23.23)
ShareStorm	-0.0369***	-0.000217	-0.0407***	-0.00120	0.0000540	-0.000100	0.000647
	(-23.62)	(-0.24)	(-20.18)	(-0.97)	(0.08)	(-0.12)	(0.82)
L.ShareStorm					-0.00115	-0.00103	-0.00109
					(-1.29)	(-1.51)	(-1.54)
L2.ShareStorm					-0.00143*	-0.000825	-0.000819
					(-2.12)	(-1.27)	(-1.40)
L3.ShareStorm						0.00124*	0.00129
						(1.98)	(1.80)
L4.ShareStorm						0.00252	0.00345
						(1.47)	(1.72)
Female dummy							-0.00193***
							(-14.26)
Edu dummies							YES
Occupation dummies							YES
Constant	0.249***	0.164***	0.248***	0.162***	0.0444***	0.0204***	0.0180***
	(65.09)	(60.10)	(70.35)	(61.54)	(39.01)	(12.71)	(9.42)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 30: Impact of shock on new 90-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00110*	-0.000700	0.00166***	-0.0000947	-0.00200***	-0.00214***	0.00465***
	(2.54)	(-1.63)	(4.13)	(-0.24)	(-4.94)	(-4.87)	(11.33)
agesq	-0.0000861***	-0.0000714***	-0.0000924***	-0.0000780***	-0.0000596***	-0.0000587***	-0.000121***
	(-17.93)	(-15.17)	(-20.39)	(-17.57)	(-13.20)	(-12.35)	(-24.83)
ShareStorm	-0.00140	0.00755	-0.0109**	-0.00195	-0.00171	-0.000381	-0.00149
	(-0.14)	(0.79)	(-2.83)	(-1.35)	(-1.16)	(-0.24)	(-0.81)
L.ShareStorm					-0.00448*	-0.00141	-0.000629
					(-2.16)	(-0.91)	(-0.37)
L2.ShareStorm					-0.00469	-0.00344*	-0.00204
					(-1.96)	(-2.42)	(-1.38)
L3.ShareStorm						-0.00287	-0.00266
						(-1.55)	(-1.22)
L4.ShareStorm						-0.00151	-0.000431
						(-1.47)	(-0.38)
Female dummy							0.0136***
							(9.47)
Edu dummies							YES
Occupation dummies							YES
Constant	0.497***	0.547***	0.486***	0.535***	0.589***	0.600***	0.433***
	(39.27)	(41.47)	(49.30)	(52.68)	(57.15)	(52.25)	(39.23)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 31: Impact of shock on current 120-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00614***	-0.00315***	-0.00610***	-0.00308***	0.00000210	0.000937***	0.00105***
	(-45.43)	(-29.93)	(-45.42)	(-30.00)	(0.05)	(17.73)	(18.42)
agesq	0.0000459***	0.0000204***	0.0000454***	0.0000197***	-0.00000459***	-0.0000136***	-0.0000144***
	(37.60)	(20.93)	(37.16)	(20.68)	(-10.52)	(-25.94)	(-25.77)
ShareStorm	-0.0360***	0.000182	-0.0399***	-0.000997	0.000260	0.000114	0.000639
	(-24.40)	(0.22)	(-20.13)	(-0.84)	(0.46)	(0.17)	(1.07)
L.ShareStorm					-0.00103	-0.00109	-0.00100
					(-1.44)	(-1.88)	(-1.78)
L2.ShareStorm					-0.00107*	-0.000786	-0.000745
					(-2.20)	(-1.45)	(-1.52)
L3.ShareStorm						0.00105*	0.000935
						(2.19)	(1.70)
L4.ShareStorm						0.00192	0.00274*
						(1.60)	(1.97)
Female dummy							-0.00208***
							(-16.43)
Edu dummies							YES
Occupation dummies							YES
Constant	0.243***	0.160***	0.243***	0.158***	0.0446***	0.0211***	0.0178***
	(62.19)	(57.23)	(68.34)	(60.26)	(42.60)	(15.41)	(11.39)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 32: Impact of shock on new 120-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00273***	0.00229***	0.00277***	0.00233***	0.00237***	0.00250***	0.00255***
	(23.90)	(26.59)	(23.37)	(26.08)	(23.06)	(17.93)	(17.14)
agesq	-0.0000305***	-0.0000268***	-0.0000308***	-0.0000271***	-0.0000278***	-0.0000294***	-0.0000298***
	(-24.20)	(-26.32)	(-23.94)	(-26.12)	(-23.82)	(-19.52)	(-18.76)
ShareStorm	-0.00472*	-0.00238*	-0.00285	-0.000241	0.000748	0.000645	0.000921
	(-2.57)	(-2.12)	(-1.57)	(-0.25)	(1.19)	(1.02)	(1.22)
L.ShareStorm					-0.00163	-0.000199	0.000314
					(-1.08)	(-0.29)	(0.43)
L2.ShareStorm					-0.00271	-0.00165	-0.00134
					(-1.56)	(-1.74)	(-1.31)
L3.ShareStorm						-0.00158	-0.00134
						(-1.41)	(-1.08)
L4.ShareStorm						-0.000593	-0.000172
						(-0.98)	(-0.25)
Female dummy							-0.00586***
							(-17.50)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.0382***	-0.0263***	-0.0393***	-0.0275***	-0.0256***	-0.0254***	-0.0253***
	(-22.53)	(-23.11)	(-15.56)	(-15.38)	(-12.38)	(-8.33)	(-7.00)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 33: Impact of shock on current foreclosures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000708***	0.000708***	0.000716***	0.000718***	0.000587***	0.000629***	0.000589***
	(24.55)	(26.23)	(24.01)	(25.78)	(17.99)	(13.13)	(11.66)
agesq	-0.00000834***	-0.00000828***	-0.00000841***	-0.00000836***	-0.00000704***	-0.00000751***	-0.00000710***
	(-26.86)	(-28.65)	(-26.39)	(-28.29)	(-20.74)	(-15.53)	(-14.07)
ShareStorm	-0.000938	-0.000910	-0.000528	-0.000478	-0.000293	-0.000141	0.000103
	(-1.15)	(-1.66)	(-0.64)	(-0.90)	(-0.68)	(-0.30)	(0.21)
L.ShareStorm					-0.00114	-0.000930*	-0.000602
					(-1.79)	(-1.99)	(-1.32)
L2.ShareStorm					-0.00108	-0.000845	-0.000613
					(-1.83)	(-1.68)	(-1.20)
L3.ShareStorm						0.000718	0.000901
						(1.29)	(1.48)
L4.ShareStorm						0.00120	0.00153
						(1.32)	(1.45)
Female dummy							-0.00131***
							(-17.24)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00810***	-0.00828***	-0.00836***	-0.00857***	-0.00536***	-0.00587***	-0.00502***
	(-15.44)	(-16.81)	(-12.71)	(-13.84)	(-7.59)	(-4.88)	(-3.65)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 34: Impact of shock on new foreclosures

E.3.2 Shock is defined as share of individuals affected by a fire in each commuting zone in each year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00861***	0.00872***	0.00869***	0.00880***	0.00817***	0.00739***	0.00768***
	(32.02)	(32.79)	(33.15)	(33.65)	(33.61)	(29.61)	(27.11)
agesq	-0.0000942***	-0.0000950***	-0.0000952***	-0.0000960***	-0.0000893***	-0.0000812***	-0.0000839***
	(-32.81)	(-33.69)	(-35.01)	(-35.81)	(-35.99)	(-32.64)	(-30.41)
ShareF	-0.00468	-0.00465	-0.0199**	-0.0207***	-0.0188***	-0.0301***	-0.0328***
	(-0.78)	(-0.83)	(-2.80)	(-3.45)	(-3.55)	(-6.75)	(-6.49)
L.ShareF					-0.0131***	-0.0224***	-0.0248***
					(-4.86)	(-11.69)	(-12.02)
L2.ShareF					-0.0110*	-0.0145*	-0.0158*
					(-2.28)	(-2.51)	(-2.54)
L3.ShareF						-0.00912*	-0.0105*
						(-2.35)	(-2.46)
L4.ShareF						-0.00490	-0.00542
						(-1.15)	(-1.13)
Female dummy							0.00700***
							(12.42)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.116***	-0.119***	-0.118***	-0.121***	-0.107***	-0.0896***	-0.102***
	(-22.91)	(-22.84)	(-18.63)	(-18.88)	(-17.67)	(-14.21)	(-13.10)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 35: Impact of shock on chapter 7 current declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000823***	0.00149***	0.000835***	0.00151***	0.000308***	0.000342***	0.000327***
	(12.89)	(20.78)	(12.93)	(20.75)	(8.51)	(7.14)	(5.96)
agesq	-0.0000108***	-0.0000165***	-0.0000109***	-0.0000166***	-0.00000408***	-0.00000439***	-0.00000422***
	(-17.87)	(-24.02)	(-18.43)	(-24.59)	(-12.15)	(-9.70)	(-8.19)
ShareF	-0.00928***	0.00162*	-0.0150***	-0.00316	-0.000305	-0.00148	-0.00145
	(-4.57)	(2.54)	(-3.99)	(-1.61)	(-0.28)	(-1.50)	(-1.47)
L.ShareF					0.00178***	0.00245***	0.00239***
					(3.83)	(7.42)	(7.51)
L2.ShareF					0.00667***	0.00548***	0.00606***
					(5.44)	(8.15)	(8.23)
L3.ShareF						0.00546***	0.00553***
						(8.13)	(8.71)
L4.ShareF						0.00383***	0.00415***
						(4.80)	(4.80)
Female dummy							0.000540***
							(10.27)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00239	-0.0207***	-0.00258	-0.0209***	0.000901	0.0000501	-0.000314
	(-1.55)	(-12.39)	(-1.54)	(-11.33)	(0.96)	(0.04)	(-0.23)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 36: Impact of shock on chapter 7 new declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00295***	0.00293***	0.00297***	0.00295***	0.00310***	0.00326***	0.00356***
	(20.85)	(20.18)	(21.14)	(20.43)	(20.78)	(21.87)	(22.18)
agesq	-0.0000307***	-0.0000305***	-0.0000308***	-0.0000307***	-0.0000319***	-0.0000333***	-0.0000362***
	(-19.67)	(-19.20)	(-20.27)	(-19.76)	(-20.20)	(-21.34)	(-21.69)
ShareF	-0.0165***	-0.0167***	-0.00772***	-0.00744***	-0.00765***	-0.0125***	-0.0130***
	(-4.12)	(-3.82)	(-4.36)	(-4.31)	(-4.99)	(-6.79)	(-7.05)
L.ShareF					-0.00543***	-0.00878***	-0.00913***
					(-11.16)	(-16.08)	(-16.26)
L2.ShareF					-0.00386***	-0.00606***	-0.00634***
					(-5.37)	(-5.93)	(-5.47)
L3.ShareF						-0.00358***	-0.00355***
						(-7.19)	(-6.70)
L4.ShareF						-0.00175*	-0.00186**
						(-2.55)	(-2.64)
Female dummy							0.000441
							(1.69)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.0505***	-0.0500***	-0.0511***	-0.0507***	-0.0544***	-0.0585***	-0.0651***
	(-22.69)	(-21.38)	(-16.83)	(-16.09)	(-16.45)	(-17.39)	(-16.82)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 37: Impact of shock on chapter 13 current declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000538***	0.000679***	0.000541***	0.000684***	0.000400***	0.000440***	0.000468***
	(26.36)	(23.90)	(27.13)	(24.31)	(25.51)	(25.00)	(24.91)
agesq	-0.00000602***	-0.00000721***	-0.00000604***	-0.00000724***	-0.00000430***	-0.00000468***	-0.00000494***
	(-24.46)	(-22.69)	(-25.46)	(-23.40)	(-25.08)	(-25.54)	(-25.64)
ShareF	-0.00382***	-0.00208***	-0.00218***	-0.000176	-0.000897***	-0.00123***	-0.00144***
	(-6.02)	(-3.91)	(-8.99)	(-1.06)	(-4.50)	(-4.98)	(-6.64)
L.ShareF					-0.000129	-0.000131	-0.000111
					(-0.94)	(-0.82)	(-0.64)
L2.ShareF					0.00151***	0.00116***	0.00123***
					(5.37)	(4.98)	(5.38)
L3.ShareF						0.00113***	0.00133***
						(4.25)	(4.33)
L4.ShareF						0.000807***	0.000644***
						(4.08)	(3.42)
Female dummy							0.0000426
							(1.04)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00774***	-0.0116***	-0.00785***	-0.0118***	-0.00640***	-0.00736***	-0.00788***
	(-26.32)	(-25.89)	(-20.07)	(-19.72)	(-18.82)	(-18.03)	(-16.22)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 38: Impact of shock on chapter 13 new declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	1.929***	2.306***	1.796***	2.165***	1.963***	1.456***	-0.222*
	(18.24)	(21.66)	(17.89)	(21.55)	(17.35)	(11.37)	(-2.26)
agesq	0.00979***	0.00671***	0.0112***	0.00819***	0.0101***	0.0149***	0.0300***
	(8.74)	(6.13)	(10.46)	(7.87)	(9.10)	(12.42)	(30.03)
ShareF	-6.764	-11.18*	0.462	-4.247***	-4.411***	-5.561***	-6.265***
	(-1.44)	(-2.16)	(0.44)	(-4.26)	(-6.91)	(-10.28)	(-8.98)
L.ShareF					-7.975***	-9.190***	-9.749***
					(-8.64)	(-8.35)	(-8.17)
L2.ShareF					-8.154***	-8.421***	-8.751***
					(-10.05)	(-13.36)	(-14.17)
L3.ShareF						-5.208***	-5.439***
						(-10.12)	(-10.18)
L4.ShareF						-4.094***	-3.953***
						(-5.59)	(-4.99)
Female dummy							-1.528***
							(-4.59)
Edu dummies							YES
Occupation dummies							YES
Constant	567.9***	557.4***	570.8***	560.5***	564.6***	575.6***	616.2***
	(197.99)	(183.08)	(215.56)	(203.06)	(177.63)	(157.79)	(181.38)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 39: Impact of shock on credit score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00154***	-0.000412	0.00211***	0.000193	-0.00149***	-0.00136**	0.00539***
	(3.49)	(-0.95)	(5.08)	(0.47)	(-3.61)	(-2.99)	(13.43)
agesq	-0.0000923***	-0.0000762***	-0.0000986***	-0.0000828***	-0.0000666***	-0.0000685***	-0.000130***
	(-19.14)	(-16.15)	(-21.53)	(-18.53)	(-14.76)	(-14.41)	(-28.38)
ShareF	-0.0128	0.00882	-0.0257***	-0.00147	-0.00220	-0.00897	-0.00795
	(-0.50)	(0.33)	(-7.06)	(-0.49)	(-0.44)	(-1.80)	(-1.68)
L.ShareF					0.0243***	0.0201***	0.0215***
					(5.94)	(4.09)	(4.09)
L2.ShareF					0.0333***	0.0269***	0.0288***
					(8.29)	(5.84)	(6.42)
L3.ShareF						0.0190***	0.0203***
						(6.22)	(5.96)
L4.ShareF						0.0142**	0.0140**
						(3.20)	(2.95)
Female dummy							0.0133***
							(9.06)
Edu dummies							YES
Occupation dummies							YES
Constant	0.504***	0.557***	0.492***	0.545***	0.594***	0.599***	0.432***
	(39.14)	(42.47)	(47.14)	(52.35)	(55.35)	(49.90)	(38.02)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 40: Impact of shock on current 90-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00618***	-0.00316***	-0.00612***	-0.00309***	0.000162***	0.00112***	0.00118***
	(-42.01)	(-29.54)	(-41.69)	(-29.67)	(3.37)	(18.26)	(16.49)
agesq	0.0000460***	0.0000202***	0.0000454***	0.0000196***	-0.00000627***	-0.0000155***	-0.0000158***
	(34.22)	(20.44)	(33.77)	(20.21)	(-12.88)	(-25.50)	(-22.52)
ShareF	-0.0251***	0.0246***	-0.0379***	0.0166***	0.0176***	0.0184***	0.0190***
	(-5.17)	(4.27)	(-5.26)	(3.68)	(11.54)	(9.43)	(10.60)
L.ShareF					0.0211***	0.0242***	0.0249***
					(7.24)	(7.05)	(6.92)
L2.ShareF					0.0107***	0.0110***	0.0118***
					(5.88)	(4.67)	(4.36)
L3.ShareF						0.00418*	0.00428*
						(2.42)	(2.01)
L4.ShareF						0.00313**	0.00314*
						(2.91)	(2.57)
Female dummy							-0.00193***
							(-14.23)
Edu dummies							YES
Occupation dummies							YES
Constant	0.246***	0.164***	0.245***	0.162***	0.0438***	0.0200***	0.0177***
	(60.99)	(57.97)	(64.46)	(60.54)	(36.98)	(12.87)	(9.44)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 41: Impact of shock on new 90-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00110*	-0.000698	0.00167***	-0.0000949	-0.00200***	-0.00214***	0.00465***
	(2.54)	(-1.63)	(4.12)	(-0.24)	(-4.93)	(-4.87)	(11.31)
agesq	-0.0000861***	-0.0000714***	-0.0000925***	-0.0000780***	-0.0000596***	-0.0000587***	-0.000121***
	(-17.95)	(-15.19)	(-20.37)	(-17.57)	(-13.20)	(-12.34)	(-24.79)
ShareF	-0.0229	-0.000554	-0.0303***	-0.00487	-0.00558	-0.0130*	-0.0116*
	(-0.85)	(-0.02)	(-5.64)	(-1.53)	(-1.14)	(-2.44)	(-2.33)
L.ShareF					0.0148***	0.00878*	0.0101*
					(3.70)	(2.15)	(2.40)
L2.ShareF					0.0185***	0.0126*	0.0141*
					(4.86)	(2.19)	(2.49)
L3.ShareF						0.0112**	0.0122**
						(2.98)	(3.12)
L4.ShareF						0.00903	0.00867
						(1.75)	(1.59)
Female dummy							0.0136***
							(9.47)
Edu dummies							YES
Occupation dummies							YES
Constant	0.497***	0.547***	0.486***	0.535***	0.588***	0.599***	0.432***
	(38.96)	(41.58)	(48.25)	(52.61)	(56.82)	(52.69)	(39.45)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 42: Impact of shock on current 120-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00612***	-0.00315***	-0.00606***	-0.00308***	0.00000428	0.000941***	0.00105***
	(-42.13)	(-29.78)	(-41.80)	(-29.93)	(0.10)	(17.52)	(18.07)
agesq	0.0000457***	0.0000204***	0.0000451***	0.0000197***	-0.00000461***	-0.0000136***	-0.0000144***
	(34.83)	(20.89)	(34.29)	(20.62)	(-10.52)	(-25.58)	(-25.21)
ShareF	-0.0326***	0.0184***	-0.0444***	0.0117**	0.0132***	0.0143***	0.0151***
	(-7.30)	(4.07)	(-5.62)	(3.20)	(11.28)	(9.10)	(9.99)
L.ShareF					0.0152***	0.0183***	0.0189***
					(8.62)	(7.59)	(7.45)
L2.ShareF					0.00884***	0.00884***	0.00955***
					(5.37)	(5.38)	(5.65)
L3.ShareF						0.00654***	0.00690***
						(3.70)	(3.60)
L4.ShareF						0.00213**	0.00220*
						(2.74)	(2.46)
Female dummy							-0.00208***
							(-16.40)
Edu dummies							YES
Occupation dummies							YES
Constant	0.240***	0.160***	0.239***	0.158***	0.0442***	0.0208***	0.0175***
	(58.84)	(55.77)	(63.33)	(59.57)	(42.19)	(15.36)	(11.23)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 43: Impact of shock on new 120-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00274***	0.00229***	0.00277***	0.00233***	0.00237***	0.00250***	0.00255***
	(23.58)	(26.54)	(23.17)	(26.07)	(23.02)	(17.98)	(17.15)
agesq	-0.0000305***	-0.0000268***	-0.0000308***	-0.0000271***	-0.0000278***	-0.0000294***	-0.0000299***
	(-24.02)	(-26.32)	(-23.82)	(-26.11)	(-23.79)	(-19.54)	(-18.76)
ShareF	0.00799***	0.0115***	-0.000705	0.00281***	0.000902	-0.00164	-0.00216
	(3.56)	(4.60)	(-1.07)	(3.69)	(0.52)	(-0.89)	(-1.11)
L.ShareF					0.0130***	0.0128***	0.0135***
					(9.43)	(5.21)	(5.81)
L2.ShareF					0.0144***	0.0114***	0.0117***
					(11.88)	(10.44)	(10.01)
L3.ShareF						0.0106***	0.0107***
						(14.16)	(14.37)
L4.ShareF						0.0143***	0.0145***
						(10.17)	(9.91)
Female dummy							-0.00586***
							(-17.49)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.0388***	-0.0265***	-0.0396***	-0.0275***	-0.0261***	-0.0261***	-0.0259***
	(-21.22)	(-22.39)	(-15.16)	(-15.21)	(-12.06)	(-8.41)	(-7.10)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 44: Impact of shock on current foreclosures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000711***	0.000710***	0.000718***	0.000718***	0.000589***	0.000632***	0.000593***
	(23.38)	(25.74)	(23.16)	(25.56)	(17.70)	(12.93)	(11.39)
agesq	-0.00000836***	-0.00000829***	-0.00000842***	-0.00000836***	-0.00000706***	-0.00000754***	-0.00000714***
	(-26.27)	(-28.46)	(-25.86)	(-28.10)	(-20.42)	(-15.28)	(-13.73)
ShareF	0.0165***	0.0145***	0.0159***	0.0135***	0.0128***	0.0142***	0.0141***
	(5.13)	(6.17)	(5.39)	(7.36)	(14.04)	(13.28)	(13.19)
L.ShareF					0.0111***	0.0126***	0.0134***
					(13.36)	(11.29)	(12.65)
L2.ShareF					0.00572***	0.00576***	0.00585***
					(9.13)	(7.19)	(8.21)
L3.ShareF						0.00452**	0.00452**
						(3.04)	(3.19)
L4.ShareF						0.00350***	0.00371***
						(4.26)	(4.67)
Female dummy							-0.00131***
							(-17.20)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00836***	-0.00846***	-0.00855***	-0.00868***	-0.00578***	-0.00622***	-0.00533***
	(-13.01)	(-14.86)	(-11.78)	(-13.38)	(-7.41)	(-5.26)	(-3.98)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 45: Impact of shock on new foreclosures

E.4 Estimation results with the monetary damage caused by Fire used as shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00861***	0.00872***	0.00869***	0.00880***	0.00817***	0.00740***	0.00770***
	(31.93)	(32.75)	(33.00)	(33.59)	(33.45)	(29.27)	(26.66)
agesq	-0.0000942***	-0.0000950***	-0.0000952***	-0.0000960***	-0.0000893***	-0.0000813***	-0.0000840***
	(-32.76)	(-33.66)	(-34.94)	(-35.76)	(-35.86)	(-32.32)	(-29.96)
totaldamage	-0.0000686	-0.000182	-0.000340	-0.000457	-0.000358	-0.00130***	-0.00142***
	(-0.11)	(-0.31)	(-0.63)	(-1.03)	(-0.76)	(-4.20)	(-4.67)
L.totaldamage					-0.000301	-0.00110**	-0.00118**
					(-0.71)	(-2.88)	(-2.69)
L2.totaldamage					0.0000872	0.000134	0.0000924
					(0.29)	(0.37)	(0.24)
L3.totaldamage						0.000391	0.000279
						(1.75)	(1.00)
L4.totaldamage						0.000555*	0.000438
						(2.43)	(1.44)
Female dummy							0.00700***
							(12.42)
Edu dummies							YES
							YES
Occupation dummies Constant	-0.116***	-0.119***	-0.118***	-0.121***	-0.107***	-0.0904***	-0.103***
	(-22.67)	(-22.73)	(-18.44)	(-18.80)	(-17.47)	(-13.93)	(-12.80)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 46: Impact of the monetary damage caused by fire (in usd) on current Chapter 7 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000825***	0.00149***	0.000836***	0.00151***	0.000308***	0.000342***	0.000326***
	(12.75)	(20.79)	(12.76)	(20.72)	(8.47)	(7.09)	(5.93)
agesq	-0.0000108***	-0.0000165***	-0.0000109***	-0.0000166***	-0.00000408***	-0.00000439***	-0.00000422***
	(-17.78)	(-24.02)	(-18.26)	(-24.56)	(-12.11)	(-9.65)	(-8.16)
totaldamage	-0.000302***	0.000105	-0.000382***	0.0000179	0.0000913*	-0.0000324	-0.0000156
	(-5.33)	(1.60)	(-5.37)	(0.35)	(2.10)	(-0.79)	(-0.31)
L.totaldamage					0.000147	0.000201*	0.000219
					(1.61)	(2.22)	(1.62)
L2.totaldamage					0.000384***	0.000370***	0.000343**
					(3.46)	(3.59)	(3.00)
L3.totaldamage						0.000223*	0.000169
						(2.01)	(1.50)
L4.totaldamage						0.0000629	0.0000240
						(0.79)	(0.29)
Female dummy							0.000540***
							(10.27)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00249	-0.0207***	-0.00271	-0.0209***	0.000954	0.000181	-0.000169
	(-1.55)	(-12.43)	(-1.58)	(-11.28)	(1.01)	(0.15)	(-0.12)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 47: Impact of the monetary damage caused by fire (in usd) on new Chapter 7 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00295***	0.00293***	0.00297***	0.00295***	0.00310***	0.00326***	0.00356***
	(20.92)	(20.23)	(21.18)	(20.44)	(20.82)	(21.95)	(22.34)
agesq	-0.0000307***	-0.0000305***	-0.0000308***	-0.0000307***	-0.0000319***	-0.0000333***	-0.0000362***
	(-19.70)	(-19.23)	(-20.29)	(-19.77)	(-20.24)	(-21.43)	(-21.86)
totaldamage	-0.000408	-0.000392	-0.000131	-0.000115	-0.000100	-0.000301**	-0.000344***
	(-1.79)	(-1.75)	(-1.08)	(-0.96)	(-0.79)	(-3.30)	(-3.32)
L.totaldamage					-0.0000138	-0.000171*	-0.000208*
					(-0.12)	(-2.24)	(-2.51)
L2.totaldamage					0.0000669	0.0000609	0.00000536
					(0.66)	(0.59)	(0.04)
L3.totaldamage						0.000203*	0.000165
						(2.55)	(1.69)
L4.totaldamage						0.000334**	0.000283
						(2.79)	(1.84)
Female dummy							0.000441
							(1.68)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.0506***	-0.0501***	-0.0511***	-0.0507***	-0.0545***	-0.0589***	-0.0655***
	(-23.04)	(-21.71)	(-16.90)	(-16.13)	(-16.53)	(-17.54)	(-17.03)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 48: Impact of the monetary damage caused by fire (in usd) on current Chapter 13 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000538***	0.000680***	0.000541***	0.000684***	0.000400***	0.000440***	0.000468***
	(26.41)	(23.93)	(27.16)	(24.31)	(25.53)	(24.96)	(24.88)
agesq	-0.00000602***	-0.00000721***	-0.00000605***	-0.00000724***	-0.00000430***	-0.00000468***	-0.00000494***
	(-24.48)	(-22.70)	(-25.49)	(-23.40)	(-25.10)	(-25.53)	(-25.64)
totaldamage	-0.000155***	-0.0000704*	-0.000102*	-0.0000195	-0.0000294	-0.0000194	-0.0000377
	(-4.98)	(-2.57)	(-2.58)	(-0.55)	(-1.07)	(-0.65)	(-0.93)
L.totaldamage					0.0000511	0.0000651	0.0000724
					(1.42)	(1.29)	(1.42)
L2.totaldamage					0.0000861	0.0000841	0.0000982*
					(1.78)	(1.86)	(1.97)
L3.totaldamage						0.000116***	0.000137***
						(3.62)	(4.15)
L4.totaldamage						0.0000774	0.0000735
						(1.87)	(1.54)
Female dummy							0.0000425
							(1.03)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00778***	-0.0117***	-0.00787***	-0.0118***	-0.00640***	-0.00735***	-0.00787***
	(-26.02)	(-25.98)	(-20.13)	(-19.73)	(-18.77)	(-17.88)	(-16.10)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 49: Impact of the monetary damage caused by fire (in usd) on new Chapter 13 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	1.930***	2.307***	1.796***	2.165***	1.964***	1.459***	-0.219*
	(18.25)	(21.68)	(17.90)	(21.56)	(17.38)	(11.42)	(-2.22)
agesq	0.00979***	0.00670***	0.0112***	0.00819***	0.0101***	0.0149***	0.0299***
	(8.73)	(6.12)	(10.46)	(7.87)	(9.10)	(12.42)	(29.91)
totaldamage	-1.009*	-1.188*	-0.324	-0.508	-0.534*	-0.347	-0.131
	(-2.05)	(-2.47)	(-1.06)	(-1.92)	(-2.06)	(-0.99)	(-0.44)
L.totaldamage					-0.610*	-0.413	-0.248
					(-2.50)	(-1.20)	(-0.88)
L2.totaldamage					-0.494*	-0.517*	-0.314
					(-2.30)	(-2.49)	(-1.64)
L3.totaldamage						-0.386	-0.170
						(-1.93)	(-1.02)
L4.totaldamage						-0.310	-0.0768
						(-1.52)	(-0.46)
Female dummy							-1.528***
							(-4.59)
Edu dummies							YES
Occupation dummies							YES
Constant	567.8***	557.3***	570.8***	560.5***	564.4***	575.3***	615.9***
	(199.62)	(184.82)	(215.84)	(203.26)	(177.71)	(157.74)	(181.38)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 50: Impact of the monetary damage caused by fire (in usd) on credit score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00154***	-0.000413	0.00211***	0.000193	-0.00150***	-0.00136**	0.00538***
	(3.48)	(-0.95)	(5.08)	(0.47)	(-3.61)	(-3.00)	(13.42)
agesq	-0.0000923***	-0.0000762***	-0.0000986***	-0.0000828***	-0.0000666***	-0.0000684***	-0.000130***
	(-19.11)	(-16.13)	(-21.52)	(-18.53)	(-14.76)	(-14.40)	(-28.38)
totaldamage	0.00366	0.00443	0.000258	0.00106	0.00114	-0.000381	-0.00133
	(1.27)	(1.58)	(0.21)	(0.93)	(1.00)	(-0.27)	(-1.31)
L.totaldamage					0.00206*	0.000682	0.0000255
					(2.07)	(0.49)	(0.03)
L2.totaldamage					0.00173*	0.00169*	0.00102
					(2.11)	(2.11)	(1.66)
L3.totaldamage						0.00133	0.000416
						(1.38)	(0.55)
L4.totaldamage						0.00132	0.000395
						(1.59)	(0.62)
Female dummy							0.0133***
							(9.07)
Edu dummies							YES
Occupation dummies							YES
Constant	0.503***	0.558***	0.492***	0.545***	0.594***	0.599***	0.433***
	(38.87)	(42.44)	(46.94)	(52.31)	(55.23)	(49.65)	(37.94)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 51: Impact of the monetary damage caused by fire (in usd) on current 90-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00618***	-0.00316***	-0.00612***	-0.00309***	0.000159***	0.00112***	0.00117***
	(-41.86)	(-29.81)	(-41.48)	(-29.76)	(3.35)	(18.72)	(17.11)
agesq	0.0000460***	0.0000203***	0.0000454***	0.0000196***	-0.00000624***	-0.0000154***	-0.0000157***
	(34.18)	(20.54)	(33.66)	(20.28)	(-12.97)	(-26.20)	(-23.45)
totaldamage	-0.00111*	0.00105*	-0.00154**	0.000596	0.000909**	0.00105**	0.00102**
	(-2.21)	(2.45)	(-2.86)	(1.25)	(2.74)	(2.98)	(2.79)
L.totaldamage					0.000920*	0.00119**	0.00131**
					(2.34)	(2.90)	(3.13)
L2.totaldamage					0.0000982	0.0000370	0.00000225
					(0.42)	(0.17)	(0.01)
L3.totaldamage						-0.000161	-0.000328
						(-0.87)	(-1.78)
L4.totaldamage						-0.000208	-0.000322*
						(-1.19)	(-2.23)
Female dummy							-0.00193***
							(-14.26)
Edu dummies							YES
Occupation dummies							YES
Constant	0.246***	0.164***	0.244***	0.162***	0.0442***	0.0206***	0.0183***
	(60.56)	(59.67)	(64.13)	(60.96)	(38.08)	(13.85)	(10.31)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 52: Impact of the monetary damage caused by fire (in usd) on new 90-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00110*	-0.000699	0.00167***	-0.0000948	-0.00200***	-0.00214***	0.00465***
	(2.54)	(-1.63)	(4.12)	(-0.24)	(-4.94)	(-4.87)	(11.33)
agesq	-0.0000861***	-0.0000714***	-0.0000925***	-0.0000780***	-0.0000596***	-0.0000587***	-0.000121***
	(-17.92)	(-15.17)	(-20.36)	(-17.57)	(-13.20)	(-12.34)	(-24.83)
totaldamage	0.00333	0.00413	-0.0000147	0.000811	0.000913	-0.000657	-0.00152
	(1.11)	(1.42)	(-0.01)	(0.75)	(0.84)	(-0.51)	(-1.64)
L.totaldamage					0.00167	0.000218	-0.000451
					(1.67)	(0.16)	(-0.46)
L2.totaldamage					0.00126	0.00124	0.000580
					(1.62)	(1.58)	(0.95)
L3.totaldamage						0.00127	0.000440
						(1.38)	(0.63)
L4.totaldamage						0.00129	0.000358
						(1.52)	(0.56)
Female dummy							0.0136***
							(9.47)
Edu dummies							YES
							YES
Constant	0.497***	0.547***	0.485***	0.535***	0.588***	0.599***	0.433***
	(38.59)	(41.47)	(48.00)	(52.56)	(56.66)	(52.37)	(39.40)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 53: Impact of the monetary damage caused by fire (in usd) on current 120-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00611***	-0.00315***	-0.00606***	-0.00308***	0.00000204	0.000936***	0.00105***
	(-41.89)	(-29.96)	(-41.54)	(-29.99)	(0.05)	(17.78)	(18.52)
agesq	0.0000457***	0.0000204***	0.0000451***	0.0000197***	-0.00000459***	-0.0000135***	-0.0000144***
	(34.75)	(20.96)	(34.15)	(20.67)	(-10.51)	(-26.03)	(-25.93)
totaldamage	-0.00137***	0.000826**	-0.00178***	0.000385	0.000709**	0.000752**	0.000714*
	(-4.09)	(2.66)	(-4.38)	(0.96)	(2.75)	(2.68)	(2.53)
L.totaldamage					0.000876**	0.00114***	0.00117***
					(2.91)	(4.51)	(3.80)
L2.totaldamage					0.0000383	-0.0000182	-0.0000627
					(0.17)	(-0.09)	(-0.38)
L3.totaldamage						-0.0000801	-0.000151
						(-0.41)	(-0.72)
L4.totaldamage						-0.000250	-0.000385*
						(-1.36)	(-2.15)
Female dummy							-0.00208***
							(-16.42)
Edu dummies							YES
Occupation dummies							YES
Constant	0.240***	0.160***	0.239***	0.158***	0.0445***	0.0213***	0.0181***
	(58.19)	(56.88)	(62.83)	(59.84)	(42.83)	(16.25)	(12.08)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 54: Impact of the monetary damage caused by fire (in usd) on new 120-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00274***	0.00229***	0.00277***	0.00233***	0.00237***	0.00250***	0.00255***
	(23.62)	(26.59)	(23.17)	(26.08)	(23.02)	(17.94)	(17.14)
agesq	-0.0000305***	-0.0000268***	-0.0000308***	-0.0000271***	-0.0000278***	-0.0000294***	-0.0000298***
	(-24.02)	(-26.33)	(-23.81)	(-26.12)	(-23.79)	(-19.52)	(-18.76)
totaldamage	0.000561*	0.000677**	0.000377	0.000499***	0.000462**	0.000237	0.000150
	(2.16)	(2.93)	(1.95)	(3.35)	(3.20)	(1.31)	(0.64)
L.totaldamage					0.000869***	0.000766***	0.000675**
					(3.72)	(3.48)	(2.96)
L2.totaldamage					0.000680***	0.000620***	0.000457**
					(3.62)	(4.33)	(2.97)
L3.totaldamage						0.000430***	0.000266*
						(3.32)	(2.01)
L4.totaldamage						0.000535**	0.000399**
						(3.17)	(2.83)
Female dummy							-0.00586***
							(-17.50)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.0387***	-0.0264***	-0.0396***	-0.0275***	-0.0259***	-0.0257***	-0.0255***
	(-21.50)	(-22.95)	(-15.16)	(-15.21)	(-11.95)	(-8.24)	(-6.95)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 55: Impact of the monetary damage caused by fire (in usd) on current foreclosures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000709***	0.000708***	0.000717***	0.000718***	0.000587***	0.000629***	0.000588***
	(24.17)	(26.23)	(23.67)	(25.77)	(17.97)	(13.19)	(11.76)
agesq	-0.00000834***	-0.00000828***	-0.00000841***	-0.00000835***	-0.00000704***	-0.00000750***	-0.00000709***
	(-26.60)	(-28.67)	(-26.16)	(-28.29)	(-20.71)	(-15.59)	(-14.18)
totaldamage	0.000787*	0.000746**	0.000768*	0.000725**	0.000725***	0.000838***	0.000766***
	(2.36)	(2.88)	(2.57)	(3.25)	(3.38)	(4.03)	(3.37)
L.totaldamage					0.000511**	0.000612***	0.000609***
					(3.22)	(4.27)	(3.99)
L2.totaldamage					0.000120*	0.000112*	0.0000802*
					(2.19)	(2.47)	(2.22)
L3.totaldamage						-0.000215***	-0.000205***
						(-3.52)	(-3.35)
L4.totaldamage						0.0000727	0.0000912
						(1.25)	(1.46)
Female dummy							-0.00131***
							(-17.23)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00819***	-0.00834***	-0.00842***	-0.00860***	-0.00556***	-0.00584***	-0.00490***
	(-14.87)	(-16.54)	(-12.17)	(-13.49)	(-7.28)	(-5.12)	(-3.84)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 56: Impact of the monetary damage caused by fire (in usd) on new foreclosures

E.5 Estimation results with the monetary damage caused by Storm as a shock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00861***	0.00872***	0.00869***	0.00880***	0.00817***	0.00740***	0.00770***
	(31.93)	(32.75)	(33.00)	(33.59)	(33.45)	(29.27)	(26.66)
agesq	-0.0000942***	-0.0000950***	-0.0000952***	-0.0000960***	-0.0000893***	-0.0000813***	-0.0000840***
	(-32.76)	(-33.66)	(-34.94)	(-35.76)	(-35.86)	(-32.32)	(-29.96)
totaldamage	-0.0000686	-0.000182	-0.000340	-0.000457	-0.000358	-0.00130***	-0.00142***
	(-0.11)	(-0.31)	(-0.63)	(-1.03)	(-0.76)	(-4.20)	(-4.67)
L.totaldamage					-0.000301	-0.00110**	-0.00118**
					(-0.71)	(-2.88)	(-2.69)
L2.totaldamage					0.0000872	0.000134	0.0000924
					(0.29)	(0.37)	(0.24)
L3.totaldamage						0.000391	0.000279
						(1.75)	(1.00)
L4.totaldamage						0.000555*	0.000438
						(2.43)	(1.44)
Female dummy							0.00700***
							(12.42)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.116***	-0.119***	-0.118***	-0.121***	-0.107***	-0.0904***	-0.103***
	(-22.67)	(-22.73)	(-18.44)	(-18.80)	(-17.47)	(-13.93)	(-12.80)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 57: Impact of the monetary damage caused by storm (in usd) on current Chapter 7 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000825***	0.00149***	0.000836***	0.00151***	0.000308***	0.000342***	0.000326***
	(12.75)	(20.79)	(12.76)	(20.72)	(8.47)	(7.09)	(5.93)
agesq	-0.0000108***	-0.0000165***	-0.0000109***	-0.0000166***	-0.00000408***	-0.00000439***	-0.00000422***
	(-17.78)	(-24.02)	(-18.26)	(-24.56)	(-12.11)	(-9.65)	(-8.16)
totaldamage	-0.000302***	0.000105	-0.000382***	0.0000179	0.0000913*	-0.0000324	-0.0000156
	(-5.33)	(1.60)	(-5.37)	(0.35)	(2.10)	(-0.79)	(-0.31)
L.totaldamage					0.000147	0.000201*	0.000219
					(1.61)	(2.22)	(1.62)
L2.totaldamage					0.000384***	0.000370***	0.000343**
					(3.46)	(3.59)	(3.00)
L3.totaldamage						0.000223*	0.000169
						(2.01)	(1.50)
L4.totaldamage						0.0000629	0.0000240
						(0.79)	(0.29)
Female dummy							0.000540***
							(10.27)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00249	-0.0207***	-0.00271	-0.0209***	0.000954	0.000181	-0.000169
	(-1.55)	(-12.43)	(-1.58)	(-11.28)	(1.01)	(0.15)	(-0.12)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 58: Impact of the monetary damage caused by storm (in usd) on new Chapter 7 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00295***	0.00293***	0.00297***	0.00295***	0.00310***	0.00326***	0.00356***
	(20.92)	(20.23)	(21.18)	(20.44)	(20.82)	(21.95)	(22.34)
agesq	-0.0000307***	-0.0000305***	-0.0000308***	-0.0000307***	-0.0000319***	-0.0000333***	-0.0000362***
	(-19.70)	(-19.23)	(-20.29)	(-19.77)	(-20.24)	(-21.43)	(-21.86)
totaldamage	-0.000408	-0.000392	-0.000131	-0.000115	-0.000100	-0.000301**	-0.000344***
	(-1.79)	(-1.75)	(-1.08)	(-0.96)	(-0.79)	(-3.30)	(-3.32)
L.totaldamage					-0.0000138	-0.000171*	-0.000208*
					(-0.12)	(-2.24)	(-2.51)
L2.totaldamage					0.0000669	0.0000609	0.00000536
					(0.66)	(0.59)	(0.04)
L3.totaldamage						0.000203*	0.000165
						(2.55)	(1.69)
L4.totaldamage						0.000334**	0.000283
						(2.79)	(1.84)
Female dummy							0.000441
							(1.68)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.0506***	-0.0501***	-0.0511***	-0.0507***	-0.0545***	-0.0589***	-0.0655***
	(-23.04)	(-21.71)	(-16.90)	(-16.13)	(-16.53)	(-17.54)	(-17.03)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 59: Impact of the monetary damage caused by storm (in usd) on current Chapter 13 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000538***	0.000680***	0.000541***	0.000684***	0.000400***	0.000440***	0.000468***
	(26.41)	(23.93)	(27.16)	(24.31)	(25.53)	(24.96)	(24.88)
agesq	-0.00000602***	-0.00000721***	-0.00000605***	-0.00000724***	-0.00000430***	-0.00000468***	-0.00000494***
	(-24.48)	(-22.70)	(-25.49)	(-23.40)	(-25.10)	(-25.53)	(-25.64)
totaldamage	-0.000155***	-0.0000704*	-0.000102*	-0.0000195	-0.0000294	-0.0000194	-0.0000377
	(-4.98)	(-2.57)	(-2.58)	(-0.55)	(-1.07)	(-0.65)	(-0.93)
L.totaldamage					0.0000511	0.0000651	0.0000724
					(1.42)	(1.29)	(1.42)
L2.totaldamage					0.0000861	0.0000841	0.0000982*
					(1.78)	(1.86)	(1.97)
L3.totaldamage						0.000116***	0.000137***
						(3.62)	(4.15)
L4.totaldamage						0.0000774	0.0000735
						(1.87)	(1.54)
Female dummy							0.0000425
							(1.03)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00778***	-0.0117***	-0.00787***	-0.0118***	-0.00640***	-0.00735***	-0.00787***
	(-26.02)	(-25.98)	(-20.13)	(-19.73)	(-18.77)	(-17.88)	(-16.10)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 60: Impact of the monetary damage caused by storm (in usd) on new Chapter 13 declarations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	1.930***	2.307***	1.796***	2.165***	1.964***	1.459***	-0.219*
	(18.25)	(21.68)	(17.90)	(21.56)	(17.38)	(11.42)	(-2.22)
agesq	0.00979***	0.00670***	0.0112***	0.00819***	0.0101***	0.0149***	0.0299***
	(8.73)	(6.12)	(10.46)	(7.87)	(9.10)	(12.42)	(29.91)
totaldamage	-1.009*	-1.188*	-0.324	-0.508	-0.534*	-0.347	-0.131
	(-2.05)	(-2.47)	(-1.06)	(-1.92)	(-2.06)	(-0.99)	(-0.44)
L.totaldamage					-0.610*	-0.413	-0.248
					(-2.50)	(-1.20)	(-0.88)
L2.totaldamage					-0.494*	-0.517*	-0.314
					(-2.30)	(-2.49)	(-1.64)
L3.totaldamage						-0.386	-0.170
						(-1.93)	(-1.02)
L4.totaldamage						-0.310	-0.0768
						(-1.52)	(-0.46)
Female dummy							-1.528***
							(-4.59)
Edu dummies							YES
Occupation dummies							YES
Constant	567.8***	557.3***	570.8***	560.5***	564.4***	575.3***	615.9***
	(199.62)	(184.82)	(215.84)	(203.26)	(177.71)	(157.74)	(181.38)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 61: Impact of the monetary damage caused by storm (in usd) on credit score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00154***	-0.000413	0.00211***	0.000193	-0.00150***	-0.00136**	0.00538***
	(3.48)	(-0.95)	(5.08)	(0.47)	(-3.61)	(-3.00)	(13.42)
agesq	-0.0000923***	-0.0000762***	-0.0000986***	-0.0000828***	-0.0000666***	-0.0000684***	-0.000130***
	(-19.11)	(-16.13)	(-21.52)	(-18.53)	(-14.76)	(-14.40)	(-28.38)
totaldamage	0.00366	0.00443	0.000258	0.00106	0.00114	-0.000381	-0.00133
	(1.27)	(1.58)	(0.21)	(0.93)	(1.00)	(-0.27)	(-1.31)
L.totaldamage					0.00206*	0.000682	0.0000255
					(2.07)	(0.49)	(0.03)
L2.totaldamage					0.00173*	0.00169*	0.00102
					(2.11)	(2.11)	(1.66)
L3.totaldamage						0.00133	0.000416
						(1.38)	(0.55)
L4.totaldamage						0.00132	0.000395
						(1.59)	(0.62)
Female dummy							0.0133***
							(9.07)
Edu dummies							YES
Occupation dummies							YES
Constant	0.503***	0.558***	0.492***	0.545***	0.594***	0.599***	0.433***
	(38.87)	(42.44)	(46.94)	(52.31)	(55.23)	(49.65)	(37.94)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 62: Impact of the monetary damage caused by storm (in usd) on current 90-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00618***	-0.00316***	-0.00612***	-0.00309***	0.000159***	0.00112***	0.00117***
	(-41.86)	(-29.81)	(-41.48)	(-29.76)	(3.35)	(18.72)	(17.11)
agesq	0.0000460***	0.0000203***	0.0000454***	0.0000196***	-0.00000624***	-0.0000154***	-0.0000157***
	(34.18)	(20.54)	(33.66)	(20.28)	(-12.97)	(-26.20)	(-23.45)
totaldamage	-0.00111*	0.00105*	-0.00154**	0.000596	0.000909**	0.00105**	0.00102**
	(-2.21)	(2.45)	(-2.86)	(1.25)	(2.74)	(2.98)	(2.79)
L.totaldamage					0.000920*	0.00119**	0.00131**
					(2.34)	(2.90)	(3.13)
L2.totaldamage					0.0000982	0.0000370	0.00000225
					(0.42)	(0.17)	(0.01)
L3.totaldamage						-0.000161	-0.000328
						(-0.87)	(-1.78)
L4.totaldamage						-0.000208	-0.000322*
						(-1.19)	(-2.23)
Female dummy							-0.00193***
							(-14.26)
Edu dummies							YES
Occupation dummies							YES
Constant	0.246***	0.164***	0.244***	0.162***	0.0442***	0.0206***	0.0183***
	(60.56)	(59.67)	(64.13)	(60.96)	(38.08)	(13.85)	(10.31)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 63: Impact of the monetary damage caused by storm (in usd) on new 90-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00110*	-0.000699	0.00167***	-0.0000948	-0.00200***	-0.00214***	0.00465***
	(2.54)	(-1.63)	(4.12)	(-0.24)	(-4.94)	(-4.87)	(11.33)
agesq	-0.0000861***	-0.0000714***	-0.0000925***	-0.0000780***	-0.0000596***	-0.0000587***	-0.000121***
	(-17.92)	(-15.17)	(-20.36)	(-17.57)	(-13.20)	(-12.34)	(-24.83)
totaldamage	0.00333	0.00413	-0.0000147	0.000811	0.000913	-0.000657	-0.00152
	(1.11)	(1.42)	(-0.01)	(0.75)	(0.84)	(-0.51)	(-1.64)
L.totaldamage					0.00167	0.000218	-0.000451
					(1.67)	(0.16)	(-0.46)
L2.totaldamage					0.00126	0.00124	0.000580
					(1.62)	(1.58)	(0.95)
L3.totaldamage						0.00127	0.000440
						(1.38)	(0.63)
L4.totaldamage						0.00129	0.000358
						(1.52)	(0.56)
Female dummy							0.0136***
							(9.47)
Edu dummies							YES
Occupation dummies							YES
Constant	0.497***	0.547***	0.485***	0.535***	0.588***	0.599***	0.433***
	(38.59)	(41.47)	(48.00)	(52.56)	(56.66)	(52.37)	(39.40)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 64: Impact of the monetary damage caused by storm (in usd) on current 120-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	-0.00611***	-0.00315***	-0.00606***	-0.00308***	0.00000204	0.000936***	0.00105***
	(-41.89)	(-29.96)	(-41.54)	(-29.99)	(0.05)	(17.78)	(18.52)
agesq	0.0000457***	0.0000204***	0.0000451***	0.0000197***	-0.00000459***	-0.0000135***	-0.0000144***
	(34.75)	(20.96)	(34.15)	(20.67)	(-10.51)	(-26.03)	(-25.93)
totaldamage	-0.00137***	0.000826**	-0.00178***	0.000385	0.000709**	0.000752**	0.000714*
	(-4.09)	(2.66)	(-4.38)	(0.96)	(2.75)	(2.68)	(2.53)
L.totaldamage					0.000876**	0.00114***	0.00117***
					(2.91)	(4.51)	(3.80)
L2.totaldamage					0.0000383	-0.0000182	-0.0000627
					(0.17)	(-0.09)	(-0.38)
L3.totaldamage						-0.0000801	-0.000151
						(-0.41)	(-0.72)
L4.totaldamage						-0.000250	-0.000385*
						(-1.36)	(-2.15)
Female dummy							-0.00208***
							(-16.42)
Edu dummies							YES
Occupation dummies							YES
Constant	0.240***	0.160***	0.239***	0.158***	0.0445***	0.0213***	0.0181***
	(58.19)	(56.88)	(62.83)	(59.84)	(42.83)	(16.25)	(12.08)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 65: Impact of the monetary damage caused by storm (in usd) on new 120-day delinquencies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.00274***	0.00229***	0.00277***	0.00233***	0.00237***	0.00250***	0.00255***
	(23.62)	(26.59)	(23.17)	(26.08)	(23.02)	(17.94)	(17.14)
agesq	-0.0000305***	-0.0000268***	-0.0000308***	-0.0000271***	-0.0000278***	-0.0000294***	-0.0000298***
	(-24.02)	(-26.33)	(-23.81)	(-26.12)	(-23.79)	(-19.52)	(-18.76)
totaldamage	0.000561*	0.000677**	0.000377	0.000499***	0.000462**	0.000237	0.000150
	(2.16)	(2.93)	(1.95)	(3.35)	(3.20)	(1.31)	(0.64)
L.totaldamage					0.000869***	0.000766***	0.000675**
					(3.72)	(3.48)	(2.96)
L2.totaldamage					0.000680***	0.000620***	0.000457**
					(3.62)	(4.33)	(2.97)
L3.totaldamage						0.000430***	0.000266*
						(3.32)	(2.01)
L4.totaldamage						0.000535**	0.000399**
						(3.17)	(2.83)
Female dummy							-0.00586***
							(-17.50)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.0387***	-0.0264***	-0.0396***	-0.0275***	-0.0259***	-0.0257***	-0.0255***
	(-21.50)	(-22.95)	(-15.16)	(-15.21)	(-11.95)	(-8.24)	(-6.95)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 66: Impact of the monetary damage caused by storm (in usd) on current foreclosures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
age	0.000709***	0.000708***	0.000717***	0.000718***	0.000587***	0.000629***	0.000588***
	(24.17)	(26.23)	(23.67)	(25.77)	(17.97)	(13.19)	(11.76)
agesq	-0.00000834***	-0.00000828***	-0.00000841***	-0.00000835***	-0.00000704***	-0.00000750***	-0.00000709***
	(-26.60)	(-28.67)	(-26.16)	(-28.29)	(-20.71)	(-15.59)	(-14.18)
totaldamage	0.000787*	0.000746**	0.000768*	0.000725**	0.000725***	0.000838***	0.000766***
	(2.36)	(2.88)	(2.57)	(3.25)	(3.38)	(4.03)	(3.37)
L.totaldamage					0.000511**	0.000612***	0.000609***
					(3.22)	(4.27)	(3.99)
L2.totaldamage					0.000120*	0.000112*	0.0000802*
					(2.19)	(2.47)	(2.22)
L3.totaldamage						-0.000215***	-0.000205***
						(-3.52)	(-3.35)
L4.totaldamage						0.0000727	0.0000912
						(1.25)	(1.46)
Female dummy							-0.00131***
							(-17.23)
Edu dummies							YES
Occupation dummies							YES
Constant	-0.00819***	-0.00834***	-0.00842***	-0.00860***	-0.00556***	-0.00584***	-0.00490***
	(-14.87)	(-16.54)	(-12.17)	(-13.49)	(-7.28)	(-5.12)	(-3.84)
N	20688336	20688336	20688336	20688336	17198153	13843011	11200489

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 67: Impact of the monetary damage caused by storm (in usd) on new foreclosures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	move	d90_current	d90_new	d120_current	d120_new	cs	linc	lcc	ch7_current
Storm	0.00283	-0.00162	0.000995	-0.00137	0.00154	0.0171	-0.00372	-0.0222	0.00421**
	(1.68)	(-0.63)	(0.91)	(-0.54)	(1.47)	(0.03)	(-1.66)	(-1.92)	(2.92)
L.Storm	-0.00753***	-0.000900	0.00291**	-0.000621	0.00311**	-0.392	-0.00363	-0.00643	0.00390**
	(-4.66)	(-0.37)	(2.77)	(-0.26)	(3.10)	(-0.72)	(-1.69)	(-0.58)	(2.81)
L2.Storm	-0.00570***	-0.000240	0.00199	-0.00141	0.000946	-0.767	-0.00553*	-0.0191	0.00351*
	(-3.47)	(-0.10)	(1.87)	(-0.58)	(0.93)	(-1.39)	(-2.54)	(-1.70)	(2.49)
L3.Storm	-0.00675***	0.00376	0.00279**	0.00354	0.00278**	-1.249*	-0.00391	0.00435	0.00244
	(-4.09)	(1.50)	(2.59)	(1.43)	(2.72)	(-2.25)	(-1.78)	(0.39)	(1.72)
L4.Storm	-0.00574***	0.00534*	0.00151	0.00573*	0.00253*	-1.483**	-0.00430	0.00769	0.00174
	(-3.46)	(2.12)	(1.40)	(2.30)	(2.46)	(-2.66)	(-1.95)	(0.68)	(1.22)
L5.Storm	-0.00604***	0.00488	0.000824	0.00443	0.000323	-1.871**	-0.00676**	0.0135	0.000266
	(-3.49)	(1.87)	(0.73)	(1.71)	(0.30)	(-3.23)	(-2.95)	(1.16)	(0.18)
age	-0.0123***	0.00758***	0.00134***	0.00685***	0.00128***	-0.946***	0.0355***	0.102***	0.00715***
	(-119.38)	(48.71)	(20.03)	(44.47)	(20.19)	(-27.45)	(260.47)	(146.33)	(81.16)
agesq	0.0000936***	-0.000147***	-0.0000173***	-0.000138***	-0.0000166***	0.0358***	-0.000313***	-0.00105***	-0.0000779***
	(90.67)	(-93.94)	(-25.72)	(-88.92)	(-25.92)	(103.54)	(-228.39)	(-152.57)	(-88.04)
Female dummy	-0.00253***	0.00980***	-0.00165***	0.00999***	-0.00184***	-0.442***	-0.0785***	-0.0376***	0.00679***
	(-9.31)	(23.81)	(-9.33)	(24.54)	(-10.91)	(-4.85)	(-217.68)	(-21.06)	(29.15)
Edu dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Occ dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Constant	0.465***	0.353***	0.0145***	0.351***	0.0116***	639.7***	9.850***	6.274***	-0.0886***
	(164.82)	(82.67)	(7.92)	(83.01)	(6.65)	(675.71)	(2628.16)	(327.34)	(-36.62)
N	4699741	4699741	4699741	4699741	4699741	4699741	4695530	3356372	4699741

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 68: Cohort of 2010 vs never hit by a storm

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ch13_current	forecl_current	auto_orig	auto_bal_open	lauto	m_orig	m_bal_open	lmort
Storm	0.00179*	-0.000744	-0.00582***	-237.0***	-0.0671**	0.000446	-716.5	-0.00930
	(2.45)	(-0.82)	(-3.56)	(-3.58)	(-2.58)	(0.41)	(-0.77)	(-0.29)
L.Storm	0.00125	-0.000980	0.000323	-194.1**	-0.0546*	-0.000468	657.6	0.0188
	(1.79)	(-1.12)	(0.21)	(-3.06)	(-2.19)	(-0.44)	(0.74)	(0.60)
L2.Storm	0.00158*	-0.00122	-0.000577	-177.2**	-0.0711**	-0.000359	1296.3	0.0360
	(2.23)	(-1.38)	(-0.36)	(-2.75)	(-2.81)	(-0.34)	(1.44)	(1.14)
L3.Storm	0.00130	-0.000880	-0.0000475	-142.4*	-0.0444	-0.00147	1945.5*	0.0412
	(1.81)	(-0.98)	(-0.03)	(-2.20)	(-1.74)	(-1.36)	(2.14)	(1.30)
L4.Storm	0.000973	-0.000349	0.000200	-75.55	-0.0439	0.000323	890.8	0.0283
	(1.35)	(-0.39)	(0.12)	(-1.16)	(-1.72)	(0.30)	(0.97)	(0.89)
L5.Storm	-0.000213	0.00131	0.000630	-46.51	-0.0516	0.00108	1772.4	0.0403
	(-0.28)	(1.40)	(0.38)	(-0.69)	(-1.94)	(0.96)	(1.87)	(1.22)
age	0.00349***	0.00276***	-0.000716***	224.7***	0.0603***	-0.000727***	10755.8***	0.498***
	(78.34)	(49.60)	(-7.19)	(55.69)	(38.09)	(-10.85)	(190.35)	(252.57)
agesq	-0.0000351***	-0.0000321***	-0.00000374***	-2.915***	-0.000917***	0.000000640	-110.2***	-0.00485***
	(-78.51)	(-57.49)	(-3.74)	(-71.93)	(-57.67)	(0.95)	(-194.23)	(-244.88)
Female dummy	0.000120	-0.00666***	-0.0148***	-1733.8***	-0.586***	-0.00585***	-14814.0***	-0.543***
	(1.02)	(-45.28)	(-56.29)	(-162.59)	(-139.96)	(-32.99)	(-99.19)	(-104.23)
Edu dummies	YES	YES	YES	YES	YES	YES	YES	YES
Occ dummies	YES	YES	YES	YES	YES	YES	YES	YES
Constant	-0.0652***	-0.0280***	0.130***	2572.6***	2.750***	0.0695***	-161231.9***	-6.884***
	(-53.27)	(-18.35)	(47.47)	(23.22)	(63.21)	(37.74)	(-103.91)	(-127.10)
N	4699741	4699741	4699741	4699741	4699741	4699741	4699741	4699741

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 69: Cohort of 2010 vs never hit by a storm (II)

Regressions 19.10.21

F Further results on mobility

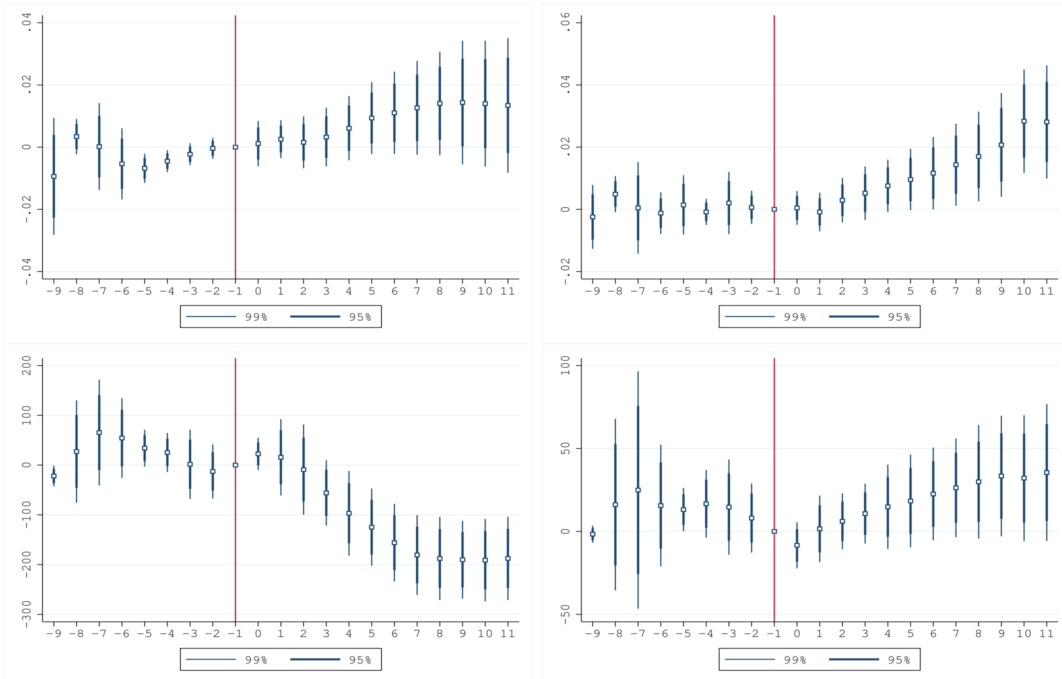

Figure 90: Event study, impact of storm on probability of moving (upper panels) and on house price index (bottom panels). The left panels are relative to individuals above the house price index median only, whereas the right panels only include those below the median house price index (in the year of the disaster).

G Results on home equity line credit

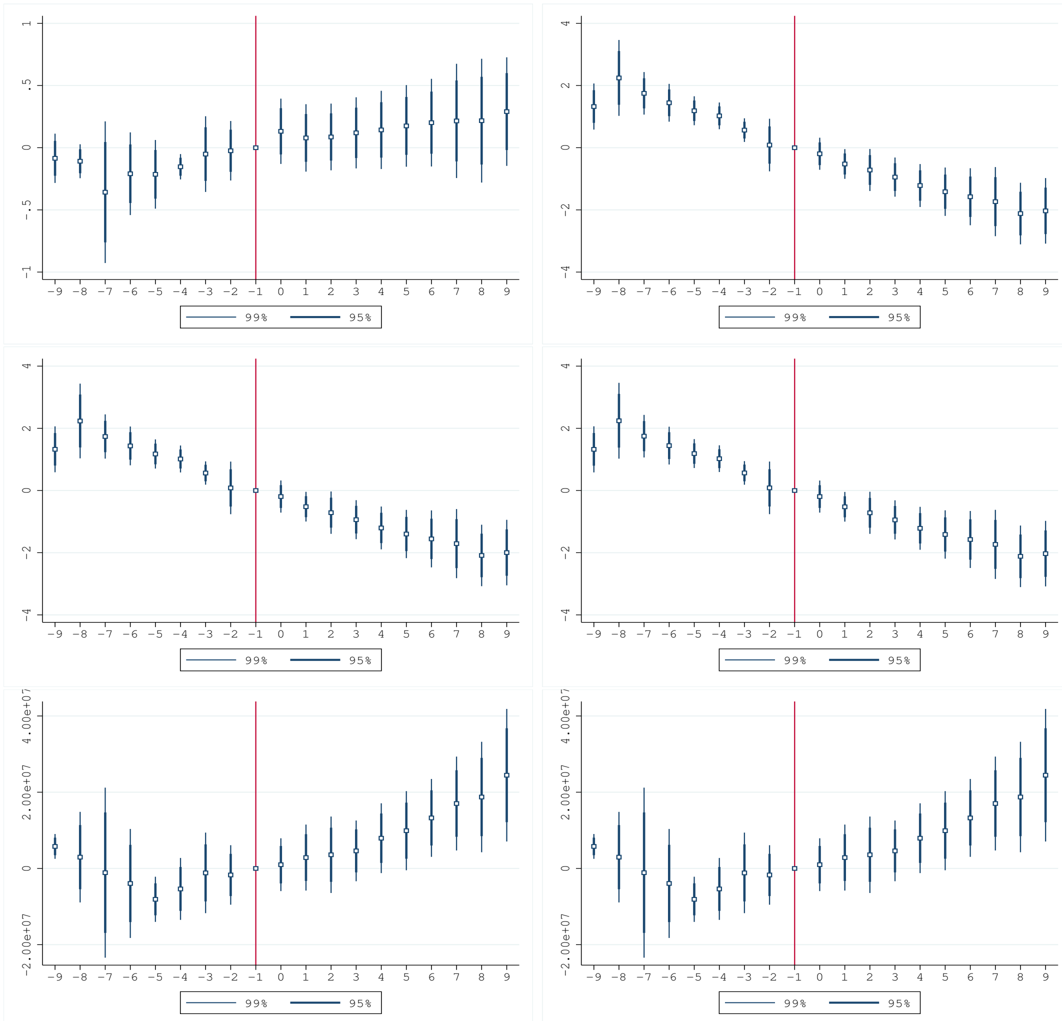

Figure 91: Event study, impact of storm on (from the top left panel to the bottom right): number of hel credit trades, n. satisfactory hel trades in last 6 months, n hel trades 30-day delinquent, n of open hel trades with balance greater than 0, tot balance on hel opened in the past 6 months, total available credit amount on open home equity line of credit trades reported in the last 6 months.