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Hurricanes and migration: New evidence from credit bureau microdata☆

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ABSTRACT

We use credit bureau microdata containing the quarterly locations of 20 million Americans to examine migration responses to 10 hurricanes between 2005 and 2017. We find that flooding from the largest hurricanes caused small increases in migration in the 2 years following the storms, while smaller hurricanes or exposure to high winds alone have limited effects on migration patterns. The results do not vary with individual credit scores, suggesting that credit constraints do not substantially affect migration. Despite short-term increases in migration following large storms, we find that Hurricane Katrina is the only storm that caused a meaningful long-run population decline in flooded areas. Our findings show that except for the most catastrophic hurricanes, post-disaster migration is unlikely to decrease population exposure in hurricane-prone areas.

1. Introduction

Over 55 million Americans currently live in areas exposed to hurricanes.[1] With the frequency of severe storms expected to increase (Mudd et al., 2014; Little et al., 2015), the costs of hurricanes are expected to continue growing. Moving populations out of high-risk areas has the potential to substantially decrease disaster-related damages, but it is also very expensive. Government-sponsored managed retreats have been used at small scales, but such retreats are costly and impractical for major population centers (Mach et al., 2019). Consequently, reducing populations in hurricane-exposed areas will likely depend on individuals voluntarily moving away from risky areas. Deciding to relocate away from hurricane prone regions may be more likely in the years following a hurricane: the occurrence of a storm often severely disrupts housing, while also providing information on current hazard risk, potentially making alternative locations more attractive.

In this paper, we examine the impacts of hurricanes on domestic migration in the United States using quarterly individual-level address data obtained from credit bureau records matched to modeled hurricane data from the First Street Foundation. These records allow us to observe domestic residential moves of any distance, to separately estimate short-term individual-level migration and longer-term place-level population changes, and to examine how migration varies with individual economic characteristics. To investigate potentially heterogeneous migration responses, we separately estimate the effects of 10 major hurricanes that impacted the U.S. between 2005 and 2017.

☆ The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the opinions of the Federal Reserve Board or of any other person associated with the Federal Reserve System. We thank Molly Harnish for expert research assistance. We also thank Jesse Gourevitch, Jasmine Griffiths, Valerie Mueller, Maureen Page, and two anonymous referees for helpful suggestions and comments on this paper.

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[1] The number of Americans living in areas exposed to hurricanes comes from the Federal Emergency Management Agency's National Risk Index data, available at https://hazards.fema.gov/nri/hurricane, and is calculated as the total population living in counties considered to be at either "very high" or "relatively high" risk of hurricane exposure.

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We find that the largest and most damaging hurricanes (e.g., Harvey, Sandy, and Ike) cause small and statistically significant increases in migration in the 2 years following storms. In contrast, relatively smaller hurricanes (e.g., Irene, Matthew, and Hermine) have no effect on migration. The outlier in our analysis is Hurricane Katrina, which caused an increase in migration almost 10 times as large as any other storm that we study. In all cases, we find that the migration response is driven by exposure to flooding, with limited migration effects from being exposed to high winds without flooding.

We next estimate whether credit score, a major determinant of one's ability to rent a property or access affordable credit, affects migration behavior. We find that individuals with high and low credit scores before a disaster are equally likely to migrate after the disaster. Somewhat surprisingly, homeowners with a mortgage are slightly more likely to migrate compared to the overall population, suggesting that owning a home does not foster immobility.

Finally, we explore whether the increases in migration rates after hurricanes reduce the number of people living in hurricane-prone areas. We find that, with the exception of Hurricane Katrina, the number of people living in hurricane-affected areas does not meaningfully decline. We attribute the lack of population decline to an increase in in-migration that typically offsets any post-hurricane out-migration. As a result, while we estimate statistically significant increases in individual migration after large storms like Harvey and Sandy, the long-run population trends in previously flooded areas remain almost unchanged compared to the unaffected control group areas. In contrast, Hurricane Katrina caused population declines of nearly 17 % in the flooded areas in the 4 years after the storm, likely reflecting the scale of the damage relative to the other storms in our study.

Our paper directly contributes to the literature on the impacts of natural disasters and their effects on migration (Strobl, 2011; Boustan et al., 2012; Gray and Mueller, 2012; Hornbeck, 2012; Marchiori et al., 2012). In the United States, several papers find large out-migration after disasters, but these studies focus on the largest events, such as Hurricane Katrina (Deryugina et al., 2018; Fussell, 2018). Our findings are similar for Hurricane Katrina and help highlight that it is an outlier compared to other hurricanes. The closest paper to ours is Sheldon and Zhan (2022), which uses the American Community Survey and county-level disaster declaration data to study migration after natural disasters. They aggregate across a large number of disasters and find a significant increase in out-migration after more severe events. Our paper builds on their findings in three key ways. First, we estimate storm-specific migration responses, showing that it is the larger hurricanes that are responsible for most of the migration. Second, the granularity of our migration, flooding, and high wind data allows us to precisely determine treated and control individuals at the census block level, and to show that it is flooding, and not high wind, that is driving migration. Third, our comprehensive panel data allows us to measure how hurricanes affect long-run populations in storm affected areas, which has not been possible in previous research. We show that despite increases in migration rates after the costliest storms, with the exception of Hurricane Katrina, there are no meaningful population declines in flood-affected areas.

Our analysis also provides new insights into migration frictions. A priori, the relatively low amounts of migration after hurricanes could be driven by financial constraints. In our analysis, we study the role of credit scores, which directly determine access to loans and are often used by landlords to select tenants. However, we find only modest differences in migration between people with higher and lower credit scores, showing that it is unlikely to be a determinant or major constraint on migration. Our findings suggest that other factors, such as non-pecuniary costs (e.g., psychological costs of moving or loss of social networks), government policies, or lack of alternative housing options, are likely responsible for the relatively small migration increases and lack of population declines in affected areas following hurricanes.

Beyond its direct contribution to the disasters and migration literature, our paper contributes to the broader adaptation literature (Kahn, 2005; Annan and Schlenker, 2015; Barreca et al., 2016; Botzen et al., 2019; Carleton et al., 2022; Burke et al., 2024). Our findings provide evidence that migration is currently an unlikely adaptation channel to reduce the cost of hurricanes. While migration rates do increase after some larger storms, we find that most increases in out-migration also have similar increases in in-migration, resulting in little to no net changes in population in affected areas. Hurricane Katrina is the only storm that caused both increases in migration and meaningful population declines after 4 years. Our results show that policies designed to reduce the cost of out-migration after a storm are unlikely to reduce the population living in the path of hurricanes since in-migration is also likely to increase. It is possible that if hurricanes continue to grow in intensity, we may see migration and depopulation effects similar to those observed after Katrina. However, our findings suggest that for most storms, the number of people living in the path of hurricanes will not meaningfully decrease as a result of post-storm migration.

2. Data

Our analysis leverages two proprietary datasets. First, we use the Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP) between 2003 and 2021. This dataset is a quarterly, individual-level dataset that contains information on people's credit and loan histories, including their Equifax Credit Risk Score. The CCP contains a nationally representative, random, anonymized 5 % sample of adults with a social security number and a credit report (see Lee and van der Klaauw (2010) for details).[2] The CCP also includes geographic information, such as census block, scrambled address, and address type (street, high rise building, Post Office box, etc.). Using these records, we construct longitudinal migration datasets at the individual level (to estimate who moves) and at the census block group level (to estimate population changes).

Second, we use simulated historical flooding and wind data from the First Street Foundation (FSF) Flood Model and Wind Model. These data contain property-level information on exposure to several historical disaster events, which are validated against ground

[2] The CCP does not effectively capture people without credit reports, which we discuss in Appendix A.2.

Table 1
Consumer Credit Panel summary statistics.

Variable	Mean	St. dev.	N
Individuals			
Migration rate	0.029	0.167	79,509,512
Avg. pre-storm credit score	694.3	102.8	73,113,967
Mortgaged homeowner status	0.251	0.433	79,509,512
Treatment (flooding)	0.061	0.24	79,509,512
Treatment (high winds)	0.289	0.453	79,509,512
Block groups			
Population (CCP)	55.5	61.8	1,476,889
Treatment (flooding)	0.111	0.315	1,476,889
Treatment (high winds)	0.312	0.463	1,476,889

Notes: Summary statistics table for the individual and block group level analyses. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

truth sources (high water mark data from river and tidal gauges, flood claims from the National Flood Insurance Program, grants from FEMA's Individual Assistance program, and loans from the Small Business Administration). The wind data leverage the National Oceanic and Atmospheric Administration's International Best Track Archive for Climate Stewardship dataset to determine experienced wind speeds in hurricane tracks. We define a "high wind" treatment variable following NOAA's definition of damaging wind as those exceeding 50 miles per hour.[3]

Table 1 summarizes our data. We focus on the 10 largest hurricanes modeled by FSF between 2005 and 2017, shown in Fig. 1A and further discussed in Appendix A. We merge the FSF and CCP data at the census block level. Our two treatments are expressed as the share of people or block groups in our sample exposed to flooding and high winds. Overall, we track the quarterly residential locations of over 20 million adults.

3. Empirical strategy

Our empirical approach departs from the literature by separately analyzing each hurricane. For each storm, the analysis sample comprises states that experienced hurricane-induced flooding. We define being "flood treated" or "wind treated" as experiencing flooding or high winds, respectively, from a given hurricane.[4] There is some overlap between the two treated groups as many areas experience both flooding and high winds. The control group is drawn from the same states in the analysis sample, and only includes people who experienced neither flooding nor high winds. In the flooding analysis, we limit our control group to individuals who did not experience flooding, but who lived in either counties that experienced flooding or in adjacent counties at the time of the hurricane.[5]

Treatment and control status are storm specific. Compared to the literature, our approach allows us to more accurately select a control group that was completely unaffected by either flooding or wind. Fig. 1B displays our approach for Hurricane Harvey, with the blue dots indicating the flood treatment blocks, and the light grey areas showing the flood control areas. The light red areas are affected by high wind, and all other non-high wind blocks in Texas and Louisiana are controls for the wind analysis.

We use two different samples and regression approaches to estimate the effects of hurricanes on migration. First, we use an individual-level approach, where we focus on the people who lived in hurricane-affected states in the quarter the hurricane hit. We look at the 2 years before and after each storm and see how migration behavior changed after the storm hit. The individual-level approach allows us to follow people even after they have left the hurricane-affected states, giving us a better understanding of what being hit by a hurricane does to individual migration. Our second approach aggregates populations to the block group level and estimates how populations in the flood- and wind-affected block groups change in the 4 years after the storm hits. The block group approach is focused more on place-based population changes as it measures the net effect of people moving to and from the region after the hurricane.

Our individual-level approach is estimated with the following equation:

$$Y_{iq} = \alpha + \beta F_{iq} + \theta W_{iq} + \gamma_i + \tau_q + \varepsilon_{iq} \tag{1}$$

where Y_{iq} represents an indicator for individual i moving to a new address in quarter-of-sample q. F_{iq} and W_{iq} are treatment indicators that equal 1 for flooded and high wind-affected individuals after the storm hit and equals 0 otherwise, while γ_i and τ_q are individual and quarter-of-sample fixed effects. Flooded areas are weighted by the percentage of properties in a block that flooded, which captures

[3] See https://www.nssl.noaa.gov/education/svrwx101/wind/.
[4] Flood treated individuals have positive flooding in their census block. Appendix C.2 investigates the role of flood depth in migration.
[5] See Appendix A.3 for a description of our sample selection and balance statistics.

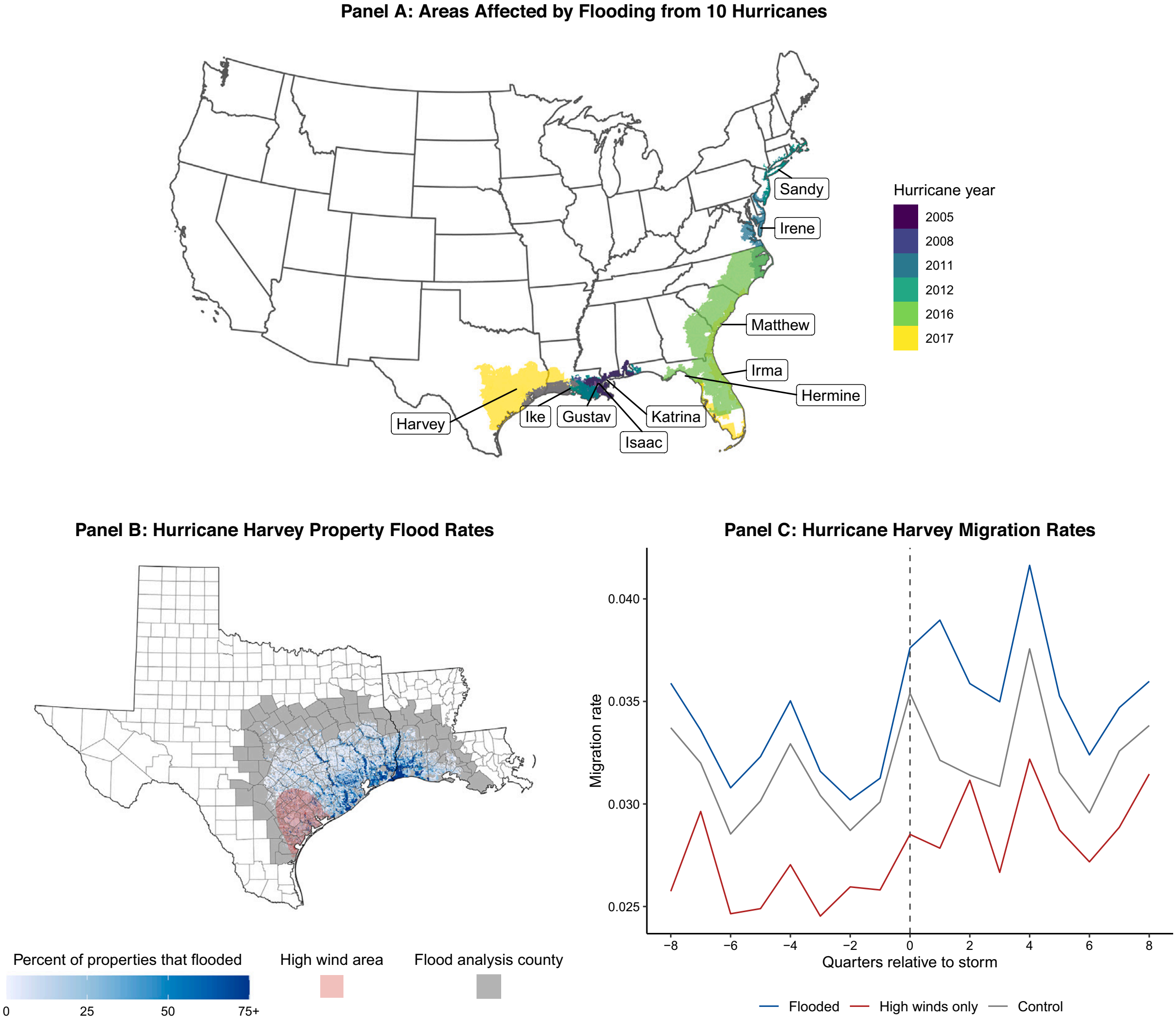

Fig. 1. Hurricanes and empirical strategy.
Notes: This figure presents the hurricanes we study and our main empirical approach. Panel A shows census tracts where at least one property in the modeled flood data is flooded by a given storm. See Appendix Fig. D.1 for the areas affected by wind. Panel B presents our empirical strategy using Hurricane Harvey as an example. Individuals are drawn from the counties in grey to obtain flood effect estimates, while individuals are drawn from the entire state to obtain high wind effect estimates. Affected census blocks are colored to show the share of properties that flooded (white to blue) or were exposed to high winds (light red) within the block. In our flooding analysis, individuals in flooded blocks are compared to individuals in control blocks (grey). In our wind analysis, individuals in high wind blocks are compared to all other non-high wind blocks in affected states. Panel C displays the average migration rates of flooded, high wind only, and control (no flooding or high winds) individuals in the flood analysis counties depicted in Panel B. The three lines show typical seasonal migration patterns and move in parallel before the storm. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

that individuals in more heavily flooded blocks are more likely to experience flooding. Standard errors are clustered at the individual level.

Our population-level approach is estimated with the following event-study specification:

$$Y_{iq} = \alpha + \sum_{k=-8}^{16} \beta_k F_i T_k + \sum_{k=-8}^{16} \theta_k W_i T_k + \gamma_i + \tau_q + \delta_i Q + \varepsilon_{iq} \tag{2}$$

where Y_{iq} is block group i's population count in quarter q relative to its pre-storm average, F_i is a *static* treatment indicator for flooded block groups that is interacted with T_k, a dummy variable that equals 1 in the kth period relative to treatment. The same is done for block groups affected by high wind. We omit the interaction term for $k = -1$, which corresponds to the quarter just before the storm hit. γ_i and τ_q are block group and quarter-of-sample fixed effects. We include block group time trends, $\delta_i Q$, to account for trends in

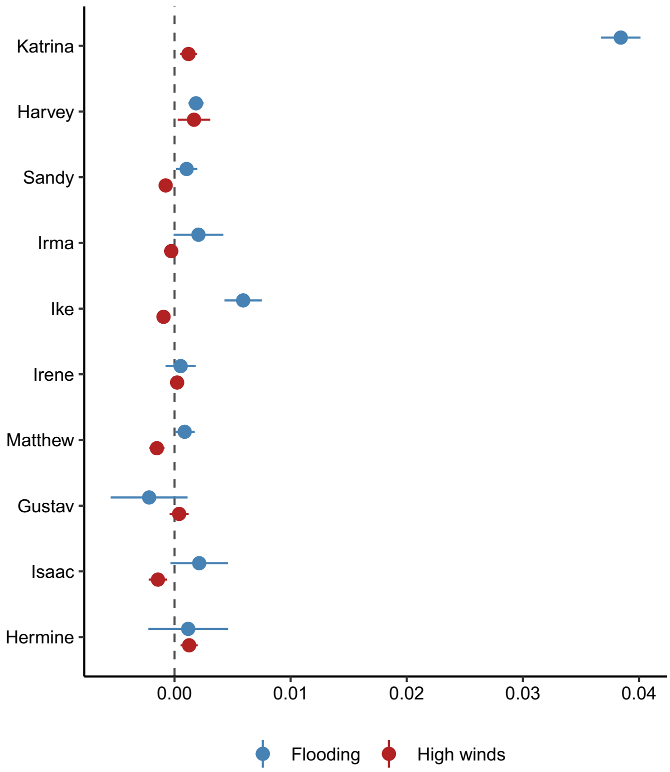

Fig. 2. Effects of flooding and high winds on short-term migration.
Notes: Regression results of Eq. (1) for the effect of flooding and high winds, estimated separately for each hurricane and ordered by storm economic damages (costliest at the top). Error bars represent 95 % confidence intervals clustered at the individual level. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

population change over time. Block groups are weighted by their pre-storm population.[6] Standard errors are clustered at the block group level.

Our identification assumption for both analyses is that in the absence of flooding or high wind exposure from a hurricane, migration rates would have evolved in parallel between treated and control individuals or block groups in impacted states. Fig. 1C shows that while migration rates exhibit a distinct seasonal pattern for individuals, they move in parallel across treated and control groups in the pre-period.[7] We use event study estimates for our population regressions to provide evidence of parallel pre-trends.

4. Results

Fig. 2 presents regression estimates separately for flooding and high wind for each hurricane, ordered by storm economic damages (costliest at the top). The figure presents regression estimates of Eq. (1) with individual-level data, showing the effects of flooding (in blue) and high wind (in red) on migration.

We find that flooding from the five costliest hurricanes in our sample caused some increase in migration in the short term. In areas impacted by Hurricane Katrina, individual migration rates increased by 4 percentage points, a 134 % increase compared to baseline. The second largest migration impacts are for Hurricane Ike, with a little less than a 0.6 percentage point increase (corresponding to a 19 % increase compared to baseline). Both Hurricanes Harvey and Sandy show small but significant increases in migration, which correspond to 5 % and 4 % increases relative to baseline, respectively. Flooding from Hurricane Gustav shows small declines in migration, which are noisy and not statistically significant.[8] Appendix C.1 analyzes how far people move, showing that most moves from flooding are out of an individual's block group and, excluding Hurricane Katrina, are within an individual's state. Appendix Fig. C.4 shows that migration effects are further concentrated in areas that had higher amounts of flooding.[9] Exposure to high wind

[6] Flooded block groups are weighted by their pre-storm population multiplied by the share of the block group that flooded, which reflects how many people in that block group experienced flooding.

[7] Fig. D.2 shows migration rates for each storm in our sample.

[8] See Appendix Fig. D.5 for a quarterly event study version of Fig. 2.

[9] An analysis that excludes temporary moves (where an individual is observed returning to a block group they lived in previously during our sample window) finds similar migration patterns.

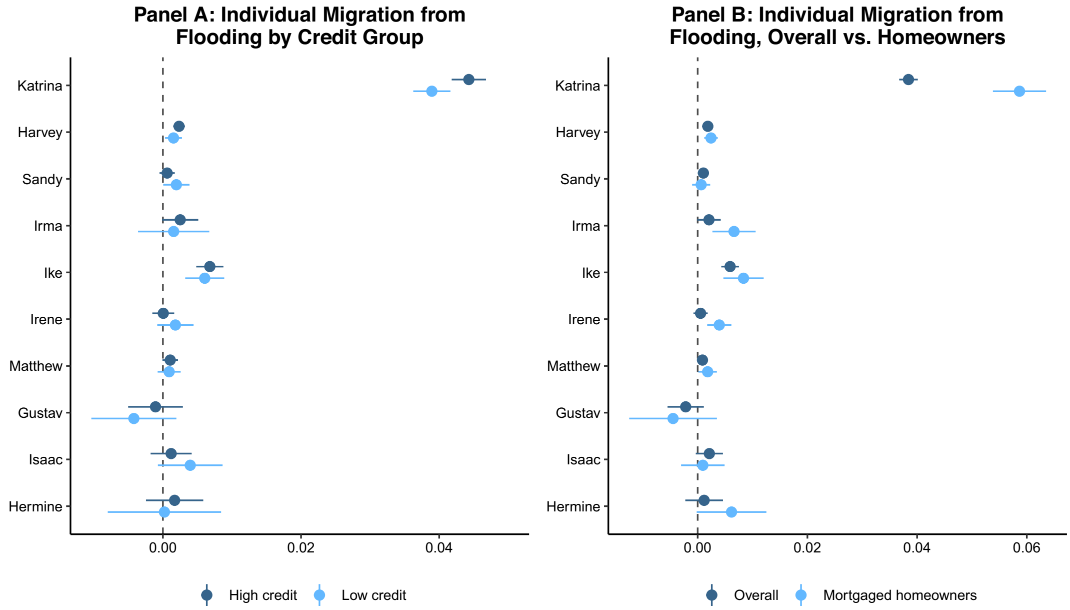

Fig. 3. Heterogeneous effects of flooding on short-term migration.
Notes: Regression results of Eq. (1) for the effect of flooding on different groups. Panel A splits the sample by average individual pre-storm credit score, with the dark blue dots corresponding to high credit (credit score ≥670) and the light blue dots corresponding to low credit (credit score <670). Error bars represent 95 % confidence intervals clustered at the individual level. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

does not meaningfully affect migration in any consistent way, with some storms causing very small increases and some even causing small decreases in migration.

Previous work found that migration responses are influenced by income (Chen and Lee, 2022; Sheldon and Zhan, 2022). To explore the role of access to credit and assets, Fig. 3 shows migration results by credit score (Panel A) and for mortgage holders (Panel B), where we estimate regressions separately within each credit score and homeownership status group.[10] Panel A shows that the migration results do not change much based on the credit score of the individual.[11] People with higher credit scores (credit scores above 670) move a little more after Hurricanes Katrina and Harvey, and a little less after Hurricane Sandy. Panel B shows that migration responses are generally higher for mortgaged homeowners compared to the overall population.[12] This finding is a bit surprising given that owning a home is a physical and economic tie to a location, and there are significant transaction costs associated with selling a home. However, it is possible that homeowners are selling their homes and moving in order to avoid future storms or potential losses in property value. The effect is largest for Hurricane Katrina, where migration was over 53 % higher for mortgaged homeowners than the overall population.[13]

Fig. 4 presents population change estimates from Eq. (2), focusing on the three costliest hurricanes. Estimates for all 10 hurricanes, including the effects of high winds, can be found in Appendix Fig. D.4. Only Hurricane Katrina caused a substantial longer-term population decline, while the other hurricanes had no meaningful impact on population. After 4 years, areas flooded by Hurricane Katrina had experienced a nearly 17 % decline in population relative to control areas. Hurricanes Harvey and Sandy, despite being the second and third costliest storms in our sample and causing significant flooding, each only led to a less-than-one percent decline in population in the flooded block groups. The areas affected by all the other storms in our study did not experience meaningful population changes (see Appendix Fig. D.4).

To better understand why some hurricanes in our sample caused increased migration in the short-run but not long-run population changes, we conduct block-group in- and out-migration analyses, which are described in Appendix B. In general, most storms that cause increased out-migration also see corresponding increases in in-migration, resulting in little to no population changes. The main

[10] Table D.1 shows pre-storm migration rates by treatment status for people with high credit scores, low credit scores, and for mortgaged homeowners. See Appendix Fig. D.3 for the effects of high wind on migration by credit score and homeownership status group

[11] Higher credit scores are generally weakly positively associated with higher incomes, although the relationship is not linear.

[12] A mortgaged homeowner is a person we observe having an active mortgage or having opened a mortgage at the same address during our sample. Mortgaged homeowners exclude renters and individuals who purchased their homes with cash.

[13] Our analysis cannot rule out the role of other factors that could affect migration including, for example, labor market conditions, local social networks, or levels of social vulnerability. We investigated the potential role of FEMA aid in migration but found that FEMA aid was likely correlated with both flood damage and wealth, making it difficult to identify whether post-disaster assistance affected migration.

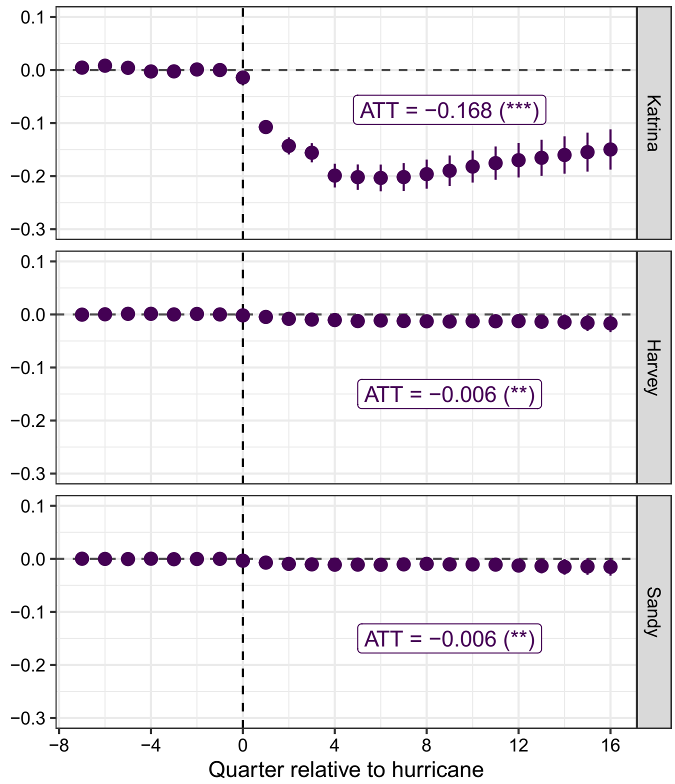

Fig. 4. Effects of flooding on block group populations over time.
Notes: This figure shows event studies of quarterly percent changes in population relative to mean pre-storm levels in areas hit by the largest three storms (Eq. 2). Error bars represent 95 % confidence intervals clustered at the block group level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

exception is Hurricane Katrina, which saw large increases in out-migration and a much smaller increase in in-migration. Over time, the mismatched out- and in-migration resulted in the significant population decline seen in Fig. 4.

Finally, to assess whether there are changes in the characteristics of the population living in flooded areas, we estimate the change in the average block group credit score after each hurricane. Fig. C.5 shows declines in average neighborhood credit scores following Hurricanes Katrina and Irma, and increases after Hurricane Harvey. Our findings are consistent with changes in neighborhood characteristics following natural disasters, which have been documented in other settings (Smith et al., 2006; Groen and Polivka, 2010; Strobl, 2011; Keenan et al., 2018; Aune et al., 2020).[14]

5. Conclusion

This paper uses credit bureau residential location data on more than 20 million American adults merged with granular flooding and wind exposure data to investigate migration responses to 10 different hurricanes. Overall, we find that hurricanes can cause small increases in migration for larger storms. In general, we find that credit score does not play a role in migration after hurricanes, with people with high and low credit migrating at similar rates following most storms.

Despite the increase in migration after some hurricanes, we do not find evidence of any meaningful long-run decline in the number of people living in flood-affected areas. Our analysis suggests that any increase in out-migration also had an associated increase in in-migration after the storm. The only exception is Hurricane Katrina, which caused large increases in out-migration without similar increases in in-migration, resulting in large population decreases.

A complete exploration of the mechanisms responsible for the lack of population declines in hurricane-affected areas is outside the scope of our analysis. However, our findings suggest that even as people leave the area, available housing will eventually become occupied via increased in-migration, even if it is in the path of future hurricanes. The lack of population declines in hurricane-affected areas means that reducing future construction in vulnerable areas may be the most effective approach to reducing how many people are exposed to hurricanes.

[14] See Appendix C.3 for a discussion of which groups are driving the compositional changes.

CRediT authorship contribution statement

Joshua Blonz: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Formal analysis, Conceptualization. **Spencer Bowdle:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis, Data curation. **Joakim A. Weill:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Data construction

Appendix A.1. First street foundation data

We use simulated historical flooding and wind data from the First Street Foundation (FSF) Flood Model and Wind Model (First Street Foundation, 2024). These data contain property-level information on exposure to a number of historical disaster events. FSF simulates historical flooding events and validates them using high water mark data from river and tidal gauges, flood claims from the National Flood Insurance Program, grants from FEMA's Individual Assistance program, and loans from the Small Business Administration.[15] The historical wind data are expressed as the speed in miles per hour experienced by a property over a sustained 1-minute period. FSF uses the National Oceanic and Atmospheric Administration's International Best Track Archive for Climate Stewardship dataset to determine experienced wind speeds in hurricane tracks. The FSF data provide information on whether each of the over 140 million geocoded U.S. properties in their data was flooded by each hurricane (including the simulated inundation depth), and the wind speed experienced at that property. We use the property coordinates to measure the share of properties in a census block or census block group with positive flood depth (in contrast, wind speed generally does not vary within a block), and calculate the average inundation depth at the block level.

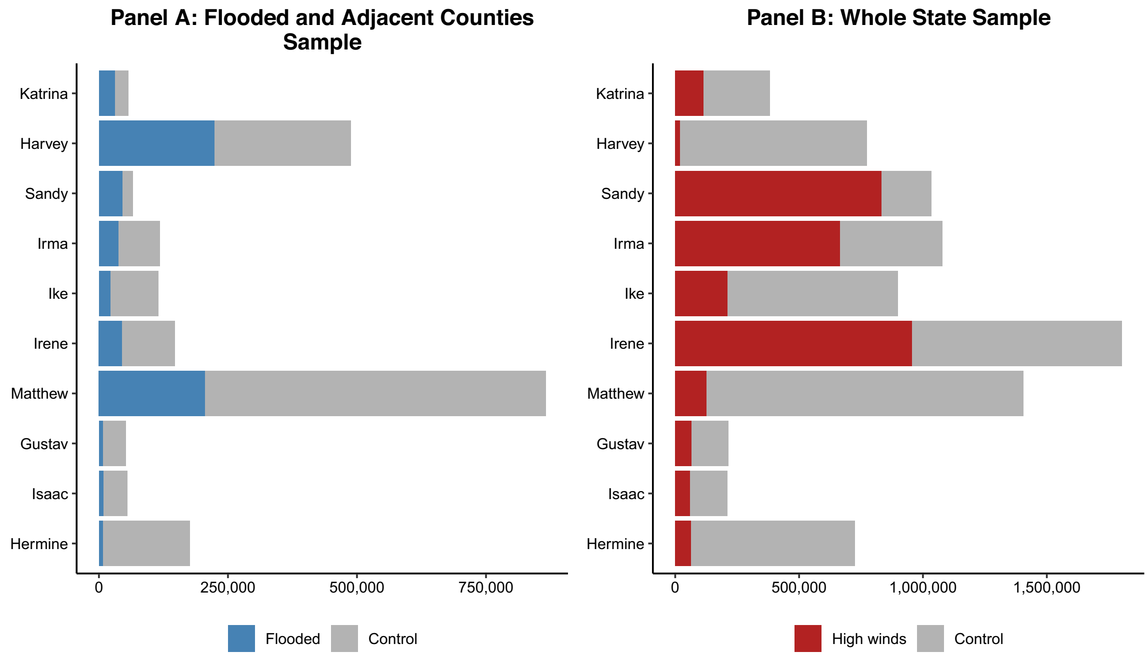

Fig. A.1. Individual counts by treatment status.
Notes: This figure displays the count of unique individuals by treatment status represented in our regressions for each storm. Panel A shows counts of flooded and control (no flooding or high winds) individuals in our sample pulling from flooded and flooding-adjacent counties. Panel B shows counts of high wind-exposed and control individuals in our sample using entire states that contain flooding. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

[15] FSF only models historical floods large enough to receive federal disaster declarations (to ensure that high water mark and claims data exist), and which have high water mark data considered reliable enough for validation.

Table A.1
Wealth comparison among flooded and adjacent counties.

Hurricane	Homeowner status			Pre-storm credit score			Median household income (tract, 2000)		
	Flooded	Control	p-value	Flooded	Control	p-value	Flooded	Control	p-value
Katrina	0.16	0.16	0.88	661	657	0.00	37,214	36,825	0.00
Harvey	0.25	0.22	0.00	685	679	0.00	52,853	44,014	0.00
Sandy	0.26	0.31	0.00	715	715	0.99	57,784	53,347	0.00
Irma	0.27	0.24	0.00	722	687	0.00	47,528	39,392	0.00
Ike	0.22	0.21	0.00	672	666	0.00	41,114	37,681	0.00
Irene	0.30	0.32	0.00	711	694	0.00	53,614	51,745	0.00
Matthew	0.28	0.25	0.00	693	688	0.00	44,816	42,958	0.00
Gustav	0.24	0.20	0.00	683	668	0.00	42,480	38,661	0.00
Isaac	0.29	0.23	0.00	691	673	0.00	44,330	34,663	0.00
Hermine	0.24	0.25	0.22	709	694	0.00	40,905	40,026	0.00

Notes: This table displays mean values of three measures of wealth for flooded and control (no flooding or high winds) individuals in our sample pulling from flooded and flooding-adjacent counties, as well as corresponding t-test p-values between the two groups. Columns 2–4 correspond to homeownership status, defined as 1 for individuals who are mortgaged homeowners at the time of the hurricane. Columns 5–7 correspond to individuals' average credit score over the 2 year pre-storm period. Columns 8–10 correspond to median household income of the census tract individuals live in at the time of the hurricane, taken from the 2000 Decennial Census. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel, First Street Foundation Flood Model and Wind Model, and U.S. Census Bureau. Authors' own calculations.

Our analysis focuses on the 10 costliest hurricanes that hit the contiguous United States between August, 2005 and September, 2017.[16] Hurricane Rita (September 2005) and Hurricane Maria (September 2017) are not included because they mostly impacted the Bahamas and Puerto Rico, which we do not consistently observe in the CCP data. We exclude Hurricane Wilma (2005) from the analysis due to difficulties in finding a reasonable control group for the areas affected in southern Florida. While the 10 hurricanes we study include the costliest to hit the contiguous US during this time period, they caused a wide range of damages: Hurricanes Gustav, Isaac, and Hermine, the three least costly hurricanes in our analysis, caused $8.6 billion, $3.8 billion, and $715 million in damages (expressed in 2024 dollars), respectively.

Appendix A.2. Consumer Credit Panel

The Federal Reserve Bank of New York/Equifax Consumer Credit Panel (CCP) is a quarterly, individual-level dataset that contains information on people's credit and loan histories, including their Equifax Credit Risk Score and outstanding mortgage balance (Federal Reserve Bank of New York/Equifax Consumer Credit Panel, 2024). The dataset contains a nationally representative, random, anonymized 5 % sample of adults with a social security number and a credit report (see Lee and van der Klaauw (2010) for details). The CCP also includes geographic information, such as census block, scrambled address, address type (street, high rise building, Post Office box, etc.), and ZIP Code. The address and ZIP Code variables come from Equifax and are selected via an algorithm as the individual's most likely mailing address based on the addresses reported by individual creditors. Address data are reliably available starting in 2003.

The CCP data is only representative of individuals with a social security number and a credit report. Individuals without a social security number are undocumented immigrants, certain ineligible resident aliens, and individuals who did not report their credit score to their lenders. In addition, we do not observe individuals without a credit score. These "credit invisible" individuals tend to be poorer than the average population (US Government Accountability Office, 2021). The CCP also does not include people under the age of 18, and in general is not as representative for people under the age of 24 who are less likely to have a credit history. Our analysis is therefore based on a sample of individuals that is likely wealthier than the average population, and our results cannot speak to the specific constraints faced by credit invisible individuals or undocumented immigrants.

Despite these shortcomings, work by DeWaard et al. (2018) demonstrates the CCP's ability to produce aggregate migration results similar to those obtained from existing data from the American Community Survey, Current Population Survey, and Internal Revenue Service. In addition, we do observe many individuals with low credit scores in the CCP—restricting the analysis to this population allows us to investigate the role of access to credit in migration.

Appendix A.3. Sample selection

For a given hurricane, we define an individual as treated by flooding if their block experienced positive inundation depth. Similarly, people are considered treated by high wind if their block experienced wind speeds greater than 50 mph during the hurricane. We have separate control groups for our flood and wind regressions. In the flood regression, the control group comprises individuals who did not experience flooding but lived in either counties that experienced flooding or in adjacent counties at the time of the hurricane.[17] The counts of individuals in the flooded treatment and control groups can be seen in Fig. A.1A. For the wind treatment, the control group consists of all the blocks in the hurricane-affected states that did not experience high winds. We expand our control group

[16] See https://www.ncei.noaa.gov/access/billions/dcmi.pdf.

[17] We thank two anonymous referees for suggesting the use of adjacent counties as a control group.

beyond adjacent counties in order to include unaffected areas. The counts of individuals in the wind treatment and control groups can be seen in Fig. A.1B.

Appendix Table A.1 presents balance statistics between the flood treatment and control groups for each storm. The first three columns show that homeownership rates are relatively similar between the treatment and control areas, although they vary across storms. The middle three columns compare credit scores between the treatment and control groups. In general, the treated areas have slightly higher credit scores on average. The last three columns show the median household income using 2000 census tract-level data. The income statistics should be interpreted with caution, because these are census tract-level statistics and people are assigned the median income of their census tract. The area affected by Hurricane Katrina has meaningfully lower average incomes than any other storm-affected area, which, along with the extent of the flooding, could have potentially contributed to the high levels of migration.

Appendix Table A.2 shows historical storm exposure between the treatment and control individuals. The measures of exposure are defined as the number of years (for different time ranges) during which the individual's county at the time of the storm experienced a hurricane based on FEMA disaster declarations data.[18] Columns 2–4 present this measure for the range of years that includes our 10 storms (2005–2017) while columns 5–7 present this measure for the 20 years prior to the corresponding storm (e.g., 1985–2004 for Hurricane Katrina). The analysis shows that our treatment and control individuals have relatively similar hurricane exposure over our sample window and in the 20 years before a storm.[19] These findings suggest that our empirical strategy of comparing affected areas to neighboring counties is likely comparing individuals with similar types of hurricane exposure.

Appendix B. Census block group migration regressions

We estimate migration regressions at the census block group level to better understand the dynamics of population-change after a hurricane. We use the same sample as the population analysis in Eq. (2), but instead calculate the in-migration rate, out-migration rate, and net out-migration rate for each census block group in a hurricane-affected state.[20] We limit the sample to the 2 years before and after each storm and estimate the following equation for each hurricane:

$$Y_{iq} = \alpha + \beta F_{iq} + \theta W_{iq} + \gamma_i + \tau_q + \varepsilon_{iq} \tag{B.1}$$

where Y_{iq} is either the in-migration rate, out-migration rate, or net out-migration rate for block group i in quarter q. F_{iq} and W_{iq} are treatment indicators that equal 1 for flooded and high wind-affected individuals after the storm hits and equals 0 otherwise, and γ_i and τ_q are unit and quarter-of-sample fixed effects. Standard errors are clustered at the block group level. Block groups are weighted by their pre-storm population. Flooded block groups are weighted by their population multiplied by the share of the block group that flooded to approximate how many people in that block group experienced flooding.

The results from estimating Eq. (B.1) can be seen in Appendix Fig. B.1. Changes in in-migration, out-migration, and net out-migration are shown in green, orange, and grey, respectively. The results show flooding increased net out-migration for Hurricanes Katrina and Harvey (Panel A). In most cases, increases in out-migration are offset by some increase in in-migration, which causes

Table A.2
Hurricane exposure comparison among flooded and adjacent counties.

Hurricane	Years with storm (county, 2005–2017)			Years with storm (county, prior 20 years)		
	Flooded	Control	p-value	Flooded	Control	p-value
Katrina	4.3	3.7	0.00	4.9	5.0	0.06
Harvey	3.7	3.6	0.00	4.7	4.5	0.00
Sandy	2.0	2.0	0.00	1.7	1.7	0.00
Irma	3.9	3.6	0.00	5.9	4.6	0.00
Ike	3.9	4.0	0.00	5.3	5.5	0.00
Irene	2.5	2.2	0.00	2.1	2.5	0.00
Matthew	2.9	2.9	0.00	3.9	3.9	0.19
Gustav	4.2	4.4	0.00	5.6	5.4	0.00
Isaac	4.2	4.0	0.00	6.9	6.1	0.00
Hermine	4.0	4.0	0.00	5.8	5.5	0.00

Notes: This table displays mean values of two measures of hurricane exposure for flooded and control (no flooding or high winds) individuals in our sample pulling from flooded and flooding-adjacent counties, as well as corresponding t-test p-values between the two groups. Columns 2–4 correspond to the number of years during our period of study (2005–2017) when the individual's county experienced a storm, where the individual's county is the one in which they lived during the hurricane in column 1. Columns 5–7 correspond to the number of years during the 20 years prior to the hurricane in column 1 when the individual's county experienced a storm, e.g., during the years 1985–2004 for Hurricane Katrina. Historical exposure is determined using the FEMA disaster declarations data. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel, First Street Foundation Flood Model and Wind Model, and FEMA. Authors' own calculations.

[18] FEMA disaster declarations data taken from https://www.fema.gov/openfema-data-page/disaster-declarations-summaries-v2.

[19] The small p-values reflect large sample sizes rather than meaningful differences in historical storm exposure.

[20] We calculate in-migration, out-migration, and net out-migration rates by dividing the amount of people that in-migrated, out-migrated, and the difference (net out-migration) each quarter by the block group population in the previous quarter.

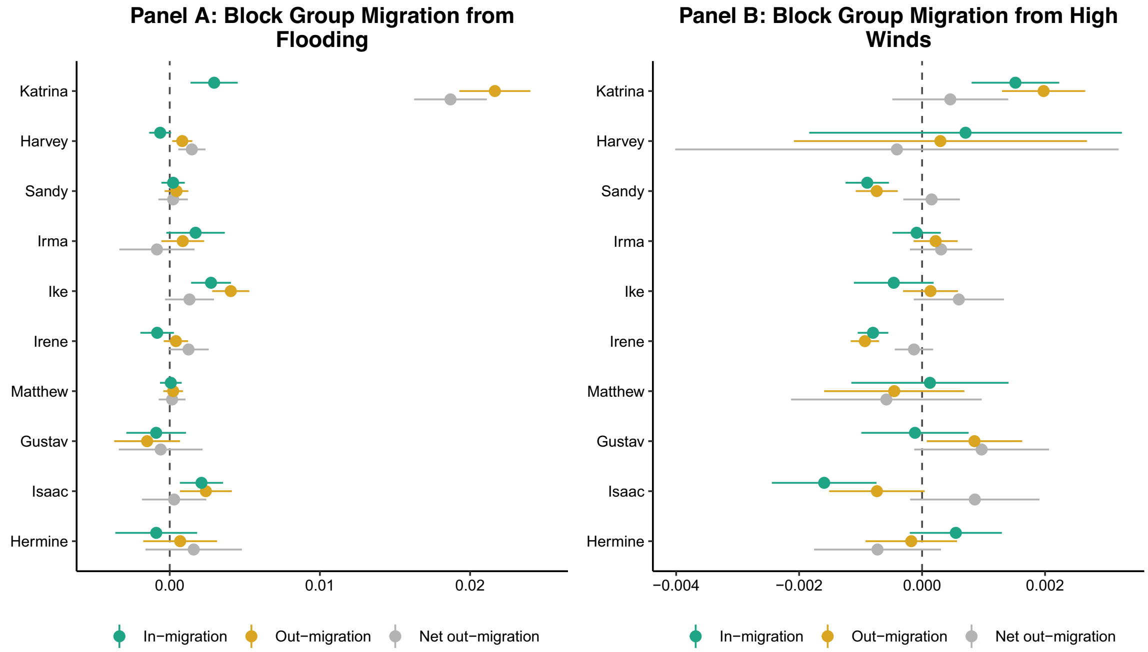

Fig. B.1. Effects of hurricanes on block group-level migration.
Notes: Regression results of Eq. (B.1) for the effect of flooding and high winds, estimated with census block group data. Panel A focuses on flooding, while Panel B focuses on high wind exposure. The figure shows estimated effects on in-migration (green dots), out-migration (orange dots), and net out-migration (grey dots) for block groups exposed to flooding or high winds in the eight quarters after a hurricane. Error bars represent 95 % confidence intervals clustered at the block group level. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

limited changes in net out-migration. This finding reflects that even if people move away from hurricane-affected areas, other people tend to move in. It is also possible that some people returned to flood-affected areas after moving away, which we are not able to identify with this approach. Appendix Fig. B.1B shows the effects of wind on block group migration. The results are much smaller: no significant net out-migration effects and changes to in- and out-migration rates of less than 0.004.

We want to note that the results are not expected to directly align with the individual-level migration regressions in Fig. 2 because they are measuring slightly different things. The individual-level regressions measure what happens to the people who lived in the flooded area at the time of hurricane. The block group regressions measure what happens to the flooded block groups compared to control block groups. By construction it includes people who moved into the affected areas after the storm. However, despite the differences, the increases in both out-migration and in-migration provide evidence as to why migration generally did not result in population declines.

Appendix C. Robustness tests

Appendix C.1. Move distance

The CCP data allow us to observe domestic moves of any distance, because we can see both the census block someone lives in and their scrambled street address. In the main analysis we define a move as an individual changing their street address, even if it is within the same census block. In Fig. C.1, we test three alternative definitions of migration and compare them to our main results, which are reproduced with grey dots. Panel A separates moves that are within versus out of a given block group, showing that the overwhelming majority of moves are out of a person's block group. Panel B separates moves that are within versus out of a given county, and shows that while some of the moves stay within county, many moves also involve people migrating out of their county. Finally, Panel C separates moves that are within versus out of state, showing that most moves, excluding moves after Hurricane Katrina, are within a person's state. Overall, these findings show that moves generally are out of a person's block group but include moves within a county, out of the county, and to a much lesser extent out of an individual's state.

Appendix C.2. Flood depth and migration

Our analysis treats flooding as a binary indicator for a census block experiencing any positive amount of flooding. We weight an individual in the regression by the share of their block that flooded to capture the fact that people in more heavily flooded blocks

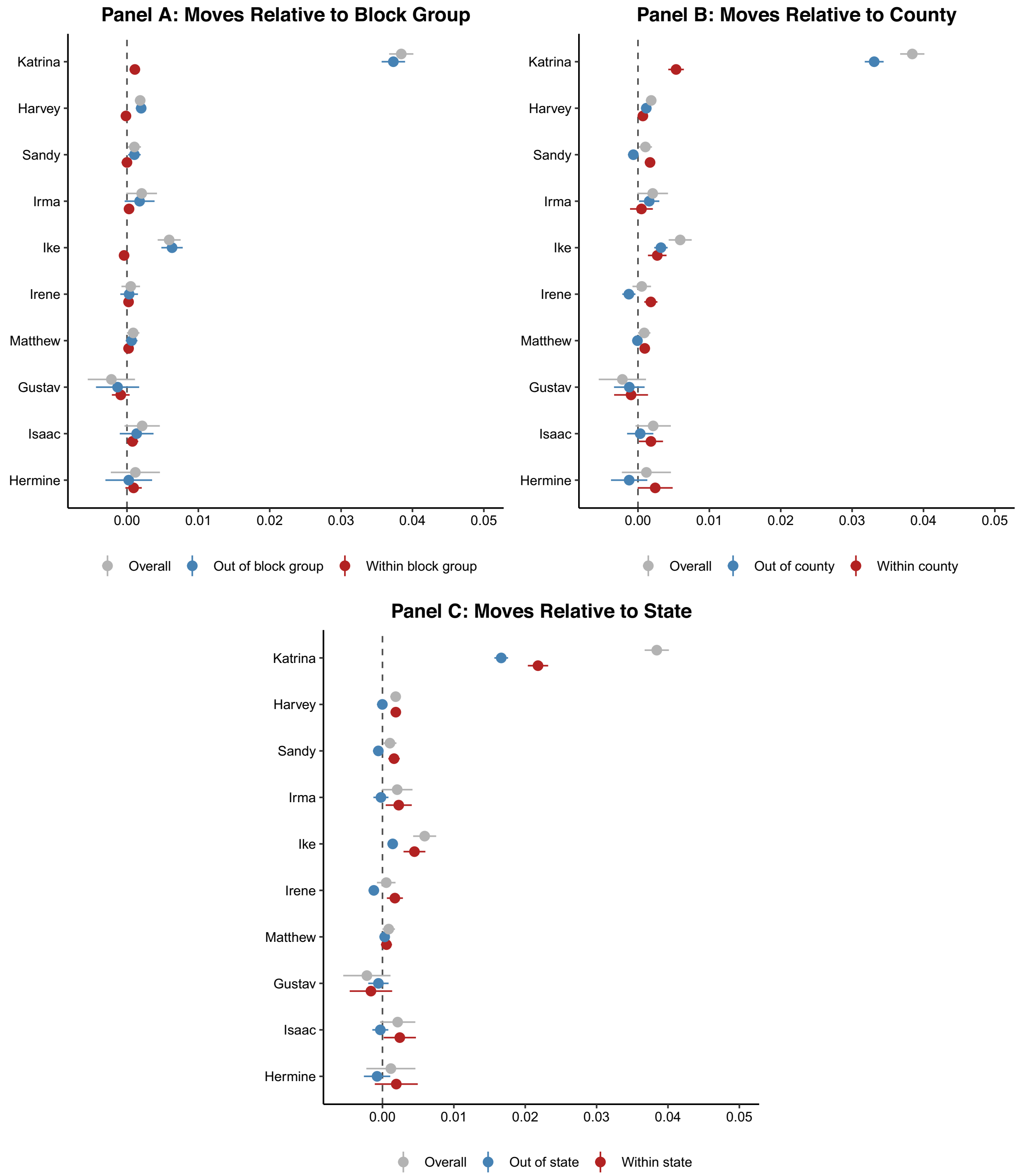

Fig. C.1. Effects of flooding on migration relative to previous location.
Notes: Regression results of Eq. (1) with varying definitions of migration based on the individuals' origin and destination locations. Panels A, B, and C separate migrations that are within vs out of a given block group, county, and state, respectively. In all three panels, the grey dots represent overall migration (i.e., the flooding estimates from Fig. 2), the blue dots represent moves out of the given area type (e.g., moves where the new county is different from the previous county), and the red dots represent moves within the given area type. Error bars represent 95 % confidence intervals clustered at the individual level. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

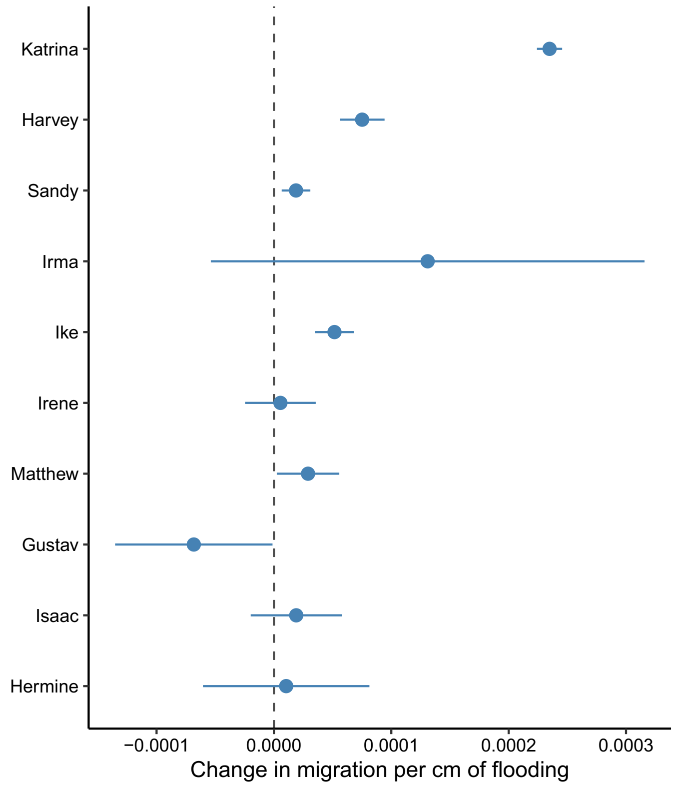

Fig. C.2. Effects of flooding on short-term migration using continuous flooding measure.
Notes: Regression results of Eq. (1) with a continuous version of the flood treatment variable (measured in centimeters) instead of a binary treatment indicator. Error bars represent 95 % confidence intervals clustered at the individual level. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

are more likely to experience flooding.[21] To better understand the relationship between flood depth and migration, in this section we estimate our results using a continuous treatment measure, where the flooding variable is expressed in cm of inundation depth. The results, shown in Appendix Fig. C.2 show a similar pattern to our overall results in Fig. 2.

Appendix Fig. C.3 shows the distribution of flood depths for each of the 10 storms studied. The distribution of flood depths helps interpret Appendix Fig. C.2 and shows that Hurricane Katrina has higher amounts of flooding than any other storm. There is also significant variation across storms, with some storms causing high amounts of flooding for large populations, and other storms primarily causing lower levels of flooding.

To better understand the role of treatment intensity, Appendix Fig. C.4 estimates the effect of flooding on migration separately for people who experienced high depth flooding of at least 6 inches (15.24 cm) and lower depth flooding of less than 6 inches.[22] The results show that higher flood depths appear to cause more migration, which is consistent with our previous finding that flooding (rather than high wind exposure) is responsible for migration effects. The results also show that for Hurricanes Harvey and Matthew, most of the migration effects come from areas with high depth flooding. Fig. C.3 shows that both of these storms had large numbers of people who did not experience high amounts of flooding.

Appendix C.3. Population composition changes

To explore the role of flooding on the composition of people in impacted areas, we estimate Eq. (2) with block group average credit scores as the outcome. Fig. C.5 shows that the average credit score for the flooded areas does change after some hurricanes, but not others. The area impacted by Hurricane Katrina experiences a decline in average credit scores, which returns to the pre-storm

[21] Our block-level assignment of flood exposure, based on property-level estimates of inundation depths, improves upon the existing literature which tends to use county-level hurricane exposure (a county contains around 1963 blocks on average).

[22] We chose 6 inches of flooding as our cutoff judgmentally and based on the flood depth histograms in Appendix Fig. C.3. We believe it is a high enough depth to reasonably assume damages to ground-level properties while being low enough to have a sufficient number of "high depth" individuals for each storm. Defining high and low flood depth based instead on the storm-specific median value of inundation depth produces very similar results.

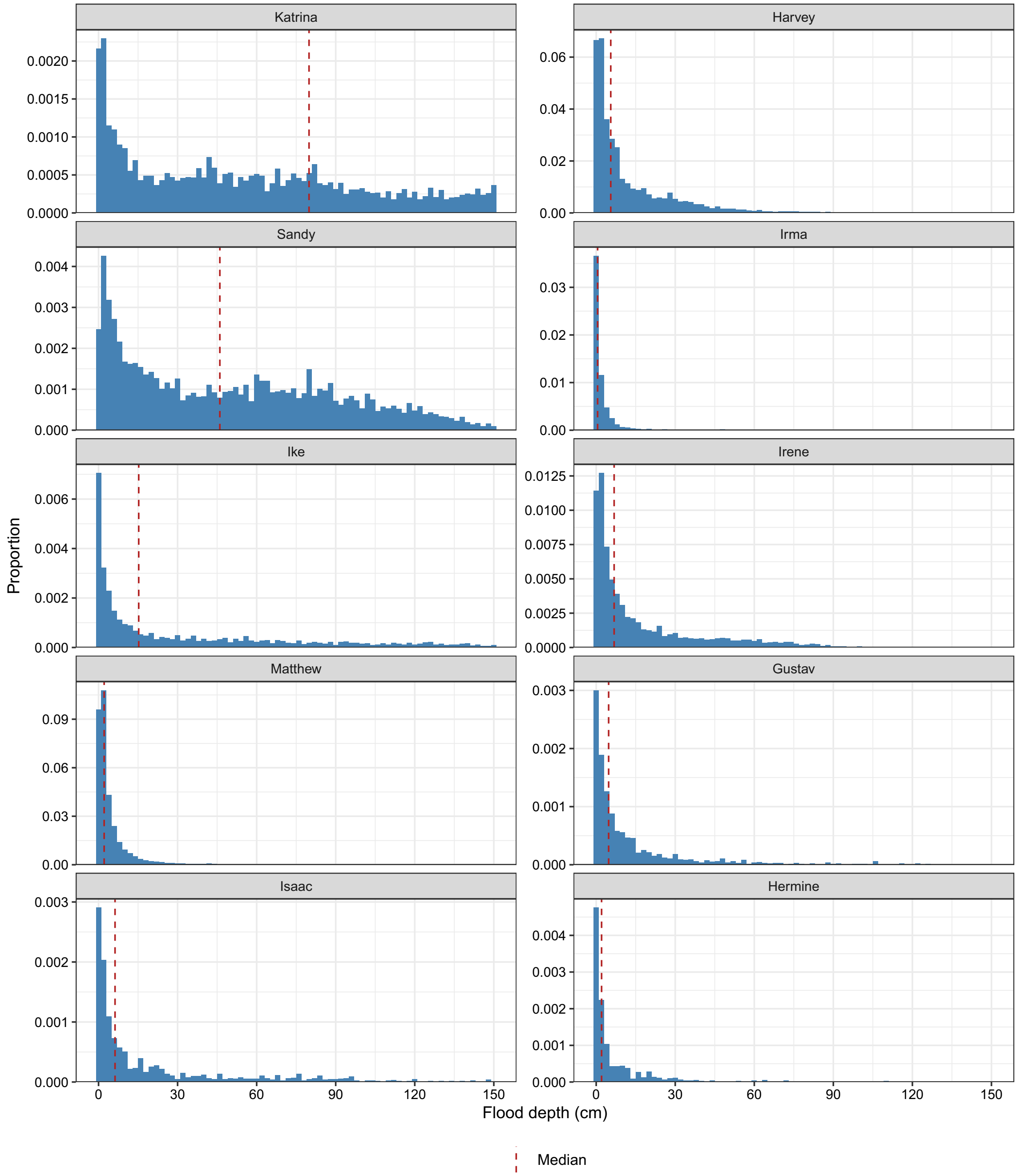

Fig. C.3. Distribution of flooded individuals' census block flood depths.
Notes: Histograms showing the distributions of flood depths (in centimeters) attributed to flooded individuals in our analysis. The ranges in these histograms have been truncated to a maximum value of 150 cm to better display the variation across storms, though the actual maximum values for some storms (particularly Hurricane Katrina) are much higher than 150 cm. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

average by 9 quarters after the storm. There are also increases in average credit scores post Hurricane Harvey and some declines post Hurricane Irma, while other areas impacted by other storms do not experience substantial changes in average credit scores.

To better understand what is driving these changes in average credit scores, Fig. C.6 shows the block group-level share of the population in each credit score bin by storm. We split people into three credit bins: below good credit (<670), good credit (between 670 and 740) and above good credit (≥740). We define these bins based on credit score prior to the storm to avoid conflating compositional changes with potential direct effects of the storm on individual-level credit scores. The coefficients should be interpreted as the change in the share that a credit bin makes up in an area relative to its average pre-storm share.

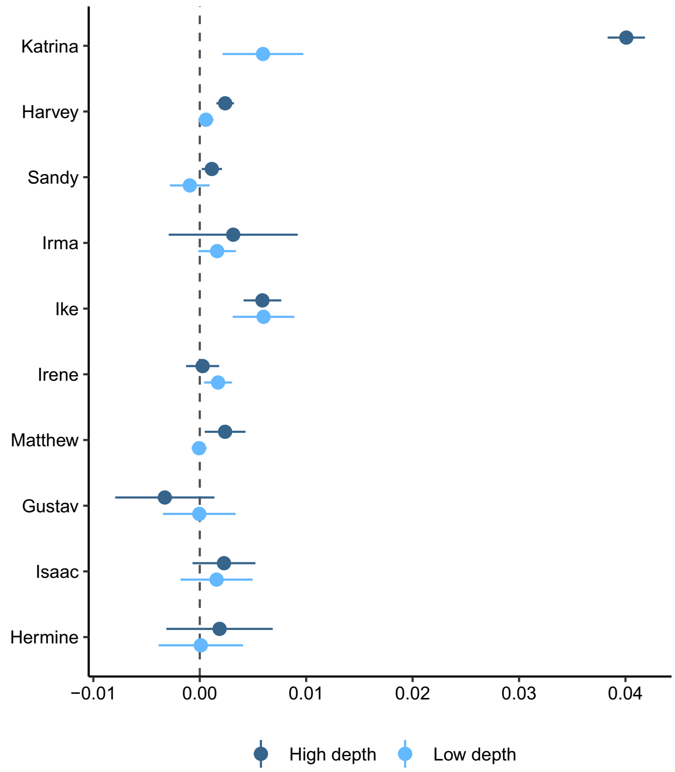

Fig. C.4. Effects of flooding on short-term migration by flood depth.
Notes: Regression results of Eq. (1) are presented separately for flooded individuals who experience high inundation depth (dark blue dots), defined as a depth of at least 6 inches (15.24 cm), and for flooded individuals who experience low inundation depth (light blue dots, inundation depth lower than 6 inches). The control group is the same for both sets of flooded individuals. Error bars represent 95 % confidence intervals clustered at the individual level. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

The results show that for Hurricane Katrina, the temporary reduction in credit scores was driven by a relative increase in the share of people with below good credit and a relative decrease in the share of people with good and above good credit. For Hurricane Harvey, the increase in block average credit scores is due to a relative decrease in the share of people with below good credit moving into the flooded areas.

The explanations for why there is a decline in credit scores after Hurricane Irma (and, although much noisier, for Gustav) are less clear. Hurricane Irma shows an increase in the share of people who have below good credit, although none of the quarterly estimates are statistically significant. The areas affected by Hurricane Gustav experience a relative increase in people with good credit compared to above good credit, which could contribute to the average decline, but the results are not strong enough to be conclusive.

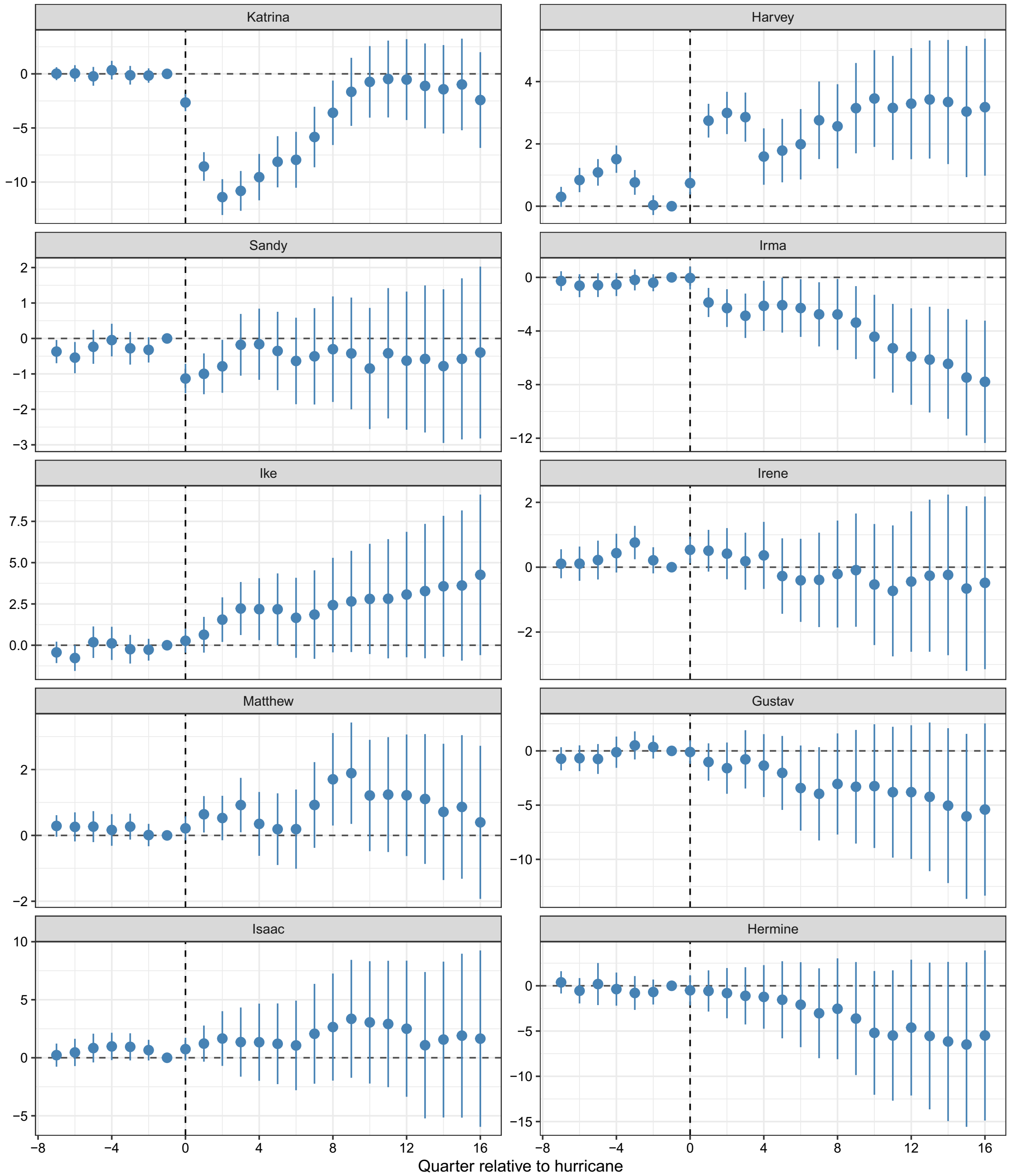

Fig. C.5. Effects of flooding on block group average credit scores over time.
Notes: Quarterly event study regression results of Eq. (2) using block group average credit score relative to the pre-storm mean as the outcome. Error bars represent 95 % confidence intervals clustered at the block group level. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

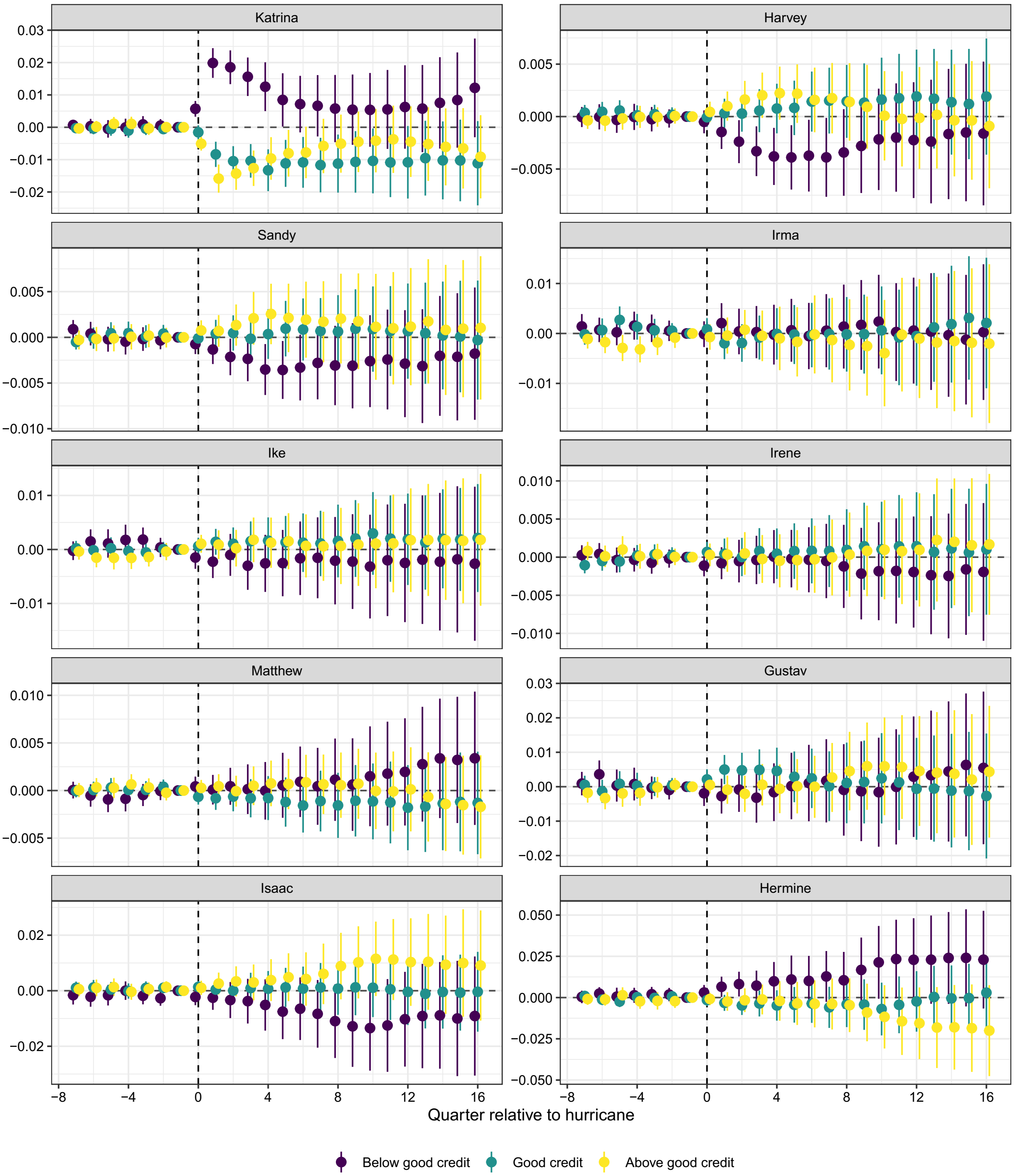

Fig. C.6. Effects of flooding on block group population shares by credit score over time.
Notes: Event studies of quarterly percent changes in block group population relative to mean pre-storm levels (Eq. 2) for three different populations based on their average pre-storm credit score: below good credit (credit score <670), good credit (credit score ≥670 and <740), and above good credit (credit score ≥740). Error bars represent 95 % confidence intervals clustered at the block group level. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

Appendix D. Additional figures

See Table D.1 and Figs. D.2–D.5.

Table D.1
Pre-storm migration rate comparison among flooded and adjacent counties.

Hurricane	Overall			High credit			Low credit			Mortgaged homeowners		
	Flooded	Control	*p*-value	Flooded	Control	*p*-value	Flooded	Control	*p*-value	Flooded	Control	*P*-value
Katrina	0.029	0.030	0.00	0.024	0.023	0.24	0.038	0.042	0.00	0.029	0.030	0.35
Harvey	0.034	0.031	0.00	0.029	0.026	0.00	0.049	0.045	0.00	0.023	0.022	0.00
Sandy	0.026	0.023	0.00	0.025	0.021	0.00	0.035	0.034	0.42	0.015	0.010	0.00
Irma	0.036	0.036	0.73	0.032	0.029	0.00	0.058	0.056	0.02	0.024	0.022	0.00
Ike	0.031	0.032	0.04	0.023	0.025	0.00	0.045	0.045	0.67	0.026	0.029	0.01
Irene	0.028	0.027	0.00	0.025	0.021	0.00	0.040	0.039	0.28	0.016	0.013	0.00
Matthew	0.033	0.032	0.00	0.028	0.026	0.00	0.049	0.049	0.68	0.021	0.020	0.00
Gustav	0.030	0.034	0.00	0.022	0.027	0.00	0.046	0.047	0.41	0.026	0.032	0.00
Isaac	0.025	0.025	0.59	0.017	0.016	0.48	0.040	0.038	0.19	0.014	0.014	0.95
Hermine	0.036	0.033	0.00	0.031	0.026	0.00	0.059	0.053	0.00	0.021	0.021	0.89

Notes: This table displays mean values of pre-storm migration rates for flooded and control (no flooding or high winds) individuals in our sample, as well as corresponding *t*-test *p*-values between the two groups. Columns 2–4 correspond to all individuals in this sample, columns 5–7 correspond to high credit individuals, columns 8–10 correspond to low credit individuals, and columns 5–7 correspond to mortgaged homeowners. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

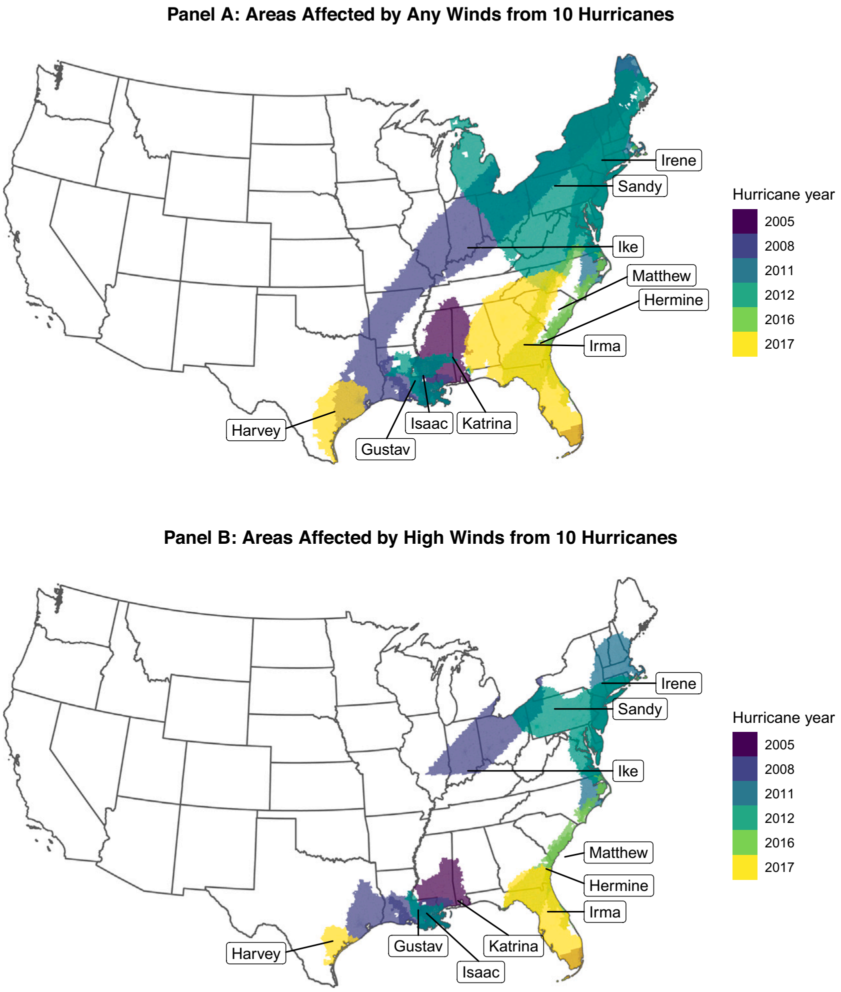

Fig. D.1. Wind exposure for each hurricane.
Notes: Panel A shows census tracts where at least one property in the modeled wind data experienced wind for a given storm, while Panel B only shows census tracts experiencing high winds (above 50mph). *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Wind Model. Authors' own calculations.

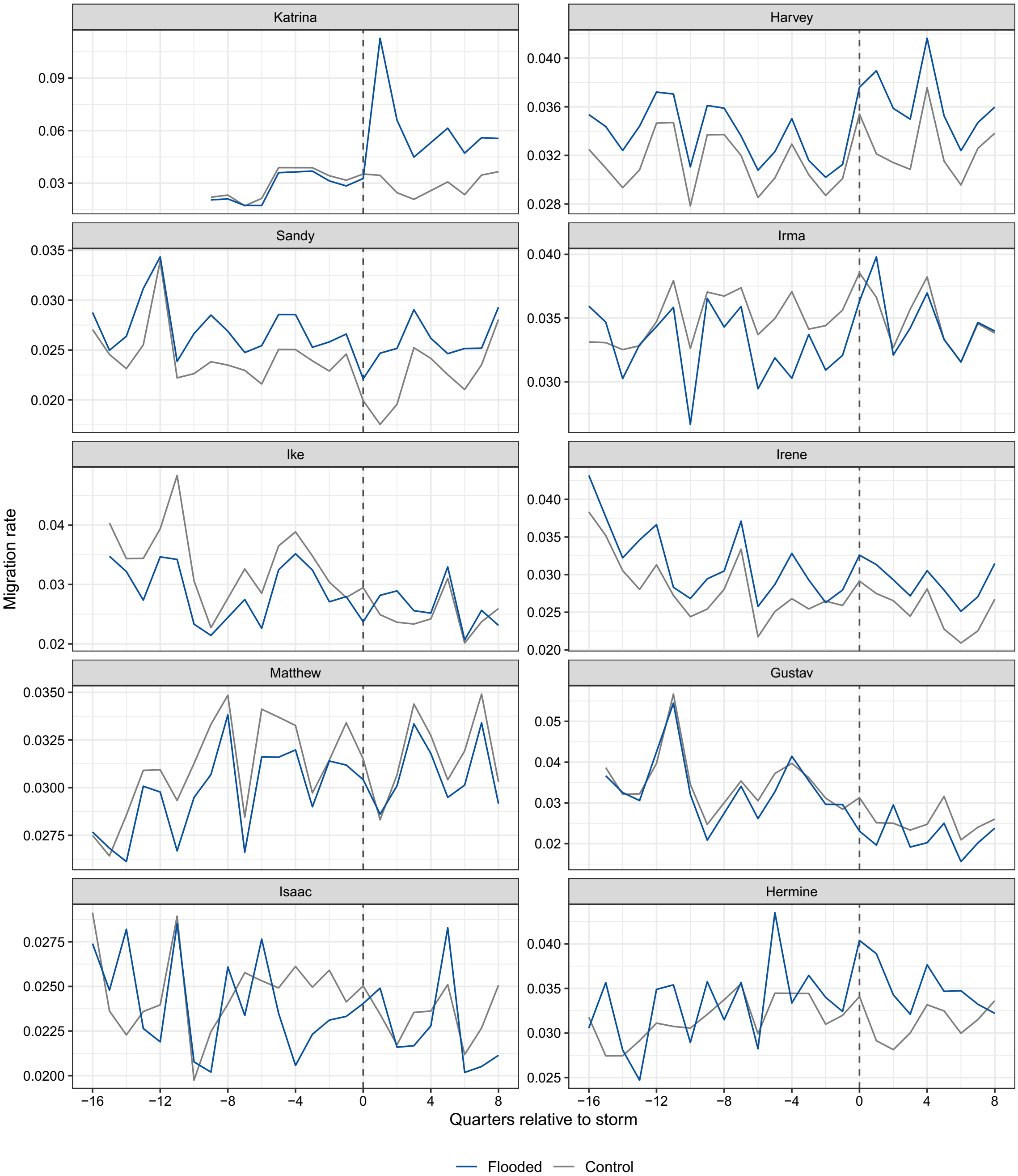

Fig. D.2. Average individual migration rates by storm.
Notes: This figure displays the average migration rates of flooded and control (no flooding or high winds) individuals in the flood and adjacent counties sample for each storm. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

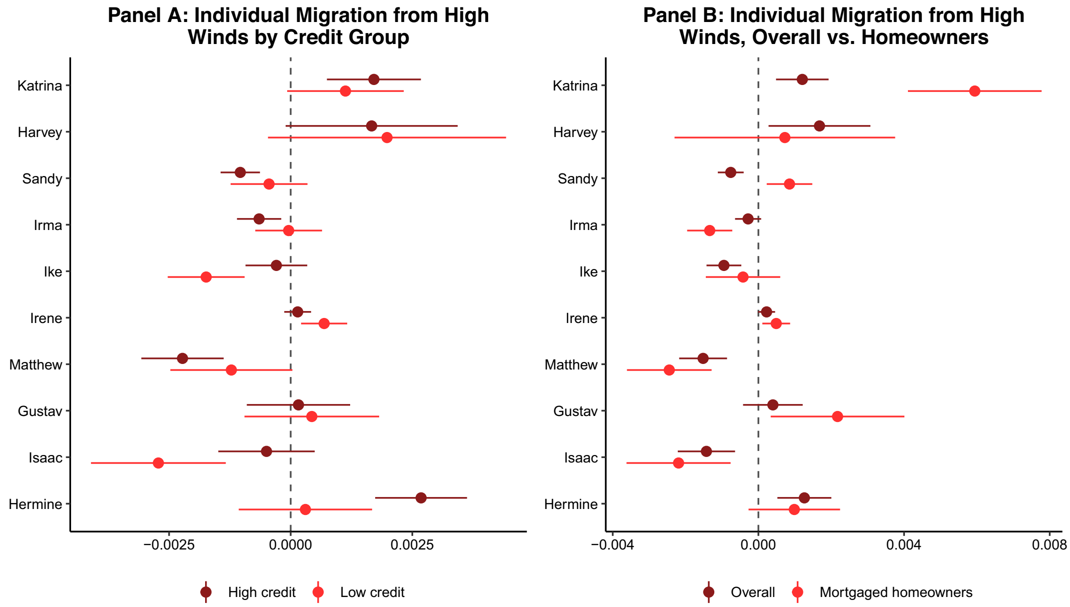

Fig. D.3. Heterogeneous effects of high winds on short-term migration.
Notes: Regression results of Eq. (1) for the effect of high winds, estimated separately for each hurricane and ordered by storm economic damages (costliest at the top). Error bars represent 95 % confidence intervals clustered at the individual level. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

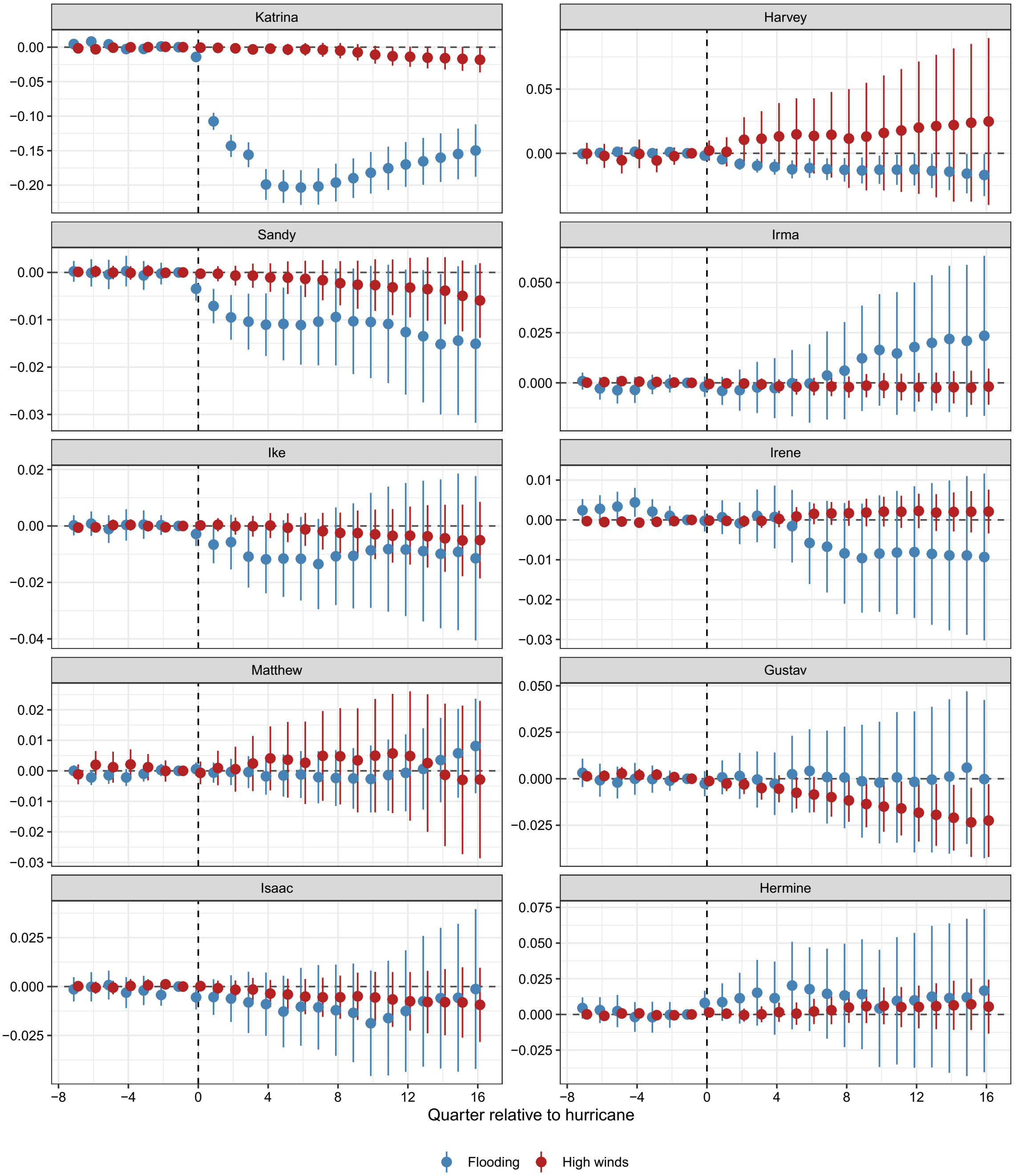

Fig. D.4. Effects of flooding and high winds on block group populations over time.
Notes: Event study estimates of Eq. (2) for quarterly changes in population at the block group level. The *y* axis is expressed in population count relative to the pre-storm period. Error bars represent 95 % confidence intervals clustered at the block group level. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

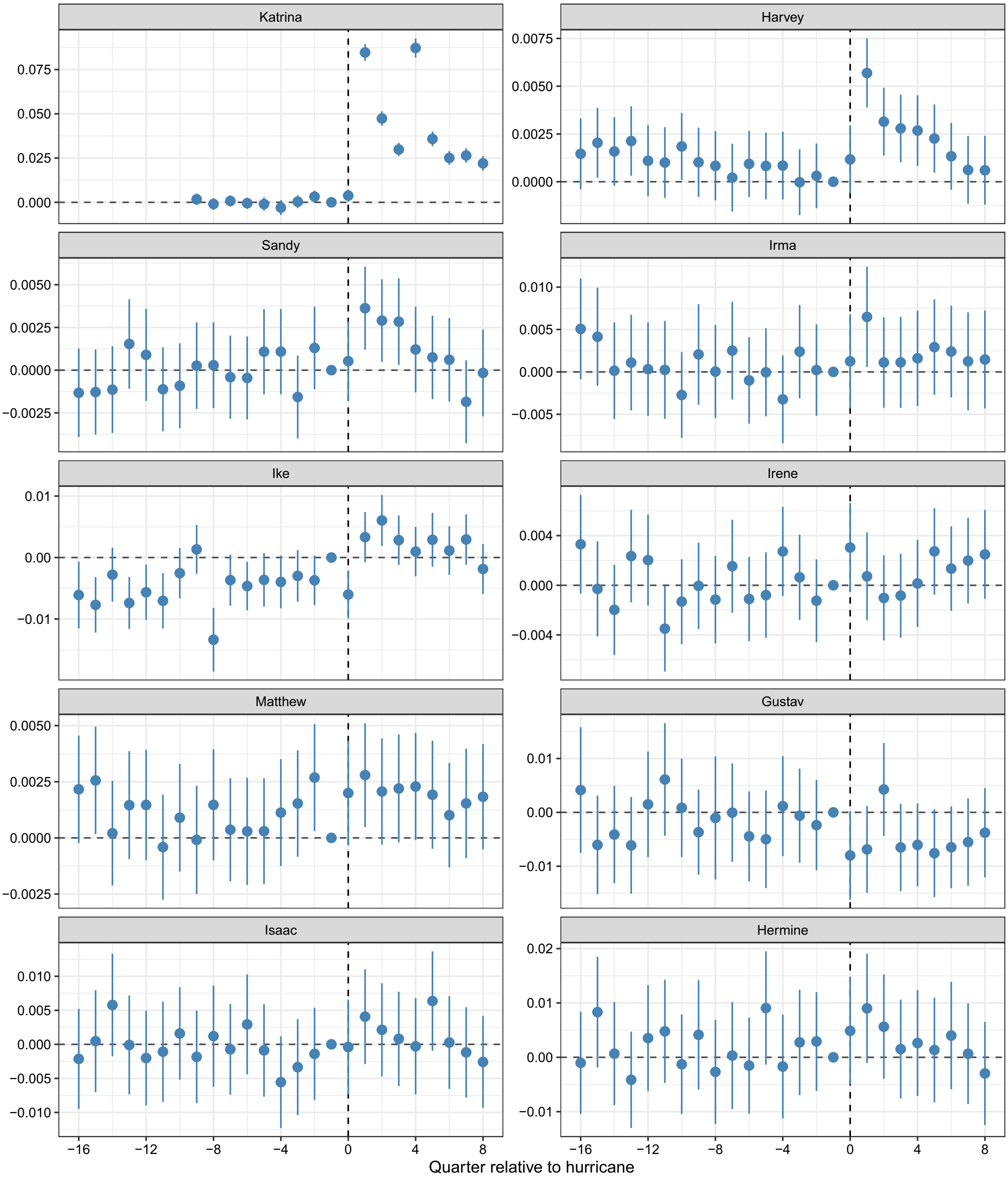

Fig. D.5. Effects of flooding on migration over time.
Notes: Quarterly event study of our migration results for flooded individuals. Error bars represent 95 % confidence intervals clustered at the individual level. *Source:* Data from Federal Reserve Bank of New York/Equifax Consumer Credit Panel and First Street Foundation Flood Model and Wind Model. Authors' own calculations.

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