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Mahieu, Jeroen

KU Leuven

8 February 2020

Online at <https://mpra.ub.uni-muenchen.de/98864/>
MPRA Paper No. 98864, posted 08 Mar 2020 08:27 UTC

Creative Destruction? Local Business Conditions, Firm Age, and Wages.

JEROEN MAHIEU^{*}

Draft: February 28, 2020

Abstract

While a growing literature has examined the relationship between economic shocks and job creation in startups and established firms, little is known about the quality of these jobs. In this paper, I examine how fluctuations in local business conditions affect the wages of employees at startups and incumbent firms. I identify shocks to local business conditions using plausibly exogenous variation of hurricane strikes in U.S. coastal counties. I find that wages of startup employees increase substantially in response to negative shocks to local business conditions, while there is only a small raise in old firms. This effect does not appear to be driven by changes in supply or demand for labor. These findings are consistent with “cleansing” theories of downturns.

Keywords: Startups; Employee Compensation; Local Business Conditions; Entrepreneurship

JEL Codes: J21; J31; L26

^{*}KU Leuven, Department of Management, Strategy and Innovation (MSI), email: jeroen.mahieu@kuleuven.be. I thank Francesca Melillo for valuable comments and feedback. I gratefully acknowledge financial support of the Research Foundation Flanders (FWO) under grant number 11B3219N.

I Introduction

Evidence from various countries and time periods has shown that entrepreneurs and new ventures play a critical role in total and net job creation (Criscuolo et al., 2014; Haltiwanger et al., 2013, 2017). Furthermore, a growing theoretical and empirical literature has emphasized the importance of new and young firms for the responsiveness of economies to exogenous economic shocks (Clementi and Palazzo, 2016; Sedláček and Sterk, 2017; Pugsley and Sahin, 2019). At the micro level, Adelino et al. (2017) find that startups account for the bulk of newly created jobs following changes in investment opportunities driven by increases in local demand. Similarly, Decker et al. (2017) find that in the wake of an oil and gas boom, newly founded business establishments contribute disproportionately to job creation.

While these studies focus on the *quantity* of jobs created by firms of different ages following local economic shocks, little is known about the *quality* of these jobs, and in particular, their wages. This is surprising, given that theoretical models of firm dynamics provide opposing predictions regarding the impact of economic shocks on earnings. On the one hand, negative aggregate shocks may increase barriers to entry and increase the opportunity costs of exit, discouraging entry (and survival) of low-quality, low-paying firms (Clementi and Palazzo, 2016). As a result, this selection effect can have a persistent positive impact on average wages within cohorts of firms, if these firms continue in operation for extended periods of time¹. On the other hand, worsening business conditions may decrease earnings and job quality in startups if they reduce the incentives of (aspiring) entrepreneurs to found ventures with high growth potential (Sedláček and Sterk, 2017), increase the exit rate of young and potentially productive firms before they learn their productivity (Ouyang, 2009), or when there are credit-market frictions (Barlevy, 2003). Hence, a better understanding of how firms adjust to local economic shocks – including potential variation across firms of different ages – informs policy makers about the

¹This is similar to a process of “creative destruction” as first described by Schumpeter (1942), in which downturns foster a more efficient allocation of resources by “cleansing” out less efficient job matches, and redirecting resources to more productive arrangements (e.g. Caballero and Hammour, 1994, 1996; Hall, 2005; Osotimehin and Pappadà, 2017)

determinants of vibrant economies and holds implications for models of firm dynamics.

One reason for why the relationship between business conditions and earnings is not well understood is the paucity of plausibly exogenous variation in economic output. This is because if the quantity and quality of new and established ventures and the jobs they create positively affects the local economy (Koellinger and Thurik, 2012; Pugsley and Sahin, 2019), simply regressing economic output on earnings will produce spurious outcomes. It is also possible that (unobserved) underlying economic forces stimulate both average on-the-job earnings and output simultaneously, leading to issues of omitted-variable bias. To overcome these challenges, I develop an empirical strategy that exploits plausibly exogenous shocks to local business conditions, giving rise to variation in output. By comparing how wages in startups adapt compared to those in established firms, I identify one channel through which firms of different ages create jobs of differing qualities.

In particular, using data for the U.S. retail sector that span all quarters in the period between 2000-2015, I estimate earnings and employment changes in startups and established firms in coastal counties in the years following a hurricane strike. I employ a differences-in-differences framework, comparing counties that experience a hurricane between 2000 and 2015 with those that do not, to estimate how fluctuations in business conditions affect the wages of individuals working for startups and existing firms. The identifying assumption is that, following Baker and Bloom (2013) and Barrot and Sauvagnat (2016), hurricane strikes are negative (temporary) first-moment shocks to output for firms in the retail sector. Importantly, this variation is exogenous to any local entrepreneurial activity, which resolves the reverse causality problem in analyzing the link between entrepreneurship and economic growth.

I find that, on average, the wages of employees in the retail sector increase following a hurricane. This effect is most pronounced for new ventures: the earnings of employees in startups increase on average by circa 12 percent 0-1 years after a hurricane, compared to an increase of only 3 percent of 11 years or older, and no apparent change for firms aged between 2 and 10 years old. This positive effect of a negative shock to the local economy on wages in startups also appears to persist several years after a hurricane

strike. Furthermore, I find similar results when I only look at the wages of new hires. Importantly, this positive effect does not seem to be driven by changes in employment or gross job flows in startups. Furthermore, analyses for firms of different sizes indicate that the increase in earnings in startups is not driven by differences in size between young and old firms.

I cannot replicate these results for individuals working in the professional, scientific, and technical services sector. This is in line with the idea that firms in this sector are less prone to the destructive impact of a hurricane than firms in the retail sector, because for the last the location of the business is non-fungible. Finally, the findings are robust to expanding the sample to all counties in Atlantic coastal states and to a variety of econometric specifications.

Linking them back to theory, these results support “cleansing” theories of economic downturns. In particular, while negative shocks to local business conditions do not seem to have an impact on the quantity of jobs created (or destroyed) by new and established ventures, they seem to have a compositional effect in the sense that they stimulate the creation and sustenance of more productive job arrangements, assuming wages are increasing in the inherent productivity of a job.

This paper contributes to a number of distinct literatures in entrepreneurship and economics. First, previous studies investigating differences in wages between young and old firms have mostly focused on the characteristics of startup employees (Burton et al., 2018; Kim, 2018; Brown and Medoff, 2003; Brixy et al., 2007), those of the ventures they join (Michelacci and Quadrini, 2009), or simultaneous worker and firm selection (Babina et al., 2019). My findings indicate the importance of considering the role of the broader economic context in explaining earnings of startup employees. Second, I contribute to the literature on the role of startups in how an economy responds to economic shocks (Adelino et al., 2017; Decker et al., 2017, 2018; Bernstein et al., 2018). While most of the papers in this literature focus on positive shocks, this papers considers negative shocks to local business conditions. This research is also related to the nascent literature measuring the impact of natural disasters on firm dynamics (e.g. Basker and Miranda, 2018; Elliott

et al., 2019). In particular, while studies on the impact of natural disasters on the aggregate economy in the U.S. have provided mixed results (Belasen and Polachek, 2009; Strobl, 2011; Deryugina, 2017; Deryugina et al., 2018), the results in this paper suggest that aggregate effects may mask important variation at the industry- or even firm-level.

2 Background and Data

2.1 Hurricane Exposure

Between 2000 and 2015 hurricanes caused more than \$345 billion damages in the U.S., with hurricane Katrina alone causing \$125 billion in damages, being the costliest hurricane to ever strike the United States². Furthermore, global warming, and increasing sea surface temperature have shown to be positively related to an increase in both the number and intensity of hurricanes in the Atlantic-basin since 1995 (Webster et al., 2005). By 2015, 60 million inhabitants of the U.S. were at risk to be hit by a hurricane³.

The empirical strategy in this paper relies on local business conditions shocks caused by hurricane strikes in the U.S. . Hurricanes that affect the United States are tropical cyclones that form over the Atlantic Ocean. When warm winds blow over the ocean’s surface, large cumulonimbus clouds are formed. When these clouds start to circulate around a center it becomes a cluster of thunderstorm clouds, called a “tropical disturbance”. Depending on the conditions, winds in the storm cloud column will spin faster and faster, circulating around the “eye”, or calm center, of the storm, which is typically 20-50 kilometers in diameter. Just outside of the eye, a dense wall of thunderstorms – the “eyewall” – surrounds the eye with the strongest winds within the storm. Tropical cyclones are strongest when they are situated above the ocean, and usually weaken quickly when they hit land, because they are no longer being fed by the energy from the warm ocean waters. Hence, counties close to the coast experience the strongest impact.

²Estimates from: <https://www.nhc.noaa.gov/dcmi.shtml>

³“Growth on the Coast”, US Census (06/06/2016): http://www.census.gov/library/visualizations/2016/comm/cb16-ff10_hurricane_coastlinecounties.html

Because typically only the geographic area relatively close to the coast is affected by hurricanes, I focus in the analysis on U.S. coastal counties in the North Atlantic-basin region. The National Oceanic and Atmospheric Administration (NOAA) considers a county to be a Coastal Watershed County if, at a minimum, 15 percent of the county’s total land area is located within a coastal watershed or it comprises at least 15 percent of a coastal cataloging unit. In total, these are 426 counties over 19 states. As a robustness check, in Section 4.4 I expand the sample to all counties within these coastal states.

North Atlantic cyclones are classified by their maximum sustained surface wind speed (peak one-minute wind at the standard meteorological observation height of 10 m over unobstructed exposure). Cyclones with one-minute sustained winds that exceed 33 m/s (64 kn) are categorized as a hurricane on the Saffir-Simpson hurricane wind scale. I will use this cutoff value to determine whether a county is exposed to a hurricane in a certain quarter or not. As shown by Deryugina (2017), counties that experience hurricane-strength winds incur substantial structural damage to buildings, and destruction of inventory, contrary to neighboring counties that do not experience winds of hurricane strength. Although the damage caused by a hurricane depends on both wind-speed, flooding/excess rainfall, and storm surge, a commonly adopted assumption in the literature is that the latter two effects, which are much more difficult to model, are highly correlated with wind speed and therefore wind speed serves as a good proxy for the potential damage due to a hurricane strike (Emanuel, 2011).

To track which counties are exposed to a hurricane in a certain quarter, I use the `stormwindmodel` software package developed by Anderson et al. (2018) to calculate maximum sustained wind speeds at the population mean center locations for all U.S. counties for all quarters between 2000 and 2015. As a starting point, I use 6-hourly location and maximum wind speed information from the Hurricane Data second generation (HURDAT2) “Best Track” hurricane track data from the National Hurricane Center⁴ for all Atlantic-basin tropical storms between 1988 and 2015, and impute it to 15-minute intervals. This imputation uses a natural cubic spline, with the degrees of freedom set as the

⁴Available from: <https://www.nhc.noaa.gov/data/#hurdat>

number of timed observations for the storm in the input data divided by two. Based on the imputed location and intensity data, the software allows users to model wind speeds at grid points in the United States using a model for wind speed developed by Willoughby et al. (2006). This model is a family of piecewise continuous parametric profiles where the profile wind is proportional to a power of radius inside the eye and decays exponentially outside the eye with a smooth transition across the eyewall. Based on information about the hurricane’s center, and the maximum wind and its radius, the model converts position and intensity into a geographical distribution of winds. As shown by Willoughby et al. (2006), this model is preferred over the commonly used model of Holland (1980) where the wind decreases too rapidly with distance from the maximum both inside and outside the eye. Furthermore, this approach of estimating wind speeds at different geographical locations is more conservative than the approach of Deryugina (2017) who assumes that all counties located within the estimated maximum wind speed radius (MWSR) experience the maximum sustained wind speed occurring within the circulation of the system, regardless of their distance to the center of the hurricane⁵.

As an illustrative example, Figure 1 plots the estimated track and wind speeds at the population mean centers in all U.S. counties for hurricane Katrina, which made landfall in Florida and Louisiana in August 2005. Katrina made its first landfall as a Category 1 hurricane on the Saffir-Simpson scale, with maximum sustained winds of 36 m/s, near the borders of Miami-Dade and Broward counties on August 25. Once back over water, it quickly gained in size and strength and made again landfall near Buras, Louisiana on August 27, heading northward. Katrina weakened rapidly after moving inland over southern and central Mississippi, turning into a tropical storm by August 30. The direct economic impact of Katrina was substantial, most notably in the counties that experienced the strongest winds, and accompanying storm surge. These are depicted in dark red in Figure 1. Katrina severely damaged or destroyed workplaces in and around

⁵In fact, a comparison with the data of Deryugina (2017) revealed that her estimated wind speeds are substantially higher than those derived from the model of Willoughby et al. (2006), especially for counties further away from the center of the hurricane. While it is difficult to say which approach is more reliable, this highly suggest that the approach used in this paper is more conservative, and less prone to “false positives”; i.e. labeling a county as being hit by a hurricane-level wind speeds when this is in fact not the case.

New Orleans, and caused widespread power outages. Also, key transportation routes were disrupted or cut off by the hurricane (Knabb et al., 2011).

Between 2000 and 2015, 2 to 14 hurricanes formed over the Atlantic Ocean each year, with an average of 7 per year. However, not all of these make landfall at hurricane strength. 17 storms caused hurricane-strength wind speeds in at least one county, with an average of 6 counties being hit by one hurricane. Furthermore, the sample period contains eight years in which no counties were hit by a hurricane. In particular, in the years 2000, 2001, and 2015 there are no hurricane strikes, which implies that I observe at least two years before a hurricane, and one year after the hurricane, for all counties that were at some point affected. This is important for the empirical strategy explained in section 3.

Figure 2 shows the geographic distribution of hurricane strikes between 2000 and 2015 for the sample of coastal counties using the above described methodology. In total, 76 coastal counties were hit at least once by a hurricane during the sample period (9 counties were hit twice). The white-colored counties are the unaffected coastal counties that will serve as the control group. The grey-colored area are the non-coastal counties in the 19 coastal states. Only 11 non-coastal counties were hit by a hurricane between 2000 and 2015, reaffirming the notion that hurricanes mostly affect the area near the coast.

2.2 Economic Data

The primary building block of the empirical analysis is publicly available county-level data from the U.S. Census Quarterly Workforce Indicators (QWI) for the retail sector (NAICS codes 44-45). The QWI is derived from the Longitudinal Employer-Household Dynamics (LEHD) linked employer-employee data, which covers 95% of U.S. private jobs, and provides information regarding employment and wages as well as job and worker flows – hires, separations, and turnover – for firms in the private sector⁶. In the main analysis

⁶The coverage of the QWI increases over time. The data covers 18 states in 1995, 42 in 2000 (the first sample year in this paper), and all 50 states plus the District of Columbia in 2015 (the last year I consider). In 2000 the data covers 15 of the 19 coastal states. By 2003 all coastal states are included in the focal sample, except for Massachusetts which is included only since 2011.

of the paper, I rely on data reported for five different firm age categories (in years): 0-1, 2-3, 4-5, 6-10, 11+.

I focus on the retail sector for several reasons: First, it represents a very large share of the local economies in the area of interest, much larger than manufacturing. Second, unlike many other service industries and some non-service industries (e.g., construction), retail firms are likely to suffer significant disruptions in activity due to the physical damage caused by the hurricane. It might be that they trigger power outages, damage buildings and inventories, or prevent employees from reaching the workplace, disrupting activity. Whereas a lawyer may continue to provide legal services, retail firms need to cease operations when the firm is damaged or even destroyed, or because of supply chain disruptions (see for example Basker and Miranda (2018) for evidence regarding the destructive impact of hurricane Katrina on activity in the non-tradable sector, and Barrot and Sauvagnat (2016) for the negative impact of natural disasters on sales and output of non-financial firms). Finally, firms in the retail trade sector mostly serve local demand. Demand for products in other sectors such as manufacturing may extend beyond the local area, depending on the size of the business and in ways that I cannot observe.

Wages are measured as average monthly earnings of employees with stable jobs (*Earns*). This measure reflects the earnings of workers who worked for a full quarter at the same firm, i.e., workers who were registered at the same firm on the first and the last day of a certain quarter. Hence, workers who intermittently change firms are also included, but this is likely to be a very small number of people. *EarnHiras* captures the average earnings of newly hired stable employees; workers who started a job that turned into a job lasting a full quarter. That is, it reflects the average monthly earnings of full-quarter employees who started working with a firm in the previous quarter. It is important to note, however, that full-quarter does not equal full-time, but will also include the wages of part-time or temporary workers (as long as the duration of the contract is longer than 3 months). All wages are reported in 2015 U.S. dollars. Employment is measured as the total number of stable jobs, i.e., the number of jobs that are held on both the first and last day of the quarter with the same employer for firms in each age

category (*Emps*). Because *Emps* only measures the *level* of employment, but provides no information about job *flows*, I also use variables on the quarterly number of workers who started or separated from a job in each county-firm age category. To analyze gross job gains, I examine the number of full-quarter jobs gained at firms (*Frmjbgns*). This measure counts the total full-quarter employment increase at firms that grew over the course of the quarter. Gross job destruction (*Frmjblss*) is calculated in the same way and counts employment decrease at firms that shrank over the course of the quarter.

One advantage of the QWI is that the unit of analysis to construct the aggregated measures is at the worker-firm-quarter level. This means that a new establishment will only be labeled as a startup when it is a separate legal entity, and not a newly formed establishment of an existing firm. Furthermore, this also implies that the employment flow measures solely reflect organic changes in job creation and destruction, and not those which are a result of mergers, acquisitions, and other types of reorganization activity.

I supplement the QWI data with information about counties' population and workforce in the year 2000 (i.e., before any county is affected by a hurricane) from several other sources. Data about a county's total population, and working population, defined as the ratio of the population aged 15-64 to the total population, comes from the Surveillance Epidemiology and End Results (SEER) population database. Information about land area comes from the Census Bureau Summary Files. Data about the total number of workers employed, the amount of retail establishments, and average wages in the retail sector come from the County Business Patterns (CBP). From this data I also construct measures of population density, measured as the number of inhabitants per square mile, and business density, measured as the number of retail establishments per square mile.

2.3 Summary Statistics

In Table 1, I compare characteristics of counties that do and do not experience at least one hurricane during the sampling period for the year 2000 (before any county is affected). While there are no differences in total population between the two groups, hurricane affected counties have a slightly lower percentage of working population (population aged

15-64). Furthermore, hurricane counties are larger, but have on average a population density that is five times lower than non-hurricane counties, although the mean difference for the last is not significant. This is likely because the distribution of population density for non-hurricane counties is highly right-skewed due to densely populated counties in the state of New York. The same appears to be true for the number of retail establishments per square mile. There are no apparent differences in terms of total employment and average wages in the retail sector.

Differences in levels are not problematic for estimation because I include county fixed effects in every specification. However, differences in levels may indicate differences in trends. To minimize concerns about differences in pretrends, I try to control for these differences by interacting the initial county characteristics reported in Table 1 with a quarter dummy to allow for differential effects over time (Acemoglu et al., 2004; Hoynes and Schanzenbach, 2009). To maintain a consistent sample across different outcomes, I require that *Earns*, *EarnHiras*, *Emps*, *Frmjbgns*, and *Frmjblss* are not missing in each county-quarter-firm age observation.

Table 2 reports summary statistics for the main variables of interest for coastal counties included in the QWI data, split up by firm age category. On average, monthly earnings of employees with stable jobs in the retail sector equal \$1886. Consistent with the findings of previous studies, startup employees earn less than their counterparts in incumbent firms: the average wage in new firms (0-1 years-olds) equals \$1640, compared to \$1900 for employees in old firms (11+ years-olds); a difference of 14 percent. However, when turning to the wages of new hires, a different picture emerges: individuals who start working for new firms earn the highest starting wages of all employees, equaling on average \$1340. On the contrary, the oldest firms pay the lowest starting wages of \$1189. These results suggest that at least part of the wage differences between startups and established firms are the results of positive returns to firm tenure, and, hence it will be important in the multivariate analysis to follow to also focus on the wages of new hires to control for this factor.

When looking at employment, we see that, on average, circa 8752 individuals are

employed in the retail sector across firms of all ages, although the employment distribution is highly right-skewed: the median county has 2036 individuals working in the retail sector. The statistics on job creation and destruction indicate that the retail sector in U.S. coastal counties is growing: on average, 396 jobs are created each quarter while 361 are destroyed. When we break down the results by firm age, several notable differences occur. First, old firms account for the overwhelming majority of employment: firms over 11 years of age employ on average 7387 individuals per county, or 84% of total employment, while new firms (0-1 years-old) account for a substantially smaller share of total employment with only 294 employees, or 3% of total employment on average⁷. In fact, the share of total employment appears to increase almost linearly with firm age. However, when we compare employment levels with job flows, we observe that startups account for a disproportionate share of job creation *and* destruction: on average, each quarter new firms create 55 jobs per county, or 14% of all gross job gains, compared to 272 jobs created by the oldest firms, or 70% of all newly created jobs. Similarly, circa 26 jobs are destroyed in startups (7% of total job destruction), compared to 154 in old firms (72% of total job destruction). These figures are similar to the findings of Adelino et al. (2017) for the non-tradable sector. Furthermore, they also indicate that in the retail sector, startups grow at a significantly faster pace than old firms, with an estimated average quarterly growth rate of nearly 10%. Firms aged 2-10 years, however, appear to be shrinking.

3 Empirical Strategy

This paper aims to study firm response to negative shocks to business conditions generated by hurricane strikes. Throughout the analysis, identification relies on the conjecture that occurrence of a hurricane is uncorrelated with unobservable economic shocks within the Atlantic-basin coastal area, conditional on the location and time. This is reasonable

⁷Because of the differences in sample size across firms of different age categories it is not possible to calculate the exact share of total employment for firms in the different categories. However the reported shares are likely to be close to the actual number.

because the complex nature of the relationship between oceanic and atmospheric variables and hurricanes make forecasting hurricane tracks and intensity even only several days in advance an extremely difficult exercise⁸.

I start by estimating a flexible event study model at the county-year-quarter level, which is useful for gauging the overall pattern of the impact of a hurricane. In addition, the coefficients for the prehurricane periods in this specification help assess any pretrends. In particular, I regress outcomes on a set of indicators for the years since a hurricane, ranging from 4 years before to 6+ years after a hurricane. I control for county and year-quarter fixed effects, county linear trends, and also include year-quarter indicators interacted with each of the following 2000 characteristics: Total population in a county (IHS transformed), percent 15-64 years-olds, land area (square miles), population density (persons/square mile), business density (retail establishments/square mile), total employment in the retail sector (IHS transformed), and the average wage of retail workers (IHS transformed). Specifically, the estimating equation is:

$$Y_{ct} = \sum_{\tau=-4, \tau \neq -1}^{6+} \beta_{\tau} H_{c\tau} + \mathbf{X}'_{c,2000} \alpha_t + \alpha_c + \alpha_t + \alpha_{ct} + \epsilon_{ct}, \quad (1)$$

where Y_{ct} is some outcome for county c in quarter t , such as the inverse hyperbolic sine (IHS) of average monthly earnings of all employees⁹. The variable $H_{c\tau}$ is an indicator equal to one if the county experienced a hurricane τ years earlier (or $-\tau$ years later if τ is negative), and zero otherwise. I include indicators for $\tau = 4$ years before a hurricane to 6+ years after a hurricane. I omit the year before a hurricane strike, so the estimated coefficients should be interpreted as the change relative to the year before the hurricane. Some of the counties in the sample are affected twice by a hurricane (cf. Figure 2). In this case, I use only the first instance of a hurricane between 2000 and 2015 in that county. Because hurricane hits are random, conditional on a county fixed effect, this should not

⁸For example, the National Hurricane Center's (NHC) average 5-day hurricane track forecast errors have averaged 550 kilometers in the last few years: <https://www.aoml.noaa.gov/hrd/tcfaq/F6.html>.

⁹The inverse hyperbolic sine transformation is defined as: $\log(y_i + (y_i^2 + 1)^{1/2})$ which is approximately equal to $\log(2y_i)$ or $\log(2) + \log(y_i)$, and so it can be interpreted in exactly the same way as a standard log-transformed dependent variable. However, unlike a log variable, the inverse hyperbolic sine is defined at zero.

bias my estimates. The variables α_c and α_t are county and year-quarter fixed effects capturing stable differences between counties and macro-economic shocks. α_{ct} are a set of county-specific linear trends, allowing for the possibility counties might have different trend rates of earnings or employment growth. Additionally, the set of interactions $\mathbf{X}'_{c,2000}$ allows the year-quarter fixed effects to differ by linear 2000 characteristics (cf. Table 1). Standard errors are clustered at the commuting zone level¹⁰. My conclusions are unchanged if I cluster standard errors at the county level or use Conley (1999) spatially clustered standard errors.

Because of its flexibility, Equation (1) is inefficient if some coefficients are not substantially different from each other. To summarize the impact of a hurricane more concisely and further increase the power of the estimates, I use another specification that combines post-hurricane indicators into bins of two years: 0-1, 2-3, 4-5, and 6+ years after a hurricane, assuming no differences between treated and control counties in the years prior to the hurricane. The exact specification is:

$$Y_{ct} = \beta_1 H_{ct,0\ to\ 1} + \beta_2 H_{ct,2\ to\ 3} + \beta_3 H_{ct,4\ to\ 5} + \beta_4 H_{ct,6+} + \mathbf{X}'_{c,2000} \alpha_t + \alpha_c + \alpha_t + \epsilon_{ct}, \quad (2)$$

where $H_{ct,0\ to\ 1}$ is equal to one in the quarter of a hurricane strike and the seven following quarters, and zero otherwise. β_1 will thus reflect the mean effect on outcome Y_{ct} in years 0-1 after the hurricane, relative to the years prior to the hurricane. $H_{ct,2\ to\ 3}$, $H_{ct,4\ to\ 5}$, and $H_{ct,6+}$ are defined in the same way. This empirical setting allows the same county to be part of the treatment and control group at different points in time. Specifically, at any year-quarter t , the control group includes both counties that are hit by a hurricane after year-quarter t (but before the end of the sample period) and so are treated eventually, and counties that never experience a hurricane between 2000 and 2015.

¹⁰I link counties to commuting zones using a county-to-commuting-zone bridge provided by the Economic Research Service of the U.S. Department of Agriculture

4 Results

This section presents the main findings linking earnings to an increase in business failure. I start by examining the connection between firm age and changes in the quarterly level of the earnings of stable employees and new hires in the retail sector in the years following a hurricane. Next, I look at the impact on employment, and gross job creation and destruction flows. Finally, I perform several robustness checks.

4.1 Earnings Effects of Hurricane Strikes

4.1.1 All Employees

Figure 3 reports the estimates of Equation (1) for the average monthly earnings of all stable employees, split up by firm age category. Figure 3a shows that for firms of all ages combined there appears to be a small positive effect on earnings in the immediate aftermath of a hurricane strike: monthly earnings increase on average by 4,2 percent in the year of the hurricane (year 0). This difference gradually decreases again over time; 2 years after a hurricane, the estimated difference in earnings between hurricane and non-hurricane counties is economically and statistically not different from zero. Furthermore, the coefficients on the pre-hurricane indicators suggest no differences in earnings pretrends between treatment and control counties, bolstering the claim that hurricanes cause a temporary increase in earnings of employees in the retail sector.

However, the results also indicate substantial variation across firms of different ages. Figure 3b shows that for startups (0-1 year-olds), the estimated increase in average monthly earnings in the year of a hurricane equals 11 percent, or more than twice the increase of firms of all ages combined. This positive effect on earnings also seems to persist longer over time: 2 years after a hurricane, earnings in startups are still estimated to be on average 5 percent higher than before. However, afterwards the estimates become more noisy, and 6+ years after a hurricane the initial positive effect has almost completely disappeared. Again, the results indicate no significant differences in earnings

trends between treatment and control counties in the periods before a hurricane that may cause the observed increase in earnings after a hurricane strike. Contrary to these positive effects for startups, I find no significant short-term or medium-term impact of hurricanes on earnings of employees in firms between 2 and 10 years old (Figures 3c-3e); for these firms, the coefficients for the post-hurricane years are close to and not significantly different from zero. The only exception is that I do observe a positive and significant effect for 2-3 years-old firms, two years after a hurricane. These firms are in fact the startups founded in the wake of a hurricane strike, and that have survived for at least two years. Hence, these findings may suggest that, conditional on survival, startups founded shortly after a hurricane strike pay higher wages for at least two years after they have been established. Finally, looking at old firms (11+ years-olds), I observe effects similar to the findings for all firms in the year of a hurricane strike¹¹, earnings of all employees go up by, on average, 4 percent. However, this initial increase quickly diminishes in the periods afterwards.

Corresponding estimates from the more concise model, Equation 2, are shown in Table 3. These confirm the results of the flexible event study, with one exception: the estimated effect for firms between 6-10 years-old in years 0-1 after a hurricane is significantly positive. However, this is likely due to the pretrend in wages for this category of firms (cf. Figure 3e). Furthermore, when grouping the indicators for the years after a hurricane into bins of two years, the estimated effects on wages in startups become larger, while the coefficients for old firms become smaller compared to the findings for the flexible model: 0-1 years after a hurricane, earnings in startups go up by about 12,2 percent, compared to 3,2 percent in old firms. The increase remains significantly positive for startups 2-3 years after a hurricane, while for old firms the effect is estimated to be close to zero and insignificant starting from two years after a hurricane.

Together, these results suggest a positive and significant short-term impact of hurricanes on wages in new and old firms, but not for firms between 2 and 10 years old. The increase in earnings is substantially larger in startups: the estimates suggest that

¹¹This is not surprising, given that old firms account for the bulk of employment

the positive impact of hurricanes on wages in startups is two to almost four times larger than in old firms, 0-1 years after a hurricane. Finally, while this initial increase quickly dissipates for old firms, it seems to persist for startups, up to three years after a hurricane strike.

4.1.2 New Hires

In the previous section I looked at the impact of hurricane strikes on the earnings of all (stable) employees in the retail sector. However, the effect may differ for employees who already have been working for some time in a certain firm, compared to those who start a new job at a firm after a hurricane strike. In case negative shocks to aggregate productivity induce a “cleansing” effect, leading to more efficient matches between workers and employers, then we would expect to observe a positive effect on the earnings of new hires as well.

To examine this possibility, I re-run Equations 1 and 2 but now with the average monthly earnings of new stable hires as outcome variable. The results for the flexible event study model are shown in Figure 4, the results of the more concise event study are presented in Table 4. Similar to the results for all employees, I find a positive and significant short-term impact of hurricane strikes on the wages of new hires, when looking at all firms combined. In the year of a hurricane, wages increase by 6,5 percent. This positive effect appears to persist for some time; up to 4 years after a hurricane, earnings are estimated to be significantly above their pre-hurricane levels. Again, the results indicate no differential pretrends in earnings between hurricane and non-hurricane counties. Also, the results for starting wages in firms in the different age categories are to a great extent in line with the findings for the earnings of all employees. One notable difference is that the increase in starting wages in startups seems to persist for a longer period than the increase in wages of all employees. However, Figure 4b indicates a slightly positive pretrend in starting wages in startups, which may cause part of the persistent positive effect. Taken together, the results suggest a positive short-term effect of hurricanes on starting wages in new and old firms, which may persist for some years in the case of

startups, although the latter results are not conclusive.

4.2 Are Changes in Employment Driving the Results?

An important factor that needs to be taken into account is the fact that changes in employment may cause the observed increase in earnings. If hurricanes lead to a decrease in the supply of labor, because a portion of the labor force flees a hurricane-stricken area, then this will cause wages to go up (Belasen and Polachek, 2009). Furthermore, as Skidmore and Toya (2002) point out, a past hurricane strike may increase the expected risk of a future hurricane passage, reducing the expected return to physical capital (which may be destroyed during the storm). In this case, demand for labor might increase due to a substitution effect toward human capital as a replacement. Again, this increase in demand would explain the observed increase in earnings, assuming the substitution effect dominates potential income effects.

As a first test for the possibility that changes in supply or demand of labor cause the estimated increase in earnings, I estimate equations 1 and 2 for net (stable) job creation in a county. In case of a negative supply shock, the expectation is that employment would decrease, at least in the short-run. On the other hand, a positive demand shock would lead to an increase in employment, *ceteris paribus*.

Figure 5 shows the results for the flexible event study framework. The findings show a drop in the year of a hurricane, although the coefficient is not significantly different from zero. Employment also appears to quickly recover, and two years after a hurricane the estimated difference is close to zero. Importantly, I do not find any noticeable effect for employment in startups, nor in the short-term, nor in the long-term. The same goes for firms between 2 and 10 years old. In fact, the observed small drop in aggregate employment in the retail sector is only replicated for old firms of 11 years or older, but the coefficients for the years after a hurricane are never significantly different from zero. The results for the concise event study framework reported in Table 5 show similar findings. Hence, these results do not indicate that changes in employment cause the observed increase in earnings in startups.

Of course, the results for overall employment may mask substantial heterogeneity in job flows. If for example, a hurricane causes a fraction of new firms to close down while at the same time it fosters the creation of new ventures, then it will have an ambiguous effect on net job creation by startups, depending on which effect dominates. To verify this, I now estimate Equation 1 with respectively gross job gains and gross job losses as outcome. The results are shown in Figures A1 and A2 in the Appendix. I find no significant change in gross job flows after a hurricane, for none of the age categories, providing further evidence that the observed increase in earnings at startups and, to a lesser extent, at old firms, do not appear to be driven by changes in the overall supply or demand for labor.

4.3 The Importance of Firm Age versus Size

So far, the empirical analysis has focused on the impact of negative shocks to local business conditions on earnings and employment for firms of different ages. However, it is possible that the observed differences in earnings effects between young and old firms stem from the fact that younger firms also tend to be smaller. If, for example, small firms are more responsive to shocks because small firms display higher levels of organizational flexibility, regardless of their age, then we would expect to observe similar or even more pronounced effects than for young firms.

To explore this possibility, I now compare the outcomes for firms of different sizes. Unfortunately, the QWI does not allow the data to be split up by firm age and size simultaneously. However, if it is firm size that is driving the results, then the expectation is that the earnings in small firms will increase substantially, whereas there will be a smaller or no effect for large firms. The QWI provides county-level information about earnings and employment for the following firm size classes: 0-19, 20-49, 50-249, 250-499, and 500+ employees.

Figure A3 displays the results for regressions of Equation (1) on the earnings of all employees. I find that for firms with less than 20 employees, quarterly earnings of stable employees go up by circa 4 percent in the year of a hurricane, but this initial increase

disappears two years after a hurricane. I also find a positive effect of similar magnitude for firms with 20-49 employees, although the results in Figure A3b suggest that this might be at least partly due to a positive pretrend in earnings. Large firms with 500+ employees also increase earnings in the initial periods after a hurricane. Finally, I do not observe an effect on earnings in firms with 50-499 employees. Comparing these results with the findings for firms in different age categories displayed in Figure 3 suggests that differences in size cannot fully explain the differential outcomes between young and old firms. In fact, while I find a positive effect for the smallest firms (0-19 employees), the magnitude of the effect is almost three times smaller than for startups, probably due to the share of old(er) firms in the small firm category.

Figure A4 shows the results for employment. Interestingly, I now observe a drop in employment for the smallest firms in the year of a hurricane (although the estimate is noisy), with only a gradual recovery in the years afterwards. I do not observe a similar drop in employment for larger firms, and in particular there is no indication that the largest firms with 500+ employees experience a decrease in employment. These results, together with the finding that there is no indication of an employment effect for startups, but a small drop in employment for old firms, may suggest that old-small firms probably account for the observed drop in the number of employees.

4.4 Robustness of the Findings

4.4.1 Earnings in the Professional, Scientific, and Technical Services Sector

In Section 2.2, I argued that the retail sector is an appropriate empirical setting, given that the location of the business is non-fungible, and, hence, retail firms are likely to be required to interrupt or stop activities when a hurricane causes damage to their infrastructure. In this section, I test this assumption by examining the effect of hurricanes on firms in the professional, scientific, and technical services sectors. The idea is that the operations of these firms are less sensitive to the destructive impact of hurricanes.

Figures A5 and A6 in the Appendix show the results for regressions of equation (1) on

the earnings of all employees and new hires in the Professional, Scientific, and Technical Services Sector. Consistent with the assumption that hurricanes do not induce a negative shock to productivity for firms in this sector, I find no significant change in earnings in the years following a hurricane, for none of the age categories. These findings also highlight that estimates of the impact of hurricanes on the aggregate economy may mask important differences. In particular, it is important not only to differentiate between young and old firms, but also between sectors, taking into account how prone business activities are to structural damage to buildings, building content, and inventory loss.

4.4.2 Expanding the Sample to All Counties in Atlantic Coastal States

Next, I relax the sample restriction of only including coastal counties in the Atlantic-basin, and broaden the sample to all counties within the 19 Atlantic coastal states (the complete area shown in Figure 2) to test the external validity of the results. It is possible that the previously observed effects on earnings following a hurricane strike are contingent on certain (unobserved) idiosyncratic characteristics of coastal counties. In that case, the positive earnings effect following a hurricane strike would decrease or even disappear when I expand the sample to all counties within Atlantic coastal states.

Figures A7 and A8 in the Appendix show the findings for the flexible event study model on the earnings of all employees and those of new hires, for the broader sample of all counties in coastal states. The results are remarkably similar in sign and magnitude to those for the restricted sample of coastal counties. This seems to suggest that the findings are not restricted to coastal counties.

4.4.3 Varying the Controls

I have also probed the robustness of the results for the regressions on earnings to varying the econometric specifications of Equation 1. In particular, I omit the county characteristics variables (Table A1), or include state-by-year fixed effects (Table A2). Overall, the point estimates and statistical significance levels are very similar across the various specifications. The estimates become a bit smaller when including state-by-year fixed

effects, which may indicate the presence of spatial spillovers.

5 Interpreting the Results

The goal of this section is to argue that the above results are consistent with models of creative destruction, like, for example, the one of Caballero and Hammour (1994), where negative shocks to aggregate output drive out the least productive job matches, and deter creation of low-quality jobs. This induces a selection effect, shifting the average productivity of job matches upwards. A simple model sketch will help to clarify the mechanism behind this intuition.

The production technology is as follows. Production units consisting of fixed proportions of labor and capital created at time t_0 produce constant flow output $q(t_0) = zA(t_0)$ over their lifetime. $z \sim \mathcal{N}(\mu_z, \sigma_z)$ is a productivity component idiosyncratic to a production unit and remains constant over its lifetime. Age a indicates the time since a production unit has been created at time t . Entrepreneurs draw a value from z , and then decide to start producing or not. However, once in production z remains constant over the lifetime of a production unit. The shared productivity component $A(t_0)$ of production units created at time t_0 embodies the most advanced technology at that point in time. Exogenous innovation causes productivity $A(t)$ of the most advanced technology at time t to grow at a rate $\gamma > 0$. Hence, older production units are less productive, for a given value of z , but old production units with high values of z can be more productive than young ones with low idiosyncratic productivity. This is different from Caballero and Hammour (1994) who assume newly created production units are always the most productive.

Production units bear a constant operating cost c_e . For simplicity, I assume workers receive a share $\beta \in (0, 1)$ of productivity. Normalizing prices to one, profits at time t are given by:

$$\pi(t) = zA(t - a) - \beta zA(t - a) - c_e. \quad (1)$$

Production units stay in the market as long as they break even:

$$[1 - \beta]zA(t - a) \geq c_e. \quad (2)$$

Consider what happens when a negative shock hits the economy. Unlike recessions, i.e. negative shocks to demand, the type of shock we are interested in here goes through the costs of operation. In particular, assume that operation costs increase from c_e to c'_e . This can happen because, for example, a hurricane destroys production facilities that need to be rebuilt. It is clear from (2) that this will affect the economy both at the entry and exit margins. At entry, the increase of c_e to c'_e acts as an entry barrier, causing a fraction of firms with low values of z not to enter. This will have a compositional effect in the sense that the average idiosyncratic productivity of newly created will go up, $E[z|A(t), c'_e] > E[z|A(t), c_e]$. Because wages are increasing in z , this can explain the observed increase in wages at startups after a hurricane.

Similarly, a fraction of established firms that would have survived under c_e , will be forced to close down now. Because common productivity $A(t)$ of cohorts of production units grows over time, this effect will be most pronounced for old firms, who are on average less productive. Hence, a fraction of production units with the lowest productivity (and wages) closes down, leading to an increase in average wages for firms of similar age. In line with the empirical findings, this simple sketch shows how firms of different ages react to a negative shock to economic conditions, and why both young and old firms are most likely to adjust.

The theory forwarded here is related to “cleansing” theories of economic downturns, which can be dated back to Schumpeter’s (1934) discussion of creative destruction. The idea is that downturns foster productivity-enhancing reallocation of resources because less efficient firms close down, reallocating resources to more productive ones. A number of theoretical models have also linked the cleansing hypothesis to empirical patterns of job creation and destruction through the business cycle. In these models, the marginal cost of job creation is lower during downturns. So while job creation falls during recessions it falls less than the rise in job destruction. This can be because capital installation

and labor training costs are convex in aggregate production (Caballero and Hammour, 1994), or the marginal cost of creating a job is lower in recessions because it is easier to fill a vacancy in slack labor markets (Mortensen and Pissarides, 1994). Regardless of the actual channel, these models all suggest that downturns are times of productivity enhancing reallocation.

It is important to point out, however, that I find no evidence for changes in gross job flows (creation and destruction), as suggested by these models, except maybe for old-small firms which appear to experience a drop in employment. Within the above framework, this can only be explained under the assumption that firms of higher productivity do not necessarily create more jobs, but invest, for example, in new technology that enhances productivity.

6 Conclusion

Academic researchers and policymakers alike have become increasingly interested in understanding the mechanisms underlying job creation by startups. Despite this focus on the quantity of jobs created by new ventures, little attention has been paid to the quality of these jobs, and in particular the earnings of individuals working for entrepreneurs. To help filling this gap, this paper explores one mechanism affecting the earnings of employees of startups. Specifically, I examine how fluctuations in local business conditions affect wages in new and existing firms.

Using all U.S. Atlantic coastal area hurricane strikes between 2000 and 2015 as shocks to local business conditions, I find that, on average, wages of employees in the retail sector increase in the short-term after a hurricane. However, this effect is most pronounced in magnitude and duration for new ventures. Furthermore, additional analyses indicate that this effect is not driven by changes in the supply or demand for labor across firms of different ages, except maybe for old-small firms. Overall, these results are consistent with a “cleansing” effect of (temporary) downturns on the quality and earnings of jobs. The idea is that negative shocks to local conditions deter creation and sustenance of

low-paying, less efficient firms, reallocating resources to more productive businesses.

Why are wages in startups more responsive to fluctuations in local economic conditions than those in older firms? One possibility, consistent with the findings, is that startups bear lower adjustment costs to labor due to the fact that they have lower-tenure workers by nature of being new (Varejão and Portugal, 2007). A better understanding of the exact reasons underlying differences in responsiveness to economic shocks between young and old firms is an important research agenda that connects questions in entrepreneurship, macroeconomics, firm productivity, and the economics of organizations.

7 Bibliography

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8 Tables

Table 1: County characteristics in 2000 by hurricane experience

	Hurricane counties			Non-hurricane counties		
	mean	median	sd	mean	median	sd
Total population (IHS)	11.94	11.75	1.39	11.84	11.60	1.41
Percent 15 - 64	64.05	65.13	3.67	65.80***	65.89	3.16
Land area (square miles)	784.72	681.58	415.11	574.02***	502.17	451.19
Population density (persons/square mile)	264.41	85.58	454.60	1115.96	119.71	4743.84
Business density (establishments/square mile)	0.24	0.08	0.42	1.43	0.11	10.13
Total employment (IHS)	7.99	8.51	2.55	8.19	8.52	2.40
Average wage (IHS)	10.40	11.09	2.80	10.64	11.08	2.21
Number of counties	76			346		

This table reports characteristics of counties that do and do not experience at least one hurricane during the sampling period for the year 2000. Monetary values are in 2015 US dollars. Stars indicate significant mean differences between the two groups. *** $p < 0.001$.

Table 2: Earnings, Employment, and Firm Age (Retail Trade)

	N	Mean	Std.Dev	p25	p50	p75
All Firms						
Avg monthly earnings – all employees	26327	1886.39	514.16	1524.36	1866.82	2178.07
Avg monthly earnings – new hires	26327	1217.45	373.15	986.82	1192.31	1396.95
Nr. of employees	26327	8751.59	17132.93	668.00	2036.00	9282.00
Gross job gains	26327	395.93	804.65	31.00	94.00	407.00
Gross job losses	26327	360.64	723.58	29.00	90.00	369.00
0-1 years-olds						
Avg monthly earnings – all employees	23402	1640.44	654.71	1210.52	1558.60	1951.62
Avg monthly earnings – new hires	23402	1340.22	659.35	931.10	1255.62	1622.40
Nr. of employees	23402	294.39	626.49	29.00	81.00	292.00
Gross job gains	23402	54.56	120.01	5.00	15.00	53.00
Gross job losses	23402	25.91	56.61	2.00	8.00	26.00
2-3 years-olds						
Avg monthly earnings – all employees	22263	1742.41	654.85	1290.17	1668.00	2092.45
Avg monthly earnings – new hires	22263	1288.45	788.87	868.71	1196.01	1570.73
Nr. of employees	22263	333.95	695.65	37.00	99.00	336.00
Gross job gains	22263	26.97	55.83	3.00	8.00	28.00
Gross job losses	22263	27.56	56.52	3.00	9.00	28.00
4-5 years-olds						
Avg monthly earnings – all employees	21446	1839.73	714.45	1344.96	1757.98	2235.12
Avg monthly earnings – new hires	21446	1309.88	736.71	868.39	1204.91	1603.05
Nr. of employees	21446	323.34	651.31	38.00	101.00	327.00
Gross job gains	21446	22.57	44.64	2.00	7.00	23.00
Gross job losses	21446	23.65	47.76	2.00	8.00	25.00
6-10 years-olds						
Avg monthly earnings – all employees	24109	1953.23	1768.81	1421.14	1861.69	2364.65
Avg monthly earnings – new hires	24109	1329.73	2085.96	913.28	1240.81	1622.08
Nr. of employees	24109	616.60	1253.40	64.00	178.00	621.00
Gross job gains	24109	37.65	75.46	4.00	11.00	39.00
Gross job losses	24109	39.67	78.78	4.00	12.00	42.00
11+ years-olds						
Avg monthly earnings – all employees	26288	1900.47	517.48	1537.64	1878.42	2187.84
Avg monthly earnings – new hires	26288	1188.59	357.59	965.43	1163.34	1361.22
Nr. of employees	26288	7386.53	14301.23	547.00	1693.00	7881.00
Gross job gains	26288	272.01	558.41	19.00	61.00	276.00
Gross job losses	26288	258.63	526.44	19.00	61.00	260.00

This table reports summary statistics for the main variables of interest for all county-quarter observations in the sample split up by firm each category, from 2000 to 2015. For each variable, the pooled average, standard deviation, 25th, 50th, and 75th percentiles are reported. Monetary values are in 2015 US dollars.

Table 3: The Effect of Hurricanes on Wages of All Employees in the Retail Sector

Avg monthly earnings all employees (IHS)	All firm ages (1)	0-1 year-olds (2)	2-3 years-olds (3)	4-5 years-olds (4)	6-10 years-olds	11+ year-olds
0-1 years after hurricane	0.038** (0.013)	0.122*** (0.029)	0.029 (0.039)	0.027 (0.035)	0.060** (0.019)	0.032* (0.015)
2-3 years after hurricane	0.017 (0.013)	0.077* (0.037)	0.062 (0.059)	0.009 (0.051)	0.054 (0.041)	0.007 (0.016)
4-5 years after hurricane	0.019 (0.014)	0.074 (0.046)	-0.010 (0.061)	0.013 (0.084)	0.032 (0.060)	0.008 (0.021)
6+ years after hurricane	0.001 (0.014)	0.039 (0.051)	-0.010 (0.089)	-0.040 (0.096)	0.014 (0.066)	-0.009 (0.023)
Observations	26,327	23,402	22,262	21,441	24,109	26,288
R^2	0.953	0.584	0.612	0.632	0.776	0.943

This table reports regressions on $asinh(Earns)$ using equation (2). Standard errors (in parentheses) are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 4: The Effect of Hurricanes on Wages of New Hires in the Retail Sector

Avg monthly earnings all employees (IHS)	All firm ages (1)	0-1 year-olds (2)	2-3 years-olds (3)	4-5 years-olds (4)	6-10 years-olds	11+ year-olds
0-1 years after hurricane	0.068** (0.020)	0.121*** (0.033)	0.048 (0.038)	0.054 (0.047)	0.054 (0.043)	0.054* (0.024)
2-3 years after hurricane	0.047* (0.019)	0.106* (0.046)	0.083 (0.051)	0.049 (0.061)	0.046 (0.046)	0.026 (0.021)
4-5 years after hurricane	0.047** (0.018)	0.115* (0.057)	0.063 (0.062)	0.067 (0.089)	0.007 (0.068)	0.028 (0.025)
6+ years after hurricane	0.045** (0.016)	0.108 (0.076)	0.019 (0.092)	0.070 (0.100)	-0.050 (0.078)	0.025 (0.022)
Observations	26,327	23,402	22,262	21,441	24,109	26,288
R^2	0.785	0.386	0.367	0.380	0.471	0.770

This table reports regressions on $asinh(Earnhiras)$ using equation (2). Standard errors (in parentheses) are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table 5: The Effect of Hurricanes on Net Employment in the Retail Sector

Stable Employment (IHS)	All firm ages (1)	0-1 year-olds (2)	2-3 years-olds (3)	4-5 years-olds (4)	6-10 years-olds	11+ year-olds
0-1 years after hurricane	-0.065 (0.036)	-0.026 (0.088)	-0.111 (0.077)	-0.002 (0.065)	-0.015 (0.069)	-0.067 (0.037)
2-3 years after hurricane	-0.028 (0.025)	-0.024 (0.078)	-0.085 (0.093)	0.013 (0.091)	0.116 (0.079)	-0.048 (0.033)
4-5 years after hurricane	-0.034 (0.026)	-0.100 (0.097)	-0.146 (0.108)	0.017 (0.108)	0.126 (0.095)	-0.065 (0.036)
6+ years after hurricane	-0.023 (0.027)	0.010 (0.109)	-0.234 (0.146)	-0.046 (0.142)	0.147 (0.113)	-0.049 (0.042)
Observations	26,327	23,402	22,262	21,441	24,109	26,288
R^2	0.998	0.917	0.926	0.918	0.959	0.997

This table reports regressions on $asinh(Emps)$ using equation (2). Standard errors (in parentheses) are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

9 Figures

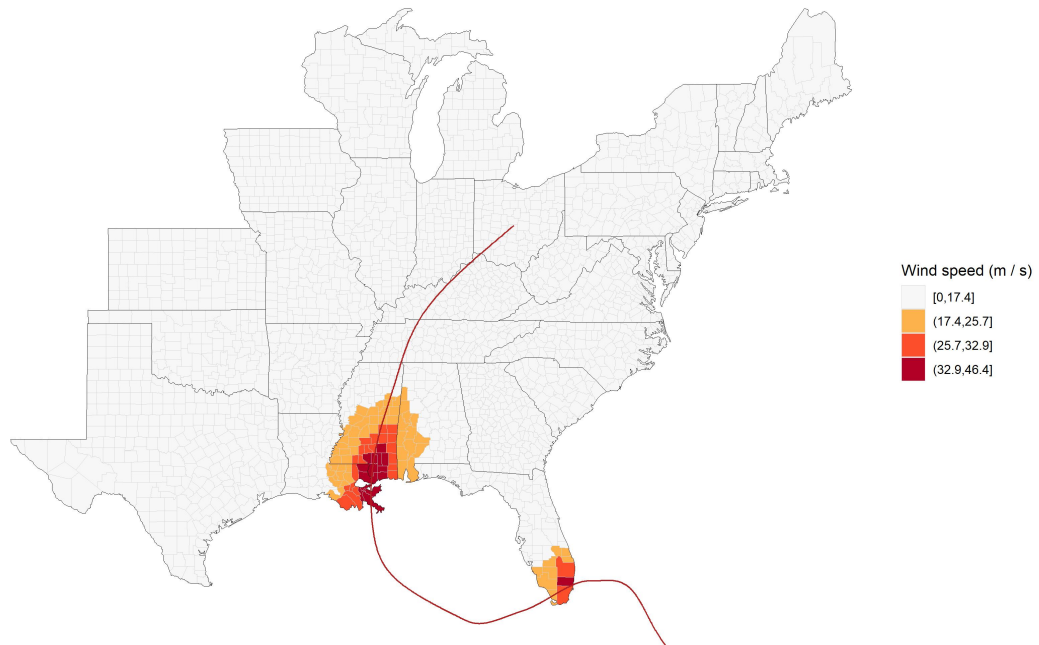


Figure 1: Estimated track and county-level wind speeds for hurricane Katrina in 2005

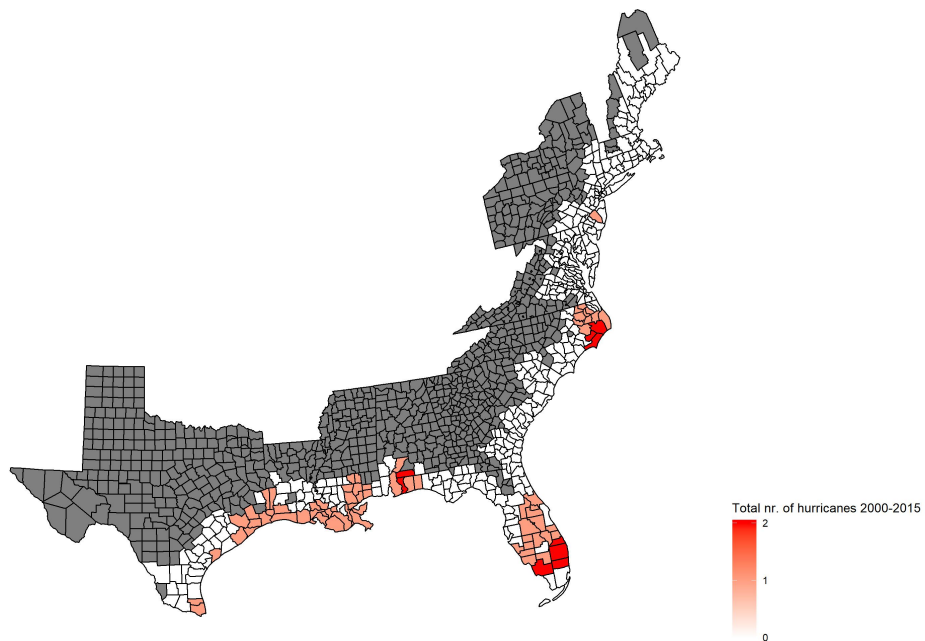
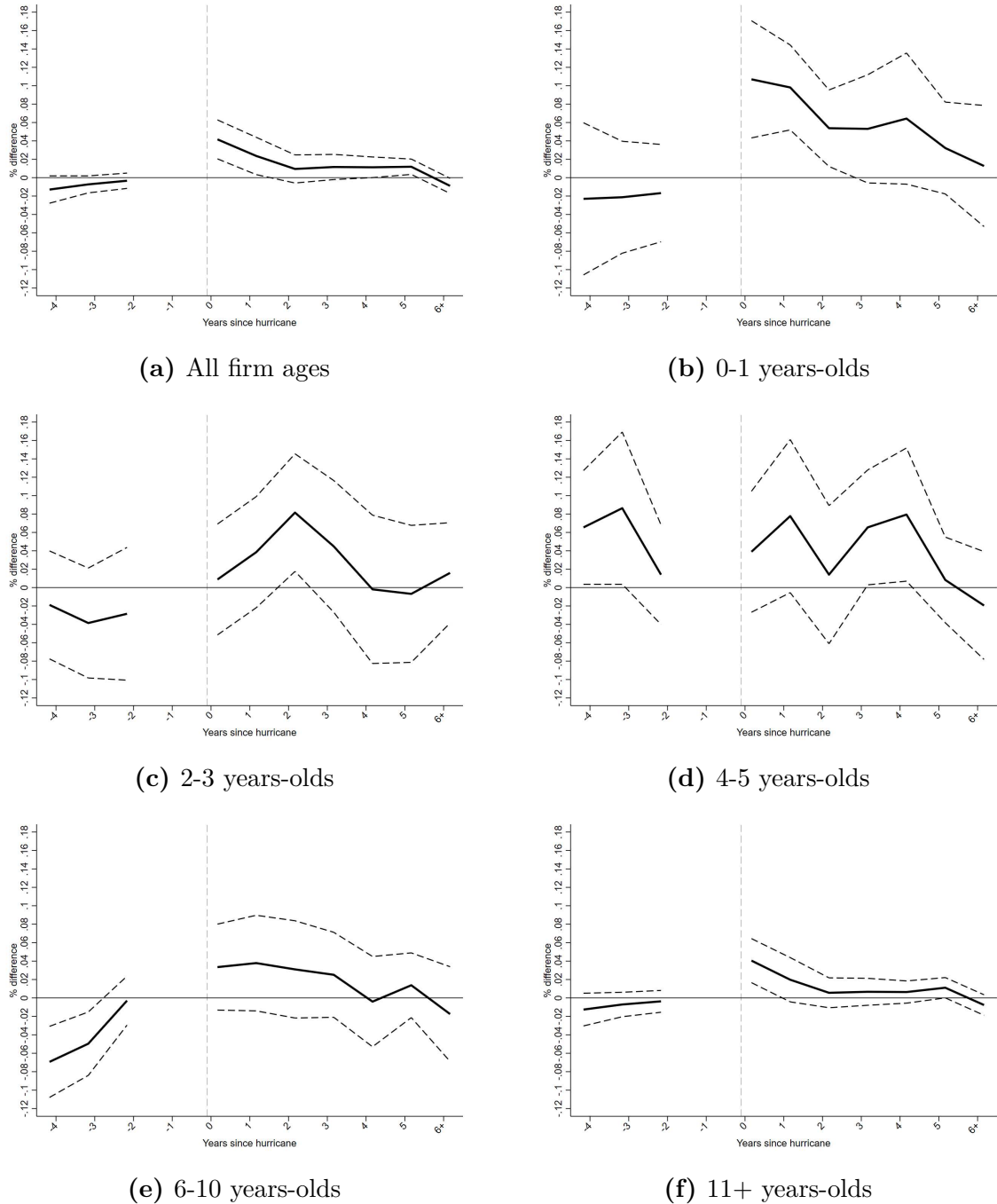


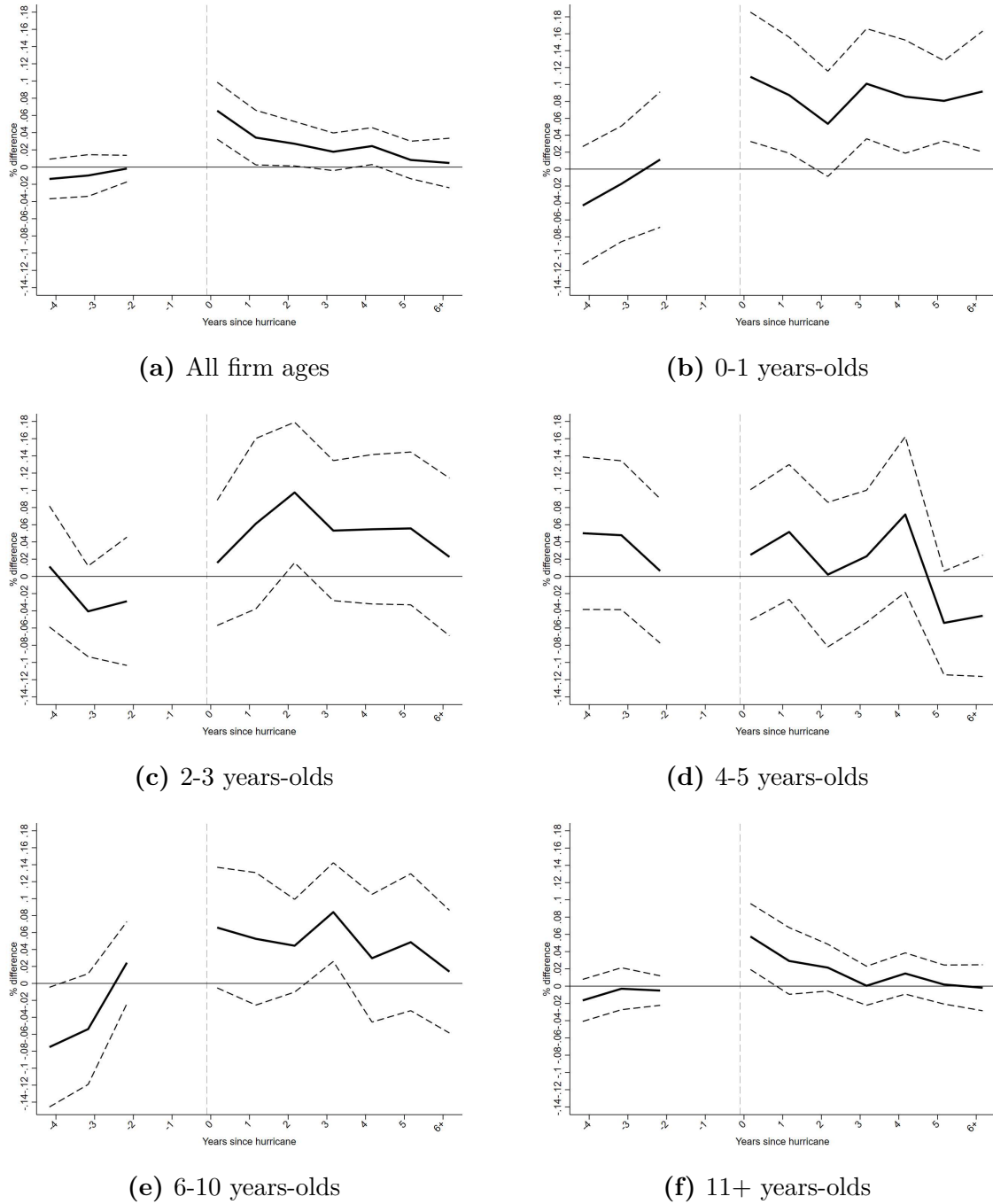
Figure 2: Spatial distribution of hurricanes in North Atlantic coastal counties, 2000-2015

Figure 3: The Effect of Hurricanes on Wages of All Employees



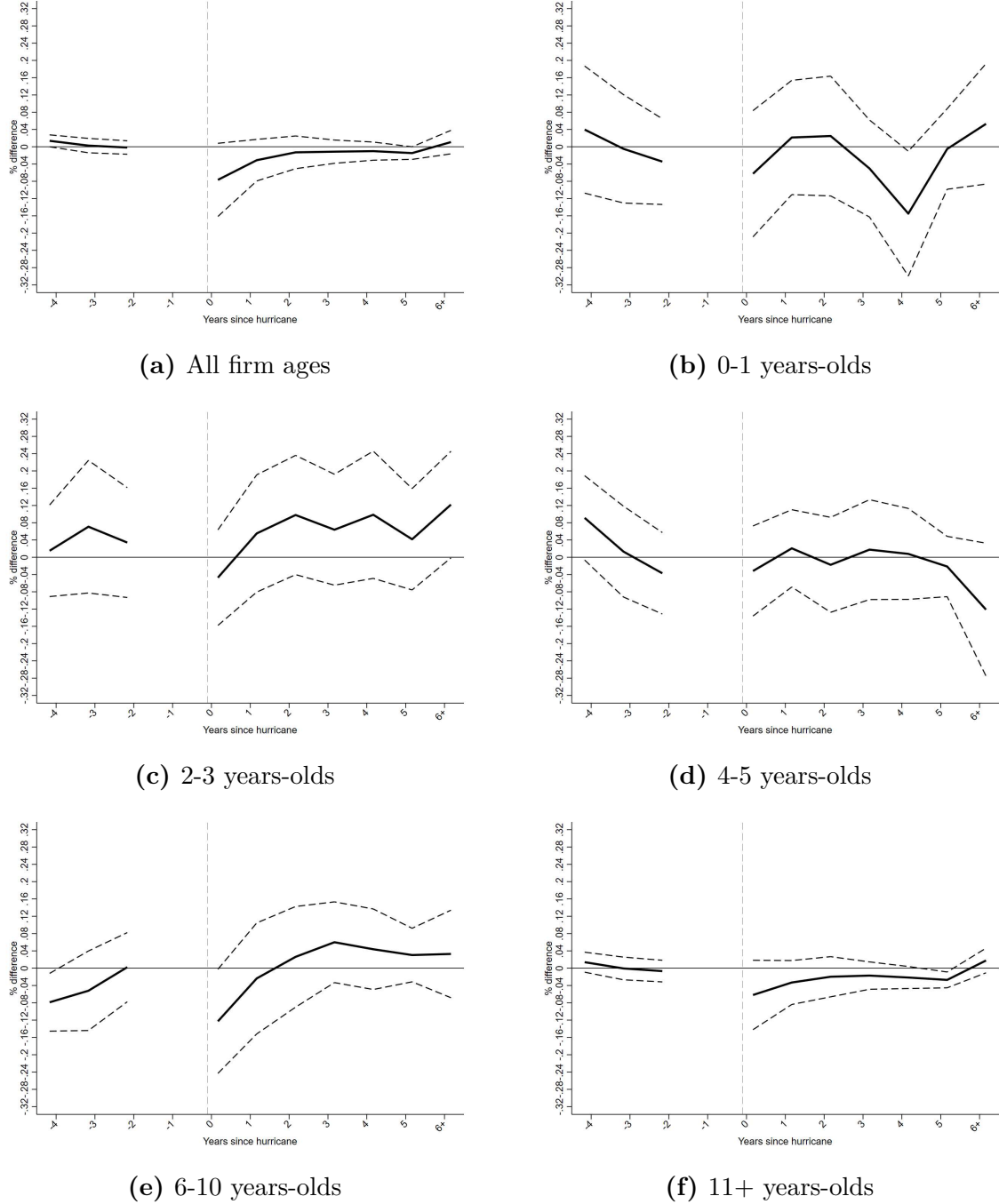
Notes: Point estimates and 95 percent confidence intervals from equation (1) for firms in different age categories are shown. The dependent variable is $asinh(Earns)$. Standard errors are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics.

Figure 4: The Effect of Hurricanes on Wages of New Hires



Notes: Point estimates and 95 percent confidence intervals from equation (1) for firms in different age categories are shown. The dependent variable is $asinh(EarnHiras)$. Standard errors are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics.

Figure 5: The Effect of Hurricanes on Employment in the Retail Sector

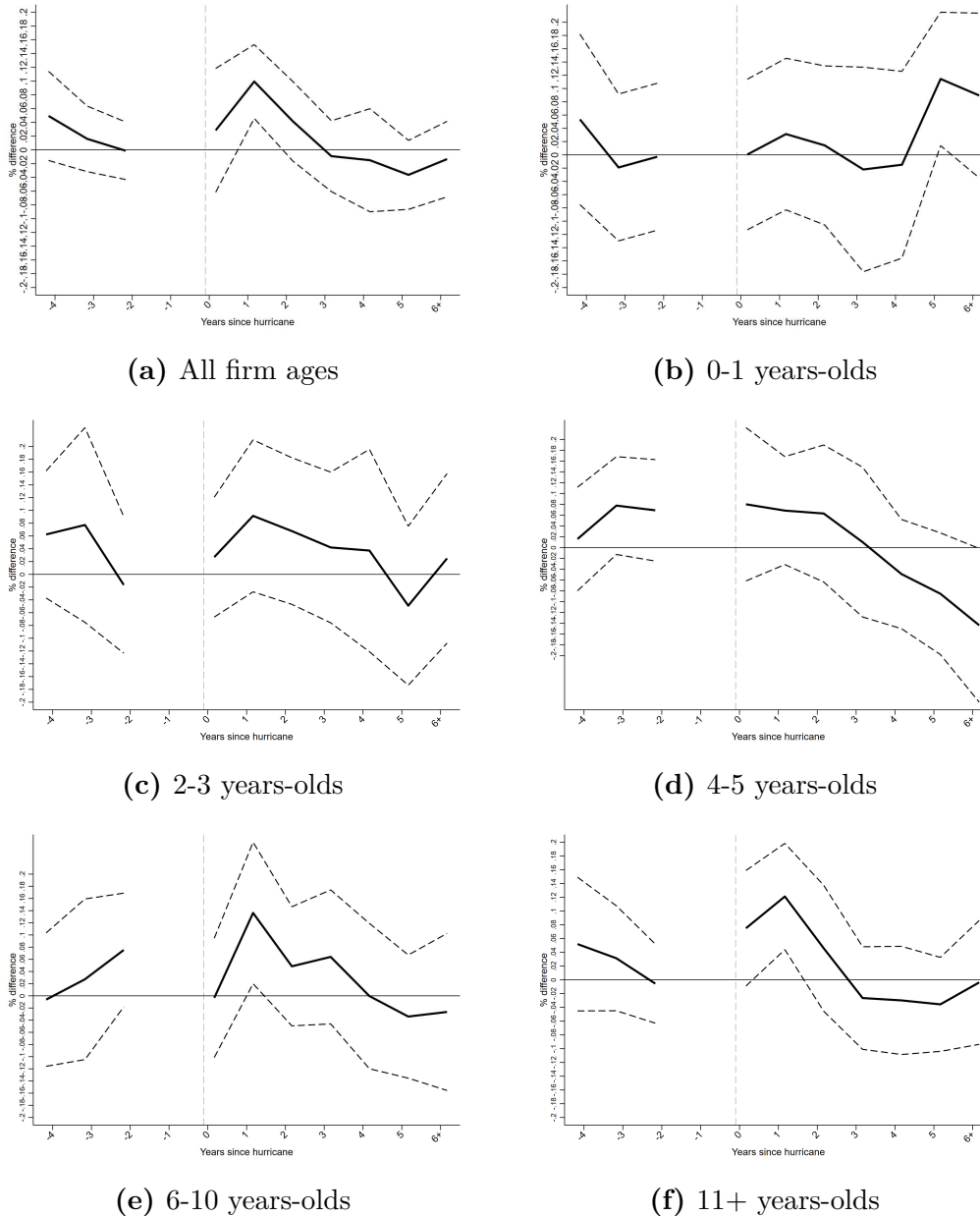


Notes: Point estimates and 95 percent confidence intervals from equation (1) for firms in different age categories are shown. The dependent variable is $asinh(Emps)$. Standard errors are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics.

A Appendix

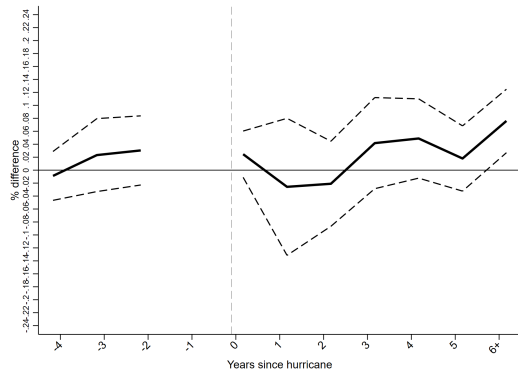
A.1 Gross Job Flows

Figure A1: The Effect of Hurricanes on Gross Job Gains in the Retail Sector

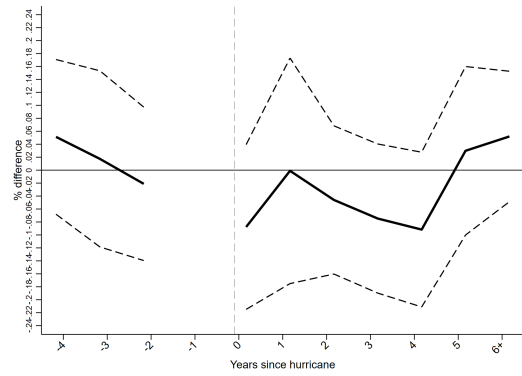


Notes: Point estimates and 95 percent confidence intervals from equation (1) for firms in different age categories are shown. The dependent variable is $asinh(Frmjbgns)$. Standard errors are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics.

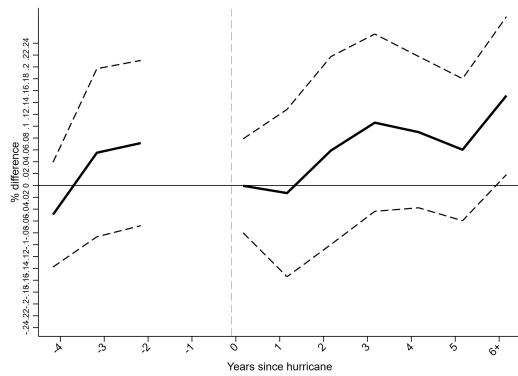
Figure A2: The Effect of Hurricanes on Gross Job Losses in the Retail Sector



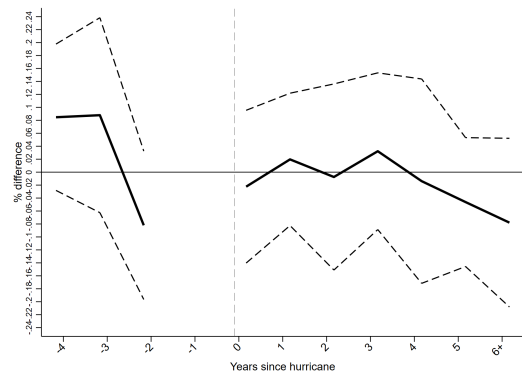
(a) All firm ages



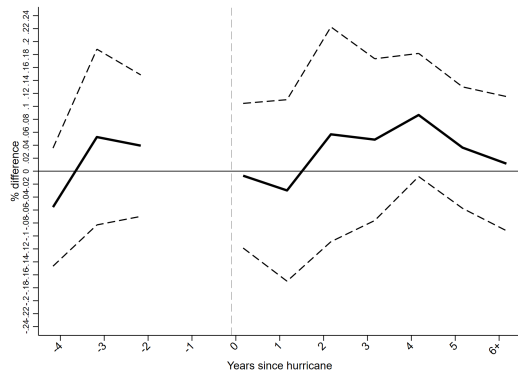
(b) 0-1 years-olds



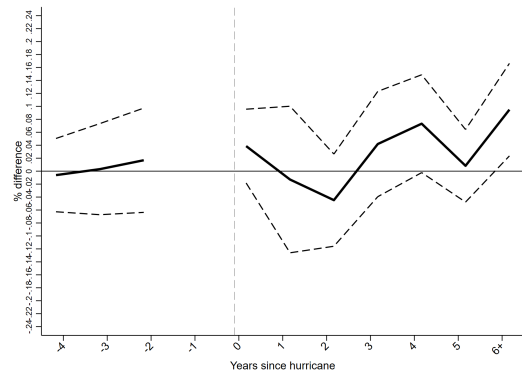
(c) 2-3 years-olds



(d) 4-5 years-olds



(e) 6-10 years-olds

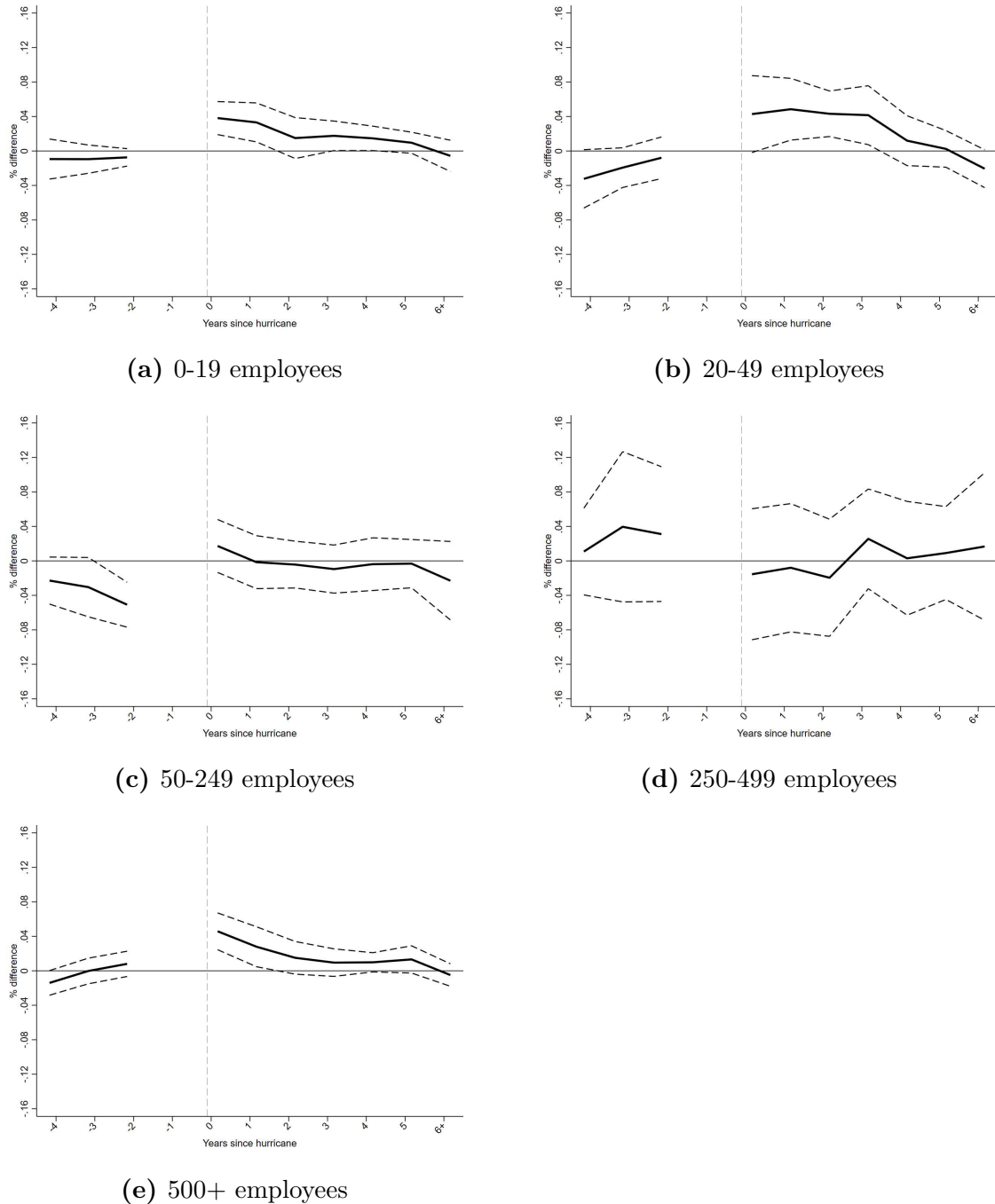


(f) 11+ years-olds

Notes: Point estimates and 95 percent confidence intervals from equation (1) for firms in different age categories are shown. The dependent variable is $\text{asinh}(\text{Frm.jblss})$. Standard errors are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics.

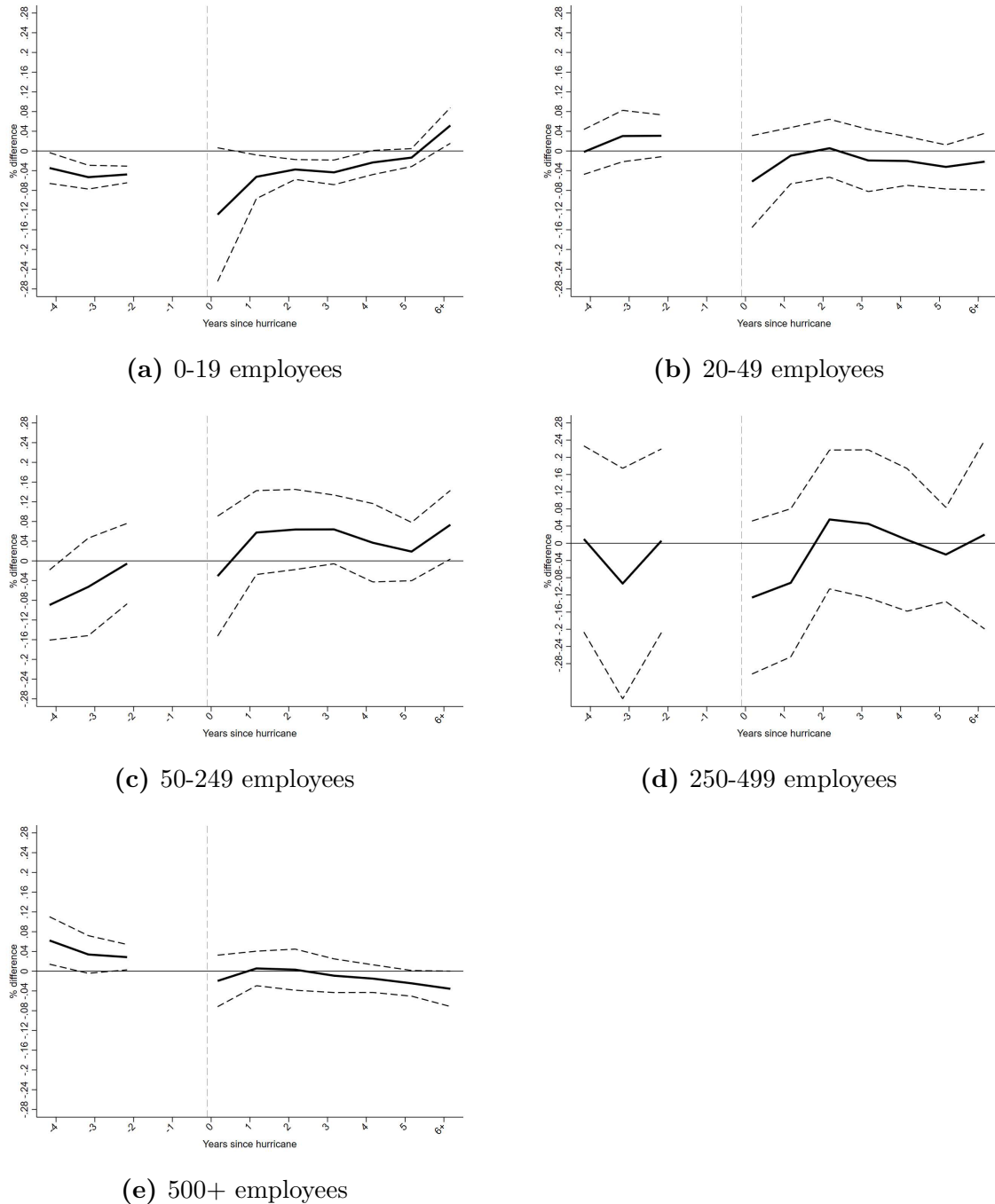
A.2 The Importance of Firm Age versus Size

Figure A3: The Effect of Hurricanes on Wages of All Employees for Firms of Different Sizes in the Retail Sector



Notes: Point estimates and 95 percent confidence intervals from equation (1) for firms in different size categories are shown. The dependent variable is $\text{asinh}(\text{Earnings})$. Standard errors are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics.

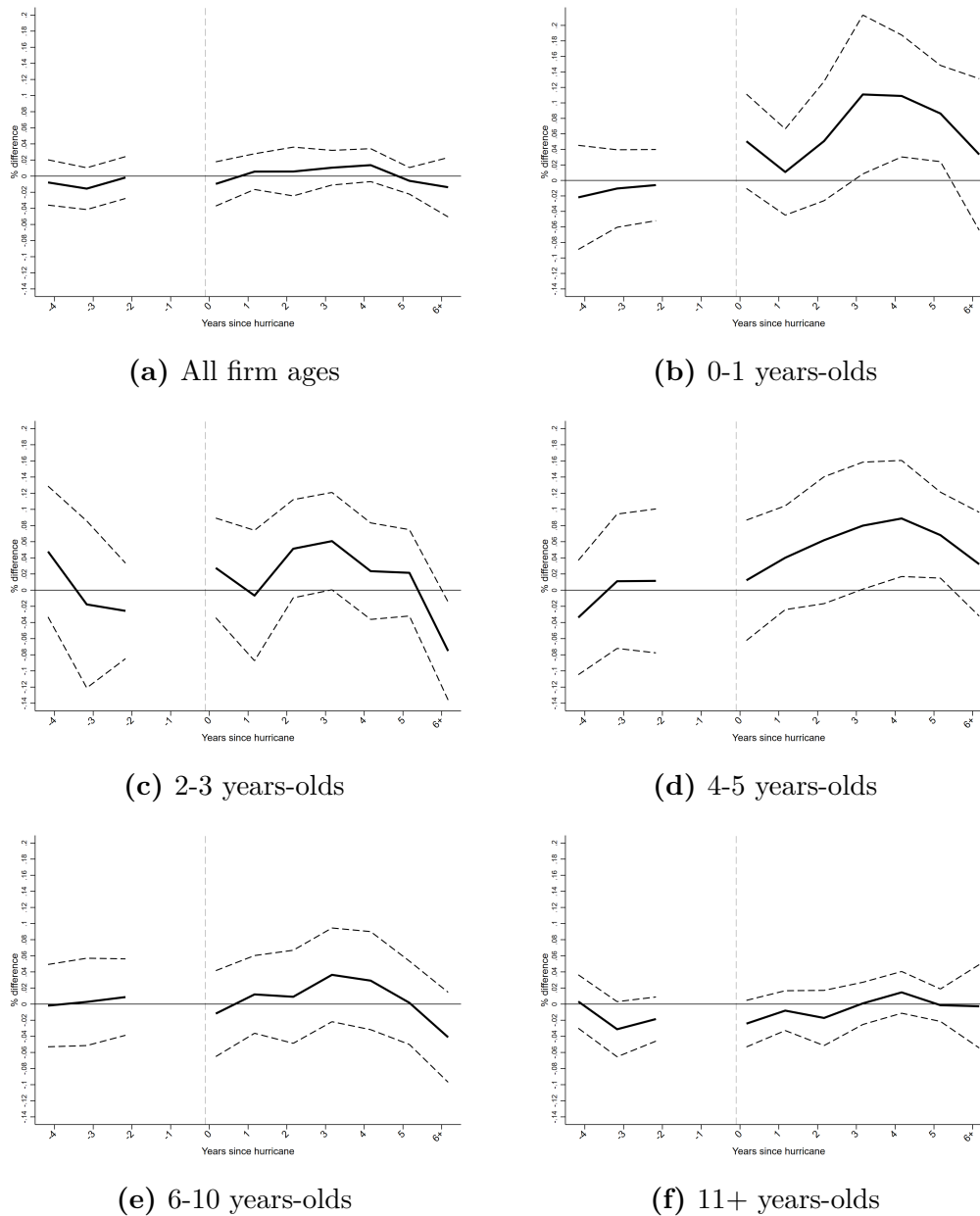
Figure A4: The Effect of Hurricanes on Employment for Firms of Different Sizes in the Retail Sector



Notes: Point estimates and 95 percent confidence intervals from equation (1) for firms in different size categories are shown. The dependent variable is $\text{asinh}(\text{Emps})$. Standard errors are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics.

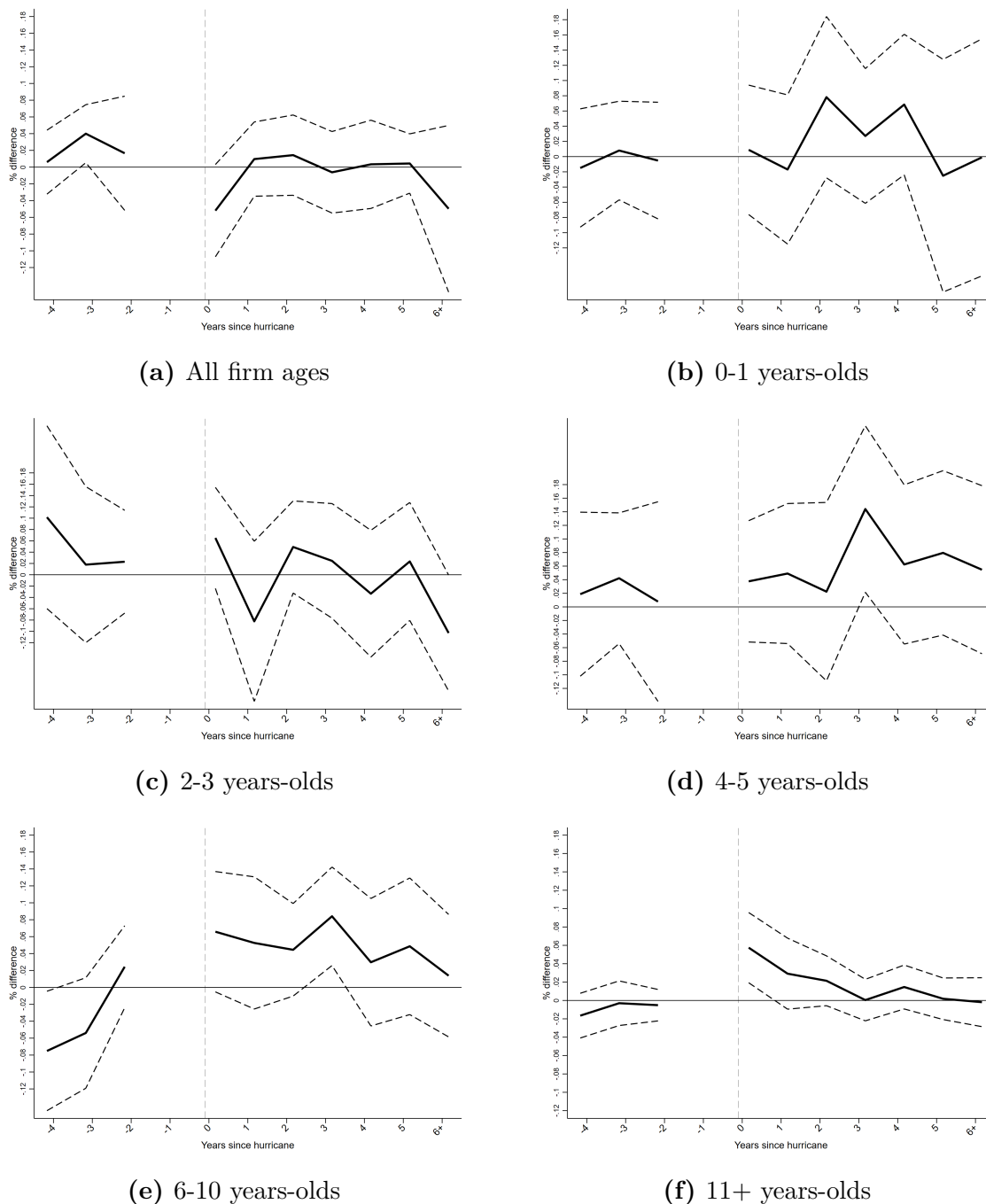
A.3 Earnings in the Professional, Scientific, and Technical Services Sector

Figure A5: The Effect of Hurricanes on Wages of All Employees in the Professional, Scientific, and Technical Services Sector



Notes: Point estimates and 95 percent confidence intervals from equation (1) for firms in different age categories are shown. The dependent variable is $asinh(Earns)$. Standard errors are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics.

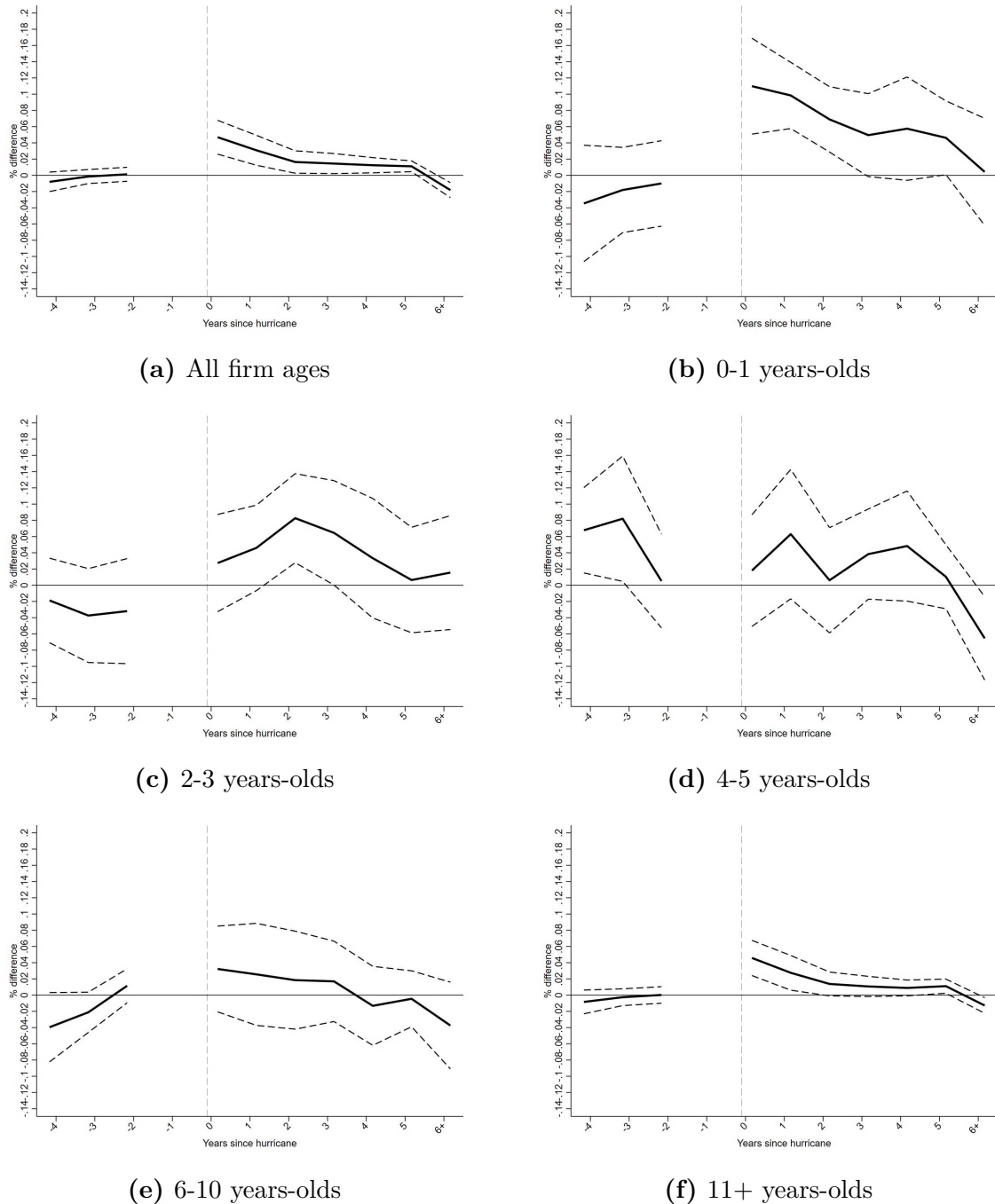
Figure A6: The Effect of Hurricanes on Wages of New Hires in the Professional, Scientific, and Technical Services Sector



Notes: Point estimates and 95 percent confidence intervals from equation (1) for firms in different age categories are shown. The dependent variable is $asinh(EarnHiras)$. Standard errors are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics.

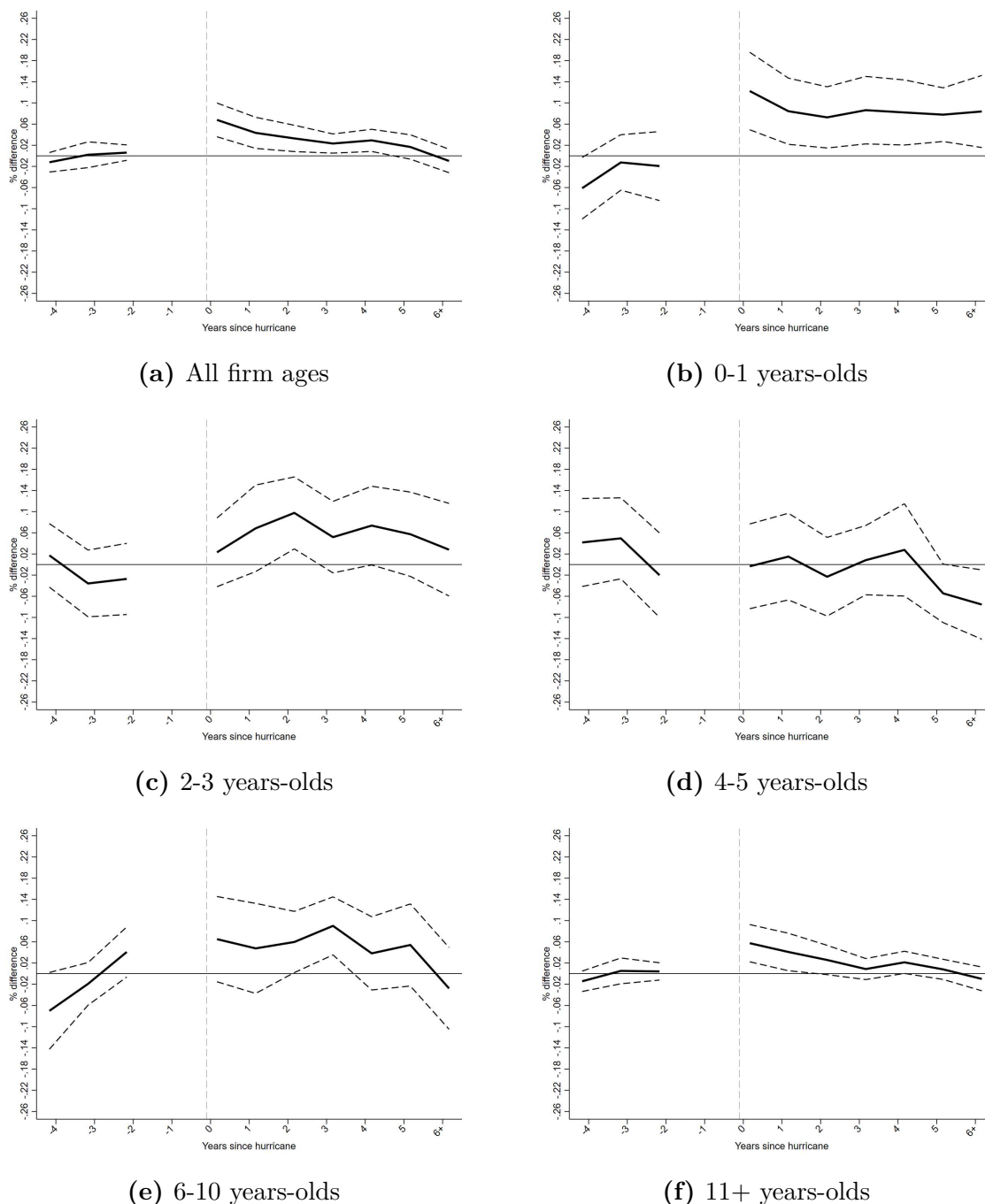
A.4 Results for the Sample of All Counties in Coastal States

Figure A7: The Effect of Hurricanes on Wages of All Employees for All Counties in Coastal States



Notes: Point estimates and 95 percent confidence intervals from equation (1) for firms in different age categories are shown. The dependent variable is $asinh(Earns)$. Standard errors are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics.

Figure A8: The Effect of Hurricanes on Wages of New Hires for All Counties in Coastal States



Notes: Point estimates and 95 percent confidence intervals from equation (1) for firms in different age categories are shown. The dependent variable is $asinh(EarnHiras)$. Standard errors are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, and quarter fixed effects linear in 2000 county characteristics.

A.5 Varying Controls

Table A1: The Effect of Hurricanes on Wages of All Employees, No Characteristics Controls

Avg monthly earnings all employees (IHS)	All firm ages (1)	0-1 year-olds (2)	2-3 years-olds (3)	4-5 years-olds (4)	6-10 years-olds	11+ year-olds
T = -4	-0.012 (0.007)	-0.016 (0.041)	-0.017 (0.029)	0.063* (0.028)	-0.069*** (0.017)	-0.011 (0.009)
T = -3	-0.007 (0.004)	-0.011 (0.029)	-0.038 (0.028)	0.072 (0.037)	-0.045** (0.015)	-0.005 (0.006)
T = -2	-0.006 (0.004)	-0.022 (0.025)	-0.024 (0.035)	0.016 (0.025)	-0.003 (0.013)	-0.005 (0.005)
T = 0	0.041*** (0.011)	0.113*** (0.031)	0.002 (0.028)	0.026 (0.032)	0.036 (0.023)	0.040** (0.012)
T = 1	0.024* (0.010)	0.097*** (0.022)	0.032 (0.029)	0.067 (0.041)	0.035 (0.025)	0.019 (0.012)
T = 2	0.011 (0.008)	0.058** (0.019)	0.070* (0.034)	0.004 (0.036)	0.031 (0.025)	0.006 (0.008)
T = 3	0.009 (0.007)	0.053 (0.028)	0.046 (0.036)	0.050 (0.032)	0.024 (0.023)	0.003 (0.007)
T = 4	0.007 (0.006)	0.063 (0.034)	0.016 (0.038)	0.057 (0.038)	-0.015 (0.025)	0.002 (0.006)
T = 5	0.011** (0.004)	0.036 (0.024)	-0.002 (0.035)	0.018 (0.024)	0.003 (0.019)	0.010 (0.005)
T = 6	-0.009* (0.004)	0.018 (0.032)	0.004 (0.026)	-0.036 (0.027)	-0.017 (0.025)	-0.007 (0.005)
Observations	26,327	23,402	22,262	21,441	24,109	26,288
R ²	0.951	0.575	0.604	0.622	0.773	0.940

This table reports regressions on $\text{asinh}(\text{Earnings})$. Standard errors (in parentheses) are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, and county linear trends. Effect in year -1 assumed to be zero. *** p<0.001, ** p<0.01, * p<0.05

Table A2: The Effect of Hurricanes on Wages of All Employees, Including State-by-Year Fixed Effects

Avg monthly earnings all employees (IHS)	All firm ages (1)	0-1 year-olds (2)	2-3 years-olds (3)	4-5 years-olds (4)	6-10 years-olds	11+ year-olds
T = -4	0.000 (0.006)	-0.017 (0.040)	-0.021 (0.035)	0.076** (0.028)	-0.054** (0.019)	0.003 (0.008)
T = -3	-0.003 (0.004)	-0.011 (0.029)	-0.047 (0.037)	0.084* (0.038)	-0.042* (0.018)	0.001 (0.006)
T = -2	-0.001 (0.005)	-0.014 (0.028)	-0.043 (0.042)	0.012 (0.023)	0.000 (0.014)	0.001 (0.006)
T = 0	0.035*** (0.010)	0.089** (0.030)	-0.010 (0.031)	-0.003 (0.032)	0.044 (0.023)	0.031** (0.011)
T = 1	0.017 (0.009)	0.093*** (0.024)	0.006 (0.037)	0.027 (0.042)	0.047 (0.030)	0.010 (0.010)
T = 2	0.010 (0.008)	0.061* (0.023)	0.047 (0.039)	-0.016 (0.043)	0.040 (0.028)	0.003 (0.008)
T = 3	0.012 (0.007)	0.058 (0.031)	0.011 (0.040)	0.030 (0.034)	0.034 (0.024)	0.005 (0.008)
T = 4	0.008 (0.005)	0.075 (0.040)	-0.027 (0.040)	0.018 (0.039)	0.007 (0.023)	0.003 (0.006)
T = 5	0.006 (0.005)	0.038 (0.029)	-0.014 (0.034)	-0.034 (0.027)	0.017 (0.019)	0.006 (0.006)
T = 6	-0.002 (0.005)	0.028 (0.037)	0.020 (0.029)	0.005 (0.033)	-0.012 (0.025)	-0.001 (0.006)
Observations	26,327	23,402	22,262	21,441	24,109	26,288
R ²	0.956	0.598	0.628	0.650	0.784	0.946

This table reports regressions on $\text{asinh}(\text{Earnings})$. Standard errors (in parentheses) are clustered at the commuting zone level. Controls include county fixed effects, quarter fixed effects, county linear trends, quarter fixed effects linear in 2000 county characteristics, and state-by-year fixed effects. Effect in year -1 assumed to be zero. *** p<0.001, ** p<0.01, * p<0.05