Investing in Automation: Evidence from Natural Disasters

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I investigate the extent to which establishments shift labor skill demand toward automation when faced with labor scarcity. Using natural disasters as an exogenous shock to local labor supply, I find that firms respond to local labor scarcity by increasing demand for automation-specific labor skills and that firms' responses vary with ex-ante adjustment costs. I show that constrained firms exhibit no significant change in demand for automation skills, while firms with production flexibility display decreased demand for automation skills following exogenous reductions in local labor supply. Firms dependent on low-skilled labor exhibit large increases in demand for automation skills.

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Preface

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1.0 Introduction

From 2010 – 2022, the United States experienced an annual average of 14.7 natural disasters with total associated damages exceeding $1 billion, adjusted for inflation. In the last five years of the sample, the average number of natural disasters with losses over $1 billion increased to 18.2 disasters per year. As firms seek to minimize climate risk exposure, disaster risk has become an increasingly relevant consideration for managers. One operational risk facing firms is the continued availability of labor, as migration from impacted areas decreases the size of the labor force and negative perceptions of economic recovery discourage offsetting migration to the affected region. One mechanism available to managers is investment in automation technologies, such as robotics and information processing, to offset labor shortages.

Technological investment is a function of the input prices of production: the cost of capital and labor. Holding the cost of capital constant, increasing labor costs makes capital investment an attractive substitute for labor. While recent media coverage highlights technology's role in offsetting labor shortages, the substitution effect oversimplifies the automation and labor.[1] Automation may reduce firm sensitivity to labor shocks, allowing firms to hedge against future labor adjustment costs. However, automation may increase demand for labor complementary to the investment, such as increasing demand for high-skill labor. In this paper, I provide systematic evidence of how local establishments adapt to increased labor scarcity through shifting labor skill demand toward automation during recovery from natural disasters.

There are two central challenges in the literature studying firms' decisions to automate: the lack of firm-level data on automation investments and the endogeneity in technological adoption schedules. Previous literature has relied on high-level proxies, such as CAPEX, PPENT, or investment in personal computing resources, to address the lack of targeted data. These estimates capture various capital expenditures but fail to isolate demand for labor-saving technologies. In my setting, I address this challenge by creating a labor-skill demand-

[1] USA Today; Fortune; The Washington Post; Associated Press.

based measure of automation using EMSI Lightcast job posting data from 2010 – 2022. As dollar investment in physical capital is not easily disentangled into automation-specific components, I assume firms must hire labor complementary to adopting, implementing, and maintaining new automation technologies. The labor-skill demand-based measure allows my setting to comment on the relationship between labor and technology, by quantifying shifts in the type of labor demanded by impacted firms. I use geo-location data from job postings to ensure the granularity of the county-level labor market shock matches firms' county-level shifts in labor demand.

As labor demand and automation adoption schedules may be jointly determined, I address possible endogeneity concerns by using the novel setting of severe natural disasters as a plausibly exogenous shock to local labor supply. As labor tends to be sticky, migration is predicated on a significant economic shock to a particular region [39]. Severe natural disasters lead to sustained declines in local labor availability, representing an exogenous shock to labor supply. I begin my analysis by documenting local labor markets' declines in available labor. I find exposed counties experience persistent average declines of 9.2% in the size of the labor force, post-disaster. This effect is economically significant, as an average county loses over 6,700 labor force participants. These effects are not driven by simultaneous changes in labor demand, as measured by the county-level job postings or total number of establishments. Consequently, labor markets become tighter in affected counties. Tighter labor markets suggest that firms should shift investment towards labor-saving technologies [1, 43, 28].

To investigate this hypothesis, I analyze changes in labor skill demand at the firm in counties affected by severe natural disasters. I find that establishments increase labor demand related to automation by 49.2% following severe disasters, a statistically significant effect at the 1% level. Next, I explore how this response varies based on firm adjustment costs. I present a conceptual framework considering adjustment costs as frictions to firms' transition towards capital-intensive production. Specifically, I explore variations in how firms' establishments respond to parent firm financing constraints (cost of capital), production network flexibility (increased friction), and technological compatibility with current labor demands (decreased friction).

Consistent with the conceptual framework, I observe that establishments with financially constrained parent firms exhibit no significant change in demand for automation-related skills. This finding aligns with the framework's prediction that higher borrowing costs, all else equal, reduce the attractiveness of automation. This result is supported by previous empirical evidence showing financially constrained firms rely more on labor than capital as inputs to production [15, 23].

Next, I exploit variation in the geographic production networks of firms with multi-county exposure to assess the capacity to redistribute production to unaffected counties. I observe that establishments with flexible production networks reduce demand for automation-related skills following severe natural disasters. This finding is consistent with previous empirical studies indicating that firms shift production away from affected establishments, thereby reducing the vulnerability of geographically diversified firms to local shocks [26, 9].

Finally, I investigate establishments' labor adjustment costs by examining labor-skill compatibility and barriers to adoption. Previous studies have highlighted the relationship between automation and low-skill labor [3, 2, 6]. I modify the labor skill index introduced by [24] to assess the exposure of a firm in a county to low-skill labor. Consistent with existing research, I define establishments reliant on low-skill labor by considering the weighted average of O*NET job zones associated with labor demand [10]. I observe that establishments with above-median demand for low-skill occupations increase demand for automation following severe natural disasters.

While reliance on low-skill labor increases demand for automation-related skills, this effect may be tempered by barriers to adoption, such as unionization [20]. Contract negotiations pose an obstacle to technological adoption in unionized workplaces. Consequently, unionized establishments are unlikely to change demand for automation-related labor skills, as any departure from existing automation schedules would require renegotiating contracts. This is consistent with my finding that establishments with high unionization rates show no significant change in demand for automation-related skills, post-disaster.

After exploring frictions to demand for automation-related skills, I explore the relationship between shifts in establishment-level labor skill demand and potential spillover effects to impacted parent firms. I analyze how unaffected establishments respond to at least one severe natural disaster by adjusting the demand for automation skills and educational/experience requirements, complements to technological adoption.

I find that following severe natural disasters unaffected establishments increase demand for automation skills by at least 84% and have higher minimum levels of educational attainment (degree levels of high school diplomas, college, and graduate/professional degrees)and related work experience (any experience and 5-10 years). This suggests that firms increase demand for high-skill labor, consistent with the technological "upskilling" effect [30, 18].

This paper contributes to the literature exploring firm adaptations to local labor supply shocks, specifically through investment in labor-saving technologies. Previous literature has relied on slow-moving, anticipated shocks that occur over extended periods, such as demographic shifts, local opioid consumption, or immigration rates [4, 12, 33, 32]. Given the extended horizon of the shock, shifts in demand for automation may be correlated with firms' prior technological adoption schedules. Additionally, unanticipated shocks alleviate concerns that adoption is associated with emerging technologies becoming more affordable and accessible over time. The discrete nature of my shock also allows me to comment on firm sensitivity to ex-ante adjustment costs.

Additionally, my setting allows me to contribute to the larger debate in the literature regarding technological investment and its relationship with labor. While automation typically is viewed as a substitute for labor, technological adoption may also have a reinstatement effect, such that firms shift labor demand towards skills complementary to the investment [2, 18, 6]. My setting extends this literature by capturing granular shifts in labor skill demand by firms and an increase in demand for automation complementary skills. In particular, my proposed measures provide additional investment proxies for labor-saving technologies, based on the content of the job posting. My measure relies on direct references to automation related-occupations and skills, rather than focusing on particular artificial intelligence applications [8] or derived measurements that introduce noise to related occupational measurements [38, 30].

Finally, I contribute to the emerging literature on the intersection of climate disasters and mitigation efforts through technological investment. While previous studies using discrete shocks have focused on historical settings with limited geographic impact [31], my contemporary setting provides greater external validity to how modern firms react across industries and geographic locations. Contemporaneous work exploits temperature shocks to measure impacts on outdoor employment [40, 41, 42]. As an anticipated shock to labor supply, abnormal temperatures suffer from similar identification challenges as other slow-moving shocks, while impacting only 5% - 10% of the total US workforce [17]. My setting provides greater external validity and focuses on local shocks across geographies. This allows me to capture shifts in labor skill demand at both the establishment and parent firm levels. In generalizing results, severe natural disasters cover a more diverse set of geographic regions and impact approximately 20-30% of the US labor force from 2010 – 2022. This provides a greater understanding of how natural disasters and migration impact firm automation decisions in local labor markets and how labor-skill demand adjusts technological investment.

2.0 Data

2.0.1 Natural Disasters and Economic Damages

Previous literature has shown that changes to migration flows are associated with localized shocks to the perception of economic opportunity in the impacted region [39, 27]. As location decisions are sticky, the effects of natural disasters must be of a sufficient magnitude to cause residents to consider costly relocation. Recurring meteorological phenomena or seasonal weather patterns are included in regional expectations. One explanation for this stability is that counties impacted by recurring phenomena may proactively adopt infrastructure minimizing economic damages associated with an event. Additionally, individuals chose to locate in areas based on the location's characteristics and compatibility with personal utility [34].

Natural disasters located in the right-most tail of the economic loss distribution are logical drivers of out-migration from impacted regions, as they are unexpected and outside regional loss expectations. Replicating previous literature examining migration impacts of natural disasters, I define treated counties as Federal Emergency Management Agency (FEMA)-declared natural disasters exceeding the 90th percentile of local economic damages [35, 37]. To capture federal major disaster declarations reported at the county level, I filter FEMA-reported disasters to exclude incidents unattributed to natural disasters (e.g., Terrorist, Chemical, Toxic Substances, or Other).

The Federal Emergency Management Authority (FEMA) regulations limit disaster declarations to events whose magnitude exceeds the capacities of state and local governments and compensation from insurance for disaster-related losses. To quantify the economic impacts of such events, I rely on estimates from the National Oceanic and Atmospheric Administration's (NOAA) Storm Events database, which reports crop and property losses at the county level.

I define treated counties as FEMA-declared disaster recipients with over the 90th percentile of annual economic damages (in 2012 dollars) from 2010 – 2022. Figure 1, Panel A shows the geographic distribution of severe natural disasters under this definition. These disasters are geographically dispersed and are not driven by recurring weather patterns or seasonal storms, such as hurricanes in the Southeast or wildfires in the Southwest. With recurring or seasonal patterns, local disaster preparedness infrastructure mitigates expected, lower-impact events. Conversely, high-economic-loss natural disasters are challenging to forecast and are likely independent of firms' predetermined automation schedules.

2.0.2 Labor Skill Demand

I use EMSI Lightcast (formerly Burning Glass Technologies) job posting data from 2010 – 2022 to capture labor demand for firms within counties, consistent with the observation level of natural disasters. EMSI Lightcast is a data provider aggregating online job posting data from job boards, company websites, and other sources in the United States, with granular geolocation information providing data on individual establishments. The data is detailed and captures local demand for labor, such as information regarding specific skills, education/experience requirements, and other responsibilities contained within the job posting.[1]

Past research exploring technological investment has typically used firm-level proxies like capital expenditures (CAPEX/PPENT) to approximate dollar investments. These measures aggregate the entire firm, distorting the investment in labor-saving technologies in affected counties. Furthermore, these measures encompass machinery, equipment, buildings, infrastructure, and other physical resources crucial to production processes, therefore including activities like rebuilding and replacing infrastructure damaged by natural disasters. Narrower measures of technological investment, such as expenditures on information processing tasks, concentrate on specific types of labor-saving technologies that may not be universally applicable across firms.

To address the shortcomings of existing measures, my empirical design enhances previous research by using the skill requirements outlined in detailed job postings to create a discrete estimate of labor demanded by firms related to automation investment. As firms increase

[1]For more in-depth analysis regarding the representativeness of the EMSI Lightcast data, please see [30].

investment in labor-saving technologies, there will be a corresponding rise in the demand for skills associated with automation.

2.0.2.1 Automation Skills

My setting focuses on automation applications utilizing labor-saving technologies for physical and computational tasks. I highlight physical and computational tasks, rather than expressly addressing artificial intelligence applications, to differentiate between the purposes of each technology. Robotics are used for autonomous or semi-autonomous physical tasks, while information processing involves systems, such as computers or telecommunications, for computational tasks. Artificial intelligence adds another layer by mimicking human decision-making, without explicit programming. While artificial intelligence may be incorporated into the robotics and information processing investment, the firm's labor skill demand will shift to support the underlying labor-saving technology.

To define my primary measure of automation skills, I utilize Lightcast's internal job posting Occupational Information Network (O*NET) mapping. Using the text of job postings, Lightcast sorts the postings into the standard classification of occupational information provided by the U.S. Department of Labor, Employment and Training Administration. This standardized classification of occupations creates a unique identifier for related occupations, regardless of the unique posting's title. Using the provided O*NET taxonomy from the Department of Labor, I begin by flagging postings using the following phrases in the Lightcast-generated O*NET code: automation, developer, infrastructure, mechatronics, microsystems, software, or systems. For example, a Robotics Engineer (O*NET: 17-2199.08) shares an O*NET code with Automation Engineers, Autonomous Vehicle Design Engineers, Design Engineers, Factory Automation Engineers, Research Engineers, and Robotic Systems Engineers.

To capture postings that require automation-related skills but belong to another O*NET occupation, I include job postings whose text references skills associated with automation activities from the library of associated O*NET skills. For example, Robotics Engineers require "object or component oriented development software (C; C++; Computer aided software engineering CASE tools; Oracle Java; Python)." Therefore, job postings that are not flagged as Robotics Engineers, but contain references to the associated skill are included in the automation postings measure. Finally, I use the list of alternative job titles associated with the O*NET code from the Department of Labor's website. Using keywords in these titles, I search the job posting text for direct references to supplement the direct Lightcast mapping and the associated skills. In my analysis, I refer to these postings as *Automation Postings*.

For robustness, as an extension for occupations that may have overlap with, but are not directly associated with automation activities, I create an extended measure of automation-related occupations, based on the Department of Labor's O*NET list of related occupations. For example, a Robotics Engineer is also associated with Aerospace Engineers (17-2141.02), Automotive Engineers (17-2061.00), Electrical Engineers (17-2072.00), and Mechanical Engineers (17-2199.05). These occupations contain activities related to automation, however, they also include responsibilities unrelated to investment in labor-saving technologies. In my analysis, I refer to these postings as *Automation and Related Postings*.

An area for future studies to expand upon previous work is the creation of a text classifier of job postings, using resume data from ultimate firm hires. The merged resume data could be used to train a model to identify required skills and job responsibilities related to automation investment not captured by the O*NET descriptions. Currently, any text classifier solely trained on the job posting data is restricted to the information contained in the posting. Current data limitations, such as the specificity of the job posting's required skills and day-to-day responsibilities, make it difficult to classify postings that may not explicitly reference automation. Supplementing resume data from firm hires would help provide greater context to the general responsibilities listed in the job posting text. This would likely expand the total set of automation-related postings, by refining the accuracy of the measure.

2.0.3 Summary Statistics

Table 1 provides summary statistics for the variables in the analyses. Parent firm data is obtained from CRSP/COMPUSTAT and is mapped to EMSI Lightcast using a cosine similarity of 95% between the company/employer names.

Panel A details firm data at the county level. This includes measures of automation, as well as local firm characteristics and parent firm controls. Panel B details labor skill demand data used in the firm-level analysis. Panel C details county-level economic data used to capture ambient economic conditions within each county and local labor market conditions. Variable definitions can be A.0.1.

3.0 Empirical Design

3.0.1 Conceptual Framework

Consider the following basic economic framework: A firm seeks to maximize profits by using production inputs of capital (K) and labor (L). To maximize profits, the firm minimizes total production costs, where costs are represented by the sum of the products of the production input and its respective cost (i.e., cost of capital (r) and cost of labor (w), respectively). Given a Cobb-Douglas production technology, rearranging first-order conditions suggests:

$$\Delta\left(\frac{K}{L}\right) \approx \sigma \times \Delta\left(\frac{w}{r}\right) \tag{1}$$

As σ represents the ratio of the output elasticities of capital to labor, it can be interpreted as "frictions" impacting the transmission of changes to the share of capital to labor in response to changes in the ratio of input costs. In my setting, σ is important in determining which firms are more/less likely to adopt automation technologies following the labor supply shock. I assume that a decrease in labor supply tightens the labor market, holding the cost of capital constant.

Equation 1 captures the shift from labor to automation, impacted by the magnitude of the associated adjustment costs. In the paper, I explore three types of adjustment costs: external financing frictions, frictions in production, and frictions to labor adjustment. External financing frictions limit firms' ability to substitute capital for labor, making capital more expensive and automation less attractive. Frictions in production, specifically the overall geographic dispersion of operations, may reduce the need to automate by allowing firms to shift production amongst locations. Finally, I explore labor adjustment costs as a friction to automate, as firms with higher compatibility with low-skill occupations share the greatest substitution with robotics and information technology automation [38].

In previous literature, capturing changes in the capital-to-labor ratio has often involved using proxies to estimate capital expenditures (CAPEX, PPENT, etc.) and labor demand (total employment). However, these estimates are aggregated at the firm level, which distorts the connection between local shocks and changes in local capital-to-labor ratios. To address this limitation, I use shifts in automation skill demand at the firm $\times$ county level as indicators of new production technologies in response to the shock. This factor-biased technical change reflects the establishment/firm's substitution of capital for labor, in response to growing labor scarcity subject to adoption frictions.

3.0.2 Identification Strategy

To examine the effects of severe natural disasters on local labor market conditions, I use the following difference-in-difference specification:

$$Y_{ct} = \alpha SevereDisaster_{ct} + X_{c,t-1} + X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ct} \tag{2}$$

Y_{ct} captures the outcome of interest for a county c in calendar-year t. I explore measures of both labor supply, such as the size of the labor force, total employment, and the unemployment rate, as well as measures of labor demand, such as the total number of job postings and total number of establishments, for a particular county. I include a suite of lagged county-level controls, $X_{c,t-1}$ to capture ambient economic conditions before the severe natural disaster. I also include contemporaneous controls for characteristics, such as receipt of FEMA recovery funding and change in the number of establishments. In addition, to control for additional time-invariant county characteristics, I include a county fixed effect (γ_c) and control for temporal variation using a calendar-year fixed effect (γ_t). The coefficient of interest α reflects the effect of a severe natural disaster on the county-level labor market subject to a severe natural disaster (treated) relative to never-treated counties. County and calendar-year fixed effects absorb the first difference estimates.

In exploring severe natural disasters as a shock to labor supply, the identifying assumption I exploit is that treated units would follow parallel migration patterns compared to counties never treated in the sample. I implement the following dynamic difference-in-differences specification to examine the parallel trends assumption:

$$ln(LaborForce_{ct}) = \delta \sum_{k=-3}^{3} SevereDisaster_{c,t+k} + X_{c,t-1} + X_{ct} + \gamma_c + \gamma_t + \varepsilon_{ct}, \tag{3}$$

where $SevereDisaster_{c,t+k}$ are indicator variables forming a symmetric three-year window around the severe natural disaster. This specification uses the year preceding the severe natural disaster as the reference year, normalized to zero. I include a county fixed effect (γ_c) to capture unobservable, time-invariant heterogeneity across counties. A calendar-year fixed effect (γ_t) is included to capture temporal variations. Lagged county-level economic controls ($X_{c,t-1}$) include GDP growth, unemployment rates, and average income. Contemporaneous controls, X_{ct}, include changes in the number of establishments and total FEMA disaster relief. Standard errors are clustered at the county level. I use the [36] cohort methodology to control for treatment heterogeneity across cohorts. Estimates and the 95% confidence interval are reported in Figure 2.

Since multiple disasters may affect a county during the study period, I define my treatment variable across all models based on the first occurrence of a severe natural disaster in that county. Thus, the indicator *Severe Disaster* takes a value of one following the initial natural disaster and remains active throughout the remaining sample period.

To ensure adequate coverage of both pre- and post-treatment periods in my panel, I require at least one year before and after the severe natural disaster. Additionally, to prevent contamination of results by severe natural disasters outside my specified sample period, I exclude counties that experienced disasters between 2006 and 2010.

Having established the migration effects of natural disasters, I investigate how labor scarcity affects establishments in impacted counties. Specifically, I analyze how these establishments adjust automation skill demand in response to severe natural disasters. I use a difference-in-difference approach to study the effect of labor scarcity on automation-related labor demand. I estimate the following Poisson regression specification at the firm-county level:

$$Y_{jct} = \beta SevereDisaster_{ct} + X_{jt} + \gamma_{j\times c} + \gamma_t + \varepsilon_{jct} \tag{4}$$

Y_{ijct} captures the outcome of interest for a firm j's establishments located in county c in calendar-year t [16]. In the baseline regressions, the primary specifications use the *Automation Postings* variable defined in Section 2.0.2.1. To control for unobserved time-invariant heterogeneity by firm-county pairs, I include a firm $\times$ county fixed effect ($\gamma_{j\times c}$). To capture temporal variation, I include a calendar-year fixed effect (γ_t). I also include a vector of parent-firm controls, X_{jt}, including measures capturing profitability, leverage, investment, dividend payouts, cash and equivalents, and financial constraints (SA index). In untabulated results, I include firm value in my set of parent-firm controls. While not perfectly correlated, I omit this specification from the reported results due to collinearity concerns with the firm size component in the SA index from [29]. The results remain consistent across specifications.

The coefficient of interest,β, measures the impact of out-migration on labor skill demand at establishments in counties affected by severe natural disasters (treated), compared to establishments never affected (untreated). The identifying assumption is that the assignment of severe natural disasters to counties is random with respect to local automation schedules, providing plausible exogeneity. Standard errors are clustered at the parent firm level.

4.0 Results

4.1 Local Labor Market Response

4.1.1 Within County Firm-Level Responses

I begin my analysis by examining the local labor market response to severe natural disasters. Severe natural disasters may shock both county-level labor supply (i.e., labor availability) and county-level labor demand (i.e., establishments). I use county-level economic data to quantify labor market responses and identify the economic mechanism through which local labor markets respond.

Figure 1, Panel B shows the geographic distribution of the change in the size of the local labor force from 2010 – 2022. In particular, the migration to and from counties is geographically dispersed and is not correlated with larger migration patterns. The migration patterns appear largely consistent with previous evidence on migration flows, such as [39, 27].

To capture changes in county-level labor supply, I examine changes in the size of the local labor force, total employment, and unemployment rates in counties impacted by severe natural disasters, compared to those never treated from 2010 – 2022. To capture changes in county-level labor demand, I examine the effects of severe natural disasters on proxies of local establishment activity. I use the total number of job postings in a county to proxy for local labor demand, while using the change in the total number of local establishments to proxy for the change in available employers. Finally, I examine the taxable wage bill to capture county-level labor costs. Table 2 reports local labor market responses of counties to severe natural disasters, using the difference-in-difference specification detailed in Equation 2. I rely on the identifying assumption that treated units would follow parallel trends in labor market conditions compared to counties never treated in the sample.

In Panel A, I analyze measures of county-level labor supply. Following a severe natural disaster, I observed a 9.2% decline in the local labor force, which is statistically significant at the 1% level. In relative terms, for an average county in the sample, the size of the available labor force decreases by over 6,700 participants in the three years following a severe natural disaster. Moreover, total employment increases slightly by 0.83%, indicating a temporary increase in local employment demand from disaster remediation and reconstruction. The rise in employment following the disaster aligns with observations from prior research [27]. There is no significant change in the unemployment rate. The decline in available labor alongside the increase in employment suggests there must be offsetting migration from the county to keep the unemployment rate constant. These findings suggest that natural disasters negatively impact local labor supply in impacted counties.

In Panel B, I examine the impact of the shock on county-level labor market demand. I find no significant change in the total number of job postings following the shock. Although there is a statistically significant increase in the number of establishments within each county, the economic effect of this increase is minor, at only 0.19%. Additionally, counties affected by a severe natural disaster show no significant change in aggregate taxable wages. Despite this stable aggregate wage bill, the counties simultaneously experience a reduction in the size of the labor force, leading to an increase in per-capita wages. These findings underscore the tightening of local labor markets: as county-level labor supply diminishes while demand remains steady, it exerts upward pressure on wages. This trend aligns with the conceptual framework proposed in Equation1, which suggests an increase in the cost of labor under such conditions.

All specifications show high reported R^2 values, particularly Panel A Columns (2) and (3) and Panel B Columns (1) and (3) which approach 1. This high R^2 is primarily due to the inclusion of county fixed effects, capturing a significant proportion of the variance in the dependent variables attributed to unobservable, time-invariant county characteristics. In econometric terms, including fixed effects is necessary to account for unobserved heterogeneity across counties that could impact local labor markets. Another metric, Within R^2, measures the variation in the dependent variable explained within the fixed effects model. Unlike overall R^2, which incorporates fixed effects as independent variables, Within R^2 values provide a more accurate indication of how well the explanatory variables predict the outcome of the response variable within the panel units. In this context, while the Within R^2 is lower, it provides a more consistent interpretation of the overall predictive power of the explanatory variables.

One concern in this setting is that the disbursement of FEMA disaster assistance may influence local labor market reactions. To control for contemporaneous disaster assistance, I include the total direct disaster assistance allocated to a county following the disaster. I use the inverse hyperbolic sine transformation to adjust for right-skewed data (FEMA, $K). While the coefficient on this control variable is statistically significant, the magnitude of the effect is small compared to coefficients for *Severe Disaster*. This suggests that federal disaster relief is not a viable channel to offset local labor market responses to severe natural disasters.

In examining severe natural disasters as a disruption to local labor supply, I assume that the counties affected by these disasters would have experienced migration patterns over time similar to counties unaffected in the sample. I employ a dynamic difference-in-difference model outlined in Equation 3 to assess parallel trends. The estimates of the dynamic effects are presented in Figure 2 and Table 3. Using a symmetric three-year window around the natural disaster, I find no evidence of pre-treatment trends in the size of the county's labor force. Following the disaster, there is an immediate and sustained decline in the labor force for up to two years. Although the coefficient in the third year is not statistically significant, the average of the coefficients in the post-period is negative. This indicates that the persistent reduction in the local labor force is not merely a temporary, salient reaction to the severe natural disaster [19].

With the rising frequency and severity of natural disasters over time, there is a concern that firms' expectations of disasters may influence local labor markets. Specifically, heightened uncertainty about labor availability could prompt firms to stockpile labor in anticipation of future disasters. I discuss potential issues of reverse causality below.

4.1.2 Labor Hoarding and Uncertainty: Anticipated Disasters

One potential concern is that firms' anticipation of county-level disasters could impact local labor markets. Research indicates that firms facing uncertainty tend to retain more workers to avoid costs associated with layoffs, rehiring, and training and reduce hiring [7, 25, 13]. If firms anticipate future severe natural disasters in counties within their geographic footprint, we should observe behaviors consistent with labor hoarding. This would suggest an expansion in the size of the county's labor force, an increase in employment (or a decrease in unemployment rates), or a decrease in the number of job postings. To address the potential concern that disaster-prone counties might face negative labor market effects due to the likelihood of future extreme climate events, I employ the following predictive regression to examine whether severe natural disasters can forecast labor market conditions:

$$SevereDisaster_{ct} = \lambda LaborMarketConditions_{c,t-1} + X_{c,t-1} + +\gamma_c + \gamma_t + \varepsilon_{ct} \tag{5}$$

I incorporate lagged measures of local labor market conditions, such as the size of the labor force, total employment, unemployment rate, job postings, number of establishments, and aggregate taxable wages, as outlined in Table 2. The findings of the linear probability model are presented in Table 4 and are consistent with logistic regression (untabulated).

In Panel A, Column (1) reveals a negative association between the size of the labor force and the occurrence of a severe natural disaster in the subsequent period. On average, a 10% increase in the labor force size correlates with a 0.11% decrease in the likelihood of a severe natural disaster occurring in a county. Despite statistical significance, this finding suggests minimal impact on the probability of future disasters and is inconsistent with labor hoarding. Similarly, in Column (2), a 10% increase in county-level employment is associated with a 3.14% increase in the likelihood of a severe natural disaster occurring in the following year. While directionally consistent with labor hoarding, the effect size appears disproportionately small compared to the reduction in disaster probability. Moreover, no significant relationship is observed between the unemployment rate and the likelihood of future severe natural disasters. Overall, these results indicate that current measures of labor supply do not have an economically significant relationship with future disaster exposure and are inconsistent with the labor hoarding alternative.

In Panel B, I conduct a similar analysis focusing on measures of labor demand. In Column (1), a 10% decrease in the total number of job postings is associated with a 0.20% increase in the likelihood of severe natural disasters occurring in the following year. While this directionally aligns with expectations of labor-hoarding behavior, the effect size appears disproportionately small relative to the observed increase in disaster probability. Additionally, there is a positive relationship between changes in the number of establishments within a county and the probability of future disasters. Although increased uncertainty generally stimulates entrepreneurship [7], administrative data does not clarify whether this rise in establishments stems from incumbent firms expanding or new firms being created. Nevertheless, a one standard deviation increase in establishment changes results in a minor rise in next year's disaster probability. Furthermore, there is no significant change observed for taxable wages. Contrary to the anticipation hypothesis, measures of labor demand indicate no economically significant association with future disaster exposure.

4.2 Establishment-Level Response

Next, I examine how labor demand at individual establishments shifts in response to the demand for automation skills. In regions devastated by severe natural disasters, where labor becomes increasingly scarce, technologies that reduce labor requirements become attractive alternatives to higher-cost human labor. According to the conceptual framework, as labor costs rise, all else equal, firms should increase demand for capital-intensive production processes. However, they also face the financial challenges of post-disaster cleanup and recovery. These recovery efforts can deplete resources for investing in new production processes, as firms prioritize liquidity following cash-flow shocks induced by disasters [14].

To capture changes in firms' county-level automation investment, I investigate the demand for labor skills among establishments affected by severe natural disasters versus those unaffected from 2010 – 2022. I assume that establishments affected by disasters would exhibit similar trends in automation adoption compared to those never affected in the sample period. Table 5 reports the automation labor skill demand in establishments subject to severe natural disasters, using the difference-in-difference specification detailed in Equation 4. I report the following results using a fixed effect strategy to control for time-invariant heterogeneity at the firm, county, and firm $\times$ county level and temporal variation.

In Table 5, Panel A, I find a positive and significant response in establishment-level labor demand for automation postings. Columns (1), (3), and (4) control for temporal variation in demand for automation skills over time. Columns (2) and (3) control for time-invariant firm and time-invariant county characteristics. Column (4) controls for both firm-specific and county-specific characteristics that do not vary over time. Across the various specifications, I find that severe disasters are associated with a 49.2%-67.4% increase in automation postings. However, as Column (4) is fully saturated it provides a more robust estimation of causal effects and is my preferred specification for the following analysis. This specification suggests that demand for automation postings increases by 49.2%.

Table 5, Panel B explores the relaxed definition of automation and related postings. While positive and significant, the effects are attenuated, due to the noise introduced by the additional postings that may have overlapping skill sets to those in the automation-related postings measures. While the effects are stable over the specifications, Column (4) is associated with a 26.2% increase in demand for automation and related postings.

This suggests that firms with declining labor availability following natural disasters increase demand for automation skills. While the economic magnitudes of these coefficients are high, the results are consistent with automation hiring as a relatively rare occurrence before the natural disaster. As job postings with direct, day-to-day exposure to automation are relatively rare I compare my measures to prior indices of technological exposure from the literature.

To capture firms' heterogeneous demand for labor skills, I decompose automation into three categories following the methodology described in [38] and compare two generalized automation indices ([22] and [21]). I report the results of this analysis in B.1. These alternative measures create continuous mappings of an occupation's exposure to automation. However, these measures do not directly capture automation and rely on the assumption that firms with higher exposure to automation will increase demand for automation in the future.

I find an economically insignificant response across specifications in establishment-level labor demand for skills associated with automation-related postings. This result highlights the noise introduced by continuous measures of occupational exposure to automation. My measure improves upon previous literature by directly mapping job postings to automation skills. While more restrictive in defining automation labor demand, this direct mapping introduces less noise than the biased continuous classifications.

4.2.1 Firm Adjustment Costs

Since severe natural disasters represent sudden and unforeseen disruptions to local labor supply, the initial characteristics of affected establishments may influence their propensity to automation, as seen in Equation 1. To address potential adjustment costs, I expand my base model, introducing an interaction term that reflects these costs across establishments or at the parent-firm level. In subsequent analyses, I investigate parent-firm adjustment costs related to automation investments, such as external financing and production constraints, alongside establishment-level challenges like labor adjustment costs.

4.2.1.1 Cost of External Financing

The automation investment decision can be expressed as a function of the costs of labor and the costs of financing [28, 43]. While decreased labor availability following severe natural disasters increases labor costs, prohibitively high financing costs may make automation an unattractive substitute. In Equation 1, the rise in the cost of capital partly counteracts wage increases resulting from a tighter post-disaster labor market. Consequently, a higher cost of capital is expected to diminish the appeal of capital-intensive production methods. However, empirically observing this trade-off is challenging due to the endogenous nature of firm financial constraints.

To address this concern, I use a quasi-natural experiment using the proportion of long-term debt, maturing in the next year, to total assets as a proxy for a firm's financial constraints. Following the methodology in [11], I create indicator variables for when a firm has over 5% or 15% of long-term debt to total assets maturing in the next year. As external financing is costly, parent firms that need to refinance large amounts of maturing long-term debt will be more financially constrained, increasing r in Equation 1.

Table 6 provides the results for establishments with financially constrained parents. Columns (1) and (2) show the results for parents with maturing long-term debt over 5% of total assets, while Columns (3) and (4) present results for the higher 15% threshold.

While there is a positive and significant relationship between a severe disaster and demand for automation postings, there is no significant change in demand for automation labor skills by financially constrained parent firms. The interaction term indicates that although labor scarcity caused by severe natural disasters may increase the appeal of labor-saving technologies for firms, financially constrained parent firms do not accelerate automation schedules in establishments located in affected counties.

4.2.1.2 Production Inflexibility

The structure of a parent firm's production network can alleviate the impact of localized shocks. Firms operating in multiple locations outside counties affected by severe natural disasters have the flexibility to transfer production to unaffected sites, reducing vulnerability to local labor shortages. Diversified production networks shield firms from localized wage fluctuations, implying a negative σ in Equation 1. Holding the cost of capital constant suggests that firms with diverse production networks are less inclined to transition toward capital-intensive production processes.

To gauge the geographic dispersion of firm production networks, I create an indicator variable, *Multiple Locations*, equal to one if a parent firm has ever had a job posting in at least two unique counties. As locations are observed using the EMSI Lightcast job posting data, my measure identifies locations by job postings in my sample. Given the data limitations, this indicator is the same across time for a parent firm, as openings and closures over the sample period are not precisely identified.

Table 7 displays county-level findings for establishments with parent firms with diversified production networks. In Columns (1) and (2), establishments affected by severe natural disasters increase demand for automation-related job postings, 65.9% and 51.9% respectively. However, I do not observe establishments within geographically dispersed production networks increase demand for automation labor skills following such disasters. Specifically, in Column (1), establishments in disaster-affected counties with diversified production networks decrease demand for automation-related labor skills by 82.55%. Although this effect becomes insignificant in the fully saturated model, it is directionally with the insights from Equation

1, suggesting that firms do not accelerate their demand for automation skills. Columns (3) and (4) replicate this analysis using a broader definition of automation including related job categories. Both interaction terms are negative and statistically significant, indicating that firms with multiple production locations reduce demand for automation and related job postings by 65.8% and 63.3%, respectively. These findings are consistent with the ability of parent firms to reallocate production from affected establishments to other locations within their network.

4.2.1.3 Labor Adjustment Costs

A significant barrier to adopting automation is the technological compatibility with an establishment's current labor demand. Automation technologies currently can replace low-skill labor [3, 2, 6]. This implies that firms heavily reliant on low-skill labor are better positioned to substitute existing labor needs with production technologies like automation. In Equation 1, this implies for firms reliant on low-skill labor an increase in wages, holding the cost of capital constant, is amplified by labor-skill compatibility. This shifts firms towards capital-intensive production.

Table 8, Panel A provides the results for establishments reliant on low-skill labor. To capture demand for low-skill labor, I use O*NET job zones as a discrete measure of labor skill content. This classification groups similar occupations by education, related experience, and on-the-job training required to satisfy occupational requirements. Job zones range from 1 to 5, where job zone 1 includes occupations requiring little/no preparation, and job zone 5 requires extensive preparation. For example, job zone 1 includes occupations, such as food preparation workers, dishwashers, baristas, and other occupations that require education no greater than a high school degree/GED. Job zone 5 requires graduate school of at least a master's degree and includes occupations, such as pharmacists, lawyers, biologists, and physician assistants.

To capture the labor skill compatibility of establishments and automation technologies, I adapt the labor-skill index from [24] to the firm $\times$ county level:

$$LSI_{jc} = \sum_{k=1}^{5} \left[\frac{Postings_{jck}}{TotalPostings_{jc}} \times \text{O*NET Job Zone}_k \right] \tag{6}$$

The labor skill index ranges from one (low-skill) to five (high-skill) and represents the establishment-level labor-demand weighted average of labor skill. The labor skill index is defined for a firm's establishments, j, in the county, c, as the weighted average of the job postings associated with a particular skill content. To proxy for establishments reliant on low-skill labor, I create an indicator variable, *Low Skill*, that is equal to one when the establishment labor skill index is below the median (i.e., higher reliance on low-skill labor) [10].

Consistent with the conceptual framework, Columns (1) and (2) show firms with establishments dependent on low-skill labor in counties impacted by severe natural disasters increase demand for automation skills by a factor of 2.0 and 2.2, respectively. While the effects are attenuated in Columns (3) and (4), the results still suggest a 50.6%-58.0% increase in demand for automation postings in low-skill dependent firms following a natural disaster. These results are both economically meaningful and statistically significant.

As the effect of *Severe Disaster* is statistically indistinguishable from zero, this implies that the increase in automation adoption by firms following severe natural disasters is primarily concentrated in firms that rely on low-skill labor. Considering the concurrent decline in the labor force size, as shown in Table 2 Column (1), this result provides suggestive evidence that out-migration is driven by low-skill workers leaving the county. However, without more detailed data on labor force participants, specifically the skill content of those entrants and exits, this shift in population cannot be observed directly. This is an area for future research.

While reduced labor adjustment costs enhance the attractiveness of automation, unionization can counteract this by increasing the difficulty of automating, despite labor skill compatibility. Empirical evidence has shown union membership primarily benefits low-skill workers [20]. Table 8, Panel B explores the effect of unionization rates on automation-related labor skill demand for establishments impacted by severe natural disasters.

To proxy for unionization rates at firms in a particular county, I create a measure of the percentage of each state's non-agricultural wage and salary employees who are covered by a collective bargaining agreement using data from the *Union Membership and Coverage Database from the CPS (Unionstats.com).* As unionization rates may vary at the state level, through Right-to-Work laws, I create an indicator variable *High State* equal to one when the state's unionization rate is above the median (i.e., a higher proportion of unionized establishments). As unionization rates can also vary by industry, I interact *High State* with an indicator, *High Industry*, equal to one when the NAICS three-digit industry is above the median (i.e., a higher proportion of unionized workers within an industry). In the regressions, the product of the two indicators is *High Union (0/1)*. This indicator helps disentangle nuances of both regional and industry-level variation in the propensity to unionize.

In establishments characterized by high unionization rates, I observe no increase in demand for automation-related skills among establishments affected by severe natural disasters and subsequent declines in labor availability. This finding aligns with contract renegotiation posing a barrier to adopting new production technologies. Consequently, unionization diminishes the advantages of automation for establishments that heavily depend on low-skill labor.

4.3 Firm-Level Response

Finally, I examine the spillover effects on parent firms with establishments in counties impacted by severe natural disasters. While the previous section establishes the direct impact of these disasters on local labor demand for affected establishments, it remains uncertain how these localized shocks spread across broader firm networks. As the effects of natural disasters are highly localized, having impacted establishments within a particular county may not necessarily result in observable differences in demand for automation-related skills across wider geographies. For example, production network flexibility decreases the demand for automation-related labor. As production can potentially be reallocated amongst the firm's geographic network, the shift in overall demand for automation-related skills across the parent firm is unclear.

To explore potential spillover effects on unaffected establishments within the firm, I begin by constructing a firm-year panel dataset. This dataset includes an indicator variable, *Impacted Establishment*, equal to one if a firm experiences at least one severe natural disaster at any of its establishments during a given year. To capture the effect of a local establishment impacted by a natural disaster on the aggregate labor demand across non-impacted establishments, I use the following difference-in-difference specification:

$$Y_{jt} = \theta ImpactedEstablishment_{jt} + X_{jt} + \gamma_j + \gamma_t + \varepsilon_{jt} \tag{7}$$

Observations in this regression are reported at the aggregate firm level, excluding the impacted establishments, such that Y_{jt} captures the labor demand for a firm j in calendar year t. The measures of labor demand remove establishments from counties affected by natural disasters throughout the sample period. I include a firm fixed effect (γ_j) to control for unobserved time-invariant heterogeneity by firms. I include a calendar-year fixed effect (γ_t) to capture temporal variation. I also include a vector of parent firm controls, X_{jt}.

The coefficient of interest, θ, captures the effect of an impacted establishment on aggregate labor skill demand at the rest of the firm, relative to firms with never-treated establishments. Firm and calendar-year fixed effects absorb the first difference estimates. My identifying assumption is that the labor skill demand at the unaffected establishments of treated firms should exhibit parallel trends compared to firms that were never treated in the sample. Standard errors are clustered by the parent firm.

Table 9 explores the parent-firm spillover effects on unaffected establishments. In Panel A, I explore the automation demand of firms, while Panels B and C focus on increases in demand for high-skill labor complementary to the implementation and support of labor-saving technologies.

In Panel A, I observe a positive and statistically significant association between the aggregate demand for automation skills at unaffected establishments and parent firms experiencing at least one severe natural disaster in another county. Columns (1) through (3) analyze the impact of one, two, or three severe disasters in a given calendar year, respectively. As the number of disasters increases, the coefficient's magnitude grows monotonically across the different specifications. On average, a severe natural disaster increases automation demand by 84% or approximately 8 additional job postings for a firm. This effect escalates with the number of disasters to approximately 13 and 14 additional postings in Columns (2) and (3) respectively. These effects are consistent with automation spillovers to unimpacted establishments of firms.

While these effects appear moderate relative to overall hiring, my measure only captures increases in labor demand and not decreases in overall employment. For example, a firm may not hire an automation engineer for each establishment but rather rotate the placement across establishments in a given territory. An area for future study is how best to capture the rotation of employment across territories, using job posting text.

Panel B examines the minimum educational qualifications specified in job postings, whereas Panel C examines the minimum experiential requirements. Previous research has used these educational and experiential requirements as proxies for the skill content of job postings. Increased educational and experiential demand is associated with firms demanding higher-skilled labor to support technological adoption, referred to as "upskilling" [30].

In Panel B, I find that parent firms with at least one impacted establishment increase the number of postings specifying a minimum educational attainment level (high school, college, and graduate/professional degrees). On average, this results in an increase of more than 1,300 job postings that require at least a high-school degree, over 650 job postings that require at least a bachelor's degree, and approximately 60 job postings that require at least a graduate or professional degree. This increase in demand for educational requirements is consistent with unimpacted establishments increasing demand for labor supportive of new production technologies.

In Panel C, I find that parent firms with at least one impacted establishment increase the number of postings specifying a minimum experiential requirement. On average this results in an increase of over 1,200 postings requiring any level of previous work experience and over 320 postings requiring seniority of 5-10 years in the field. The increase in demand for prior work experience is suggestive that firms increase demand for high-skill labor in unimpacted establishments to complement technological adoption.

In summary, I observe that unaffected establishments increase demand for automation skills and increase educational and experiential requirements following at least one severe natural disaster at another location. This suggests that severe natural disasters have spillover effects beyond the impacted establishments, influencing the labor demand of the parent firm. While consistent with previous studies focusing on parent-firm aggregates, the propagation to unaffected establishments suggests that severe natural disasters catalyze parent-firm automation demand.

5.0 Conclusion

In this paper, I provide systematic evidence of how firms' establishments adapt to increased labor scarcity through shifting labor skill demand and investment toward automation. In my study, I use labor demand for automation skills as a proxy for investment in labor-saving technologies, such as robotics and information processing. I exploit natural disasters as an exogenous shock to local labor availability. In response to severe natural disasters, I observe a 9.2% decrease in the size of the local labor force. This decline in local labor availability is persistent for up to two years following the severe natural disaster, contributing to tightening local labor markets.

To counteract decreases in local labor availability, I observe that affected establishments increase demand for automation skills. This relationship hinges on firm adjustment costs, where barriers to adoption can either enhance or diminish automation's ability to mitigate labor shortages. For instance, higher compatibility of labor skills accelerates the adoption of automation by firms following a disaster. Conversely, factors such as having financially constrained parent firms or flexible production networks reduce the appeal of automation as a substitute for declining labor availability. These findings underscore the role of adjustment costs in shaping decisions related to the demand for automation skills.

My results provide evidence of the role of automation in the labor market, as a mechanism through which establishments can offset decreases in local labor availability. To complement this analysis, I examine spillover effects on unaffected establishments when a parent firm has at least one other establishment subject to a severe natural disaster. I find an increased demand for automation skills and general high-skill labor, in terms of educational and experiential requirements. This is suggestive evidence of technological "upskilling," highlighting the parent firm's exposure to severe natural disasters and subsequent declines in labor availability through impacted establishments.

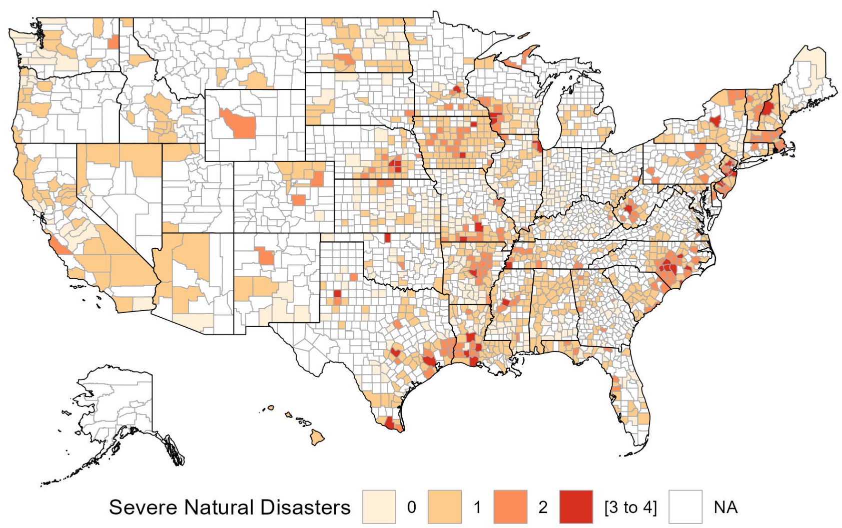
My research provides insight into how severe natural disasters impact local labor markets and how firms employ labor-saving technologies to mitigate resulting declines in labor availability. These findings provide additional context to the expanding literature on firms' adaptation to climate change. Especially as disaster mitigation strategies are increasingly important to firms' risk management, given the potential losses firms may face from future climate-related disasters.

5.1 Figures

Figure 1: Spatial Distributions

This figure compares the geographic distribution of severe natural disasters and changes in the size of the local labor force from 2010 – 2022.

Panel A: Total Severe Natural Disasters



Panel B: Changes in Local Labor Force

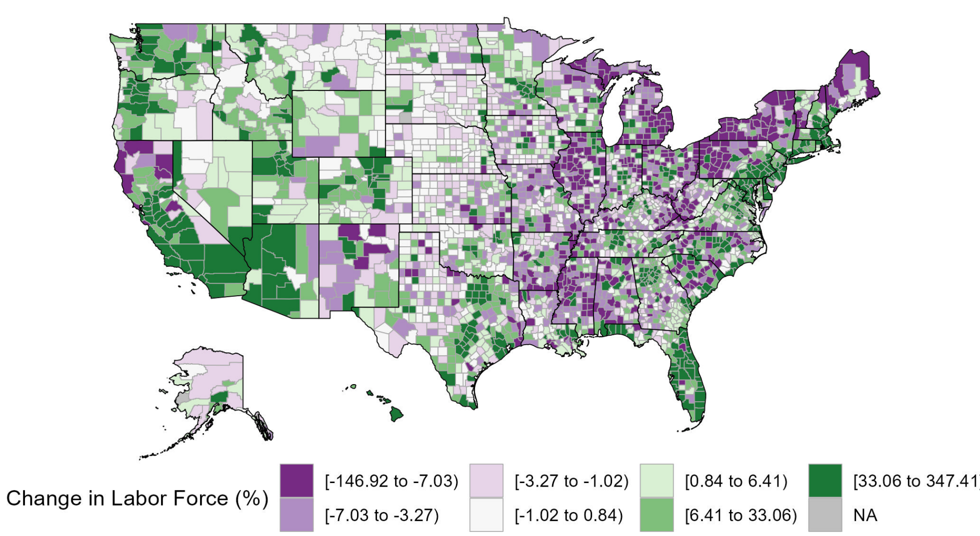
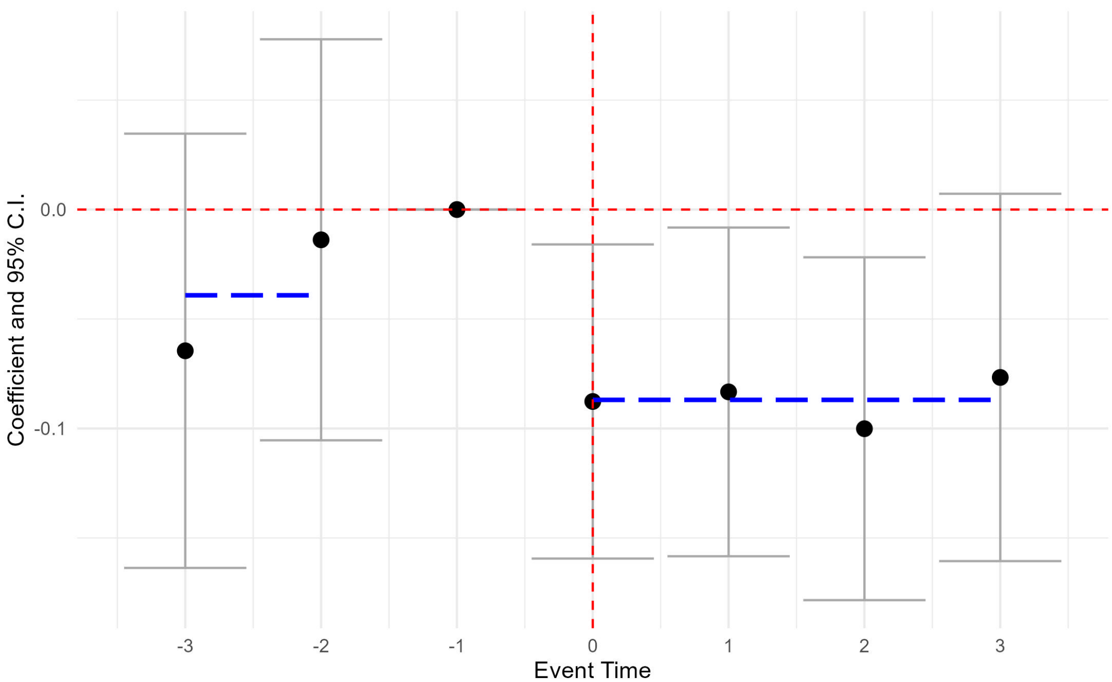


Figure 2: Parallel Trends

This figure plots the dynamics of the difference-in-differences estimates using Equation 3. The year before the severe natural disaster is the base period to normalize the coefficients. Specifications include lagged and contemporaneous county-level characteristics and direct FEMA assistance, as controls. I also include county fixed effects and calendar year fixed effects. Unbiased estimators are obtained using the cohort methodology described in [36]. The grey error bars represent the 95% confidence interval for the estimates. The blue dotted line provides the average coefficient in pre- and post- periods.



5.2 Tables

Table 1: Summary Statistics

This table provides summary statistics for the data in the analyses. Panel A summarizes firm × county data from 2010–2022. Panel B summarizes parent-firm level data from 2010–2022. Panel C summarizes county-level economic data from 2010–2022. Variable definitions can be found in A.0.1.

Panel A: Firm x County Data

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Automation Postings	490,962	0.0023	0.086	0.000	0.000	0.000	16
Automation & Related Postings	490,962	0.110	1.800	0.000	0.000	0.000	428
Maturing LTD > 5% (0/1)	490,962	0.094	0.29	0	0	0	1
Maturing LTD > 15% (0/1)	490,962	0.011	0.1	0	0	0	1
Low Skill (0/1)	490,962	0.8	0.4	0	1	1	1
Firm Size	490,962	2.3	7.8	0.51	1.2	2.3	258
Leverage	490,962	0.27	0.21	0	0.11	0.39	1
Investment	490,962	0.052	0.052	0	0.019	0.068	0.38
Dividend Payouts	490,962	0.018	0.027	0	0	0.024	0.18
Cash and Equivalents	490,962	0.11	0.13	0	0.025	0.14	0.99
SA Index hadlock2010new	490,962	3.5	1.2	-3.9	2.8	4.3	4.9

Panel B: Parent Firm Data

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Automation Postings	20,219	9.2	60	0	0	2	2080
High School	20,219	530	2,881	0	2	166	112318
College	20,219	285	1,647	0	2	106	72400
Graduate/Professional	20,219	24	189	0	0	5	7322
Any	20,219	486	3,441	0	2	152	168082
5-10 Years	20,219	153	992	0	1	57	42654

Panel C: County-Level Economic Data

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Labor Force	13,412	73,322	217,765	761	7,851	56,519	5,151,546
log(Employment)	13,412	9.90	1.40	6.60	8.90	11.0	15.0
Unemployment Rate	13,412	0.06	0.03	0.02	0.04	0.08	0.29
log(Job Postings)	10,763	6.70	2.00	0.69	5.30	8.00	13.00
Δ Establishments	13,412	0.00	0.03	-0.41	-0.01	0.01	0.31
Taxable Wages ($M)	13,412	21.00	2.00	0.00	19.00	22.00	27.00

Table 2: Local Labor Market Effects

This table studies the local labor market effects of severe natural disasters. Panel A evaluates the labor-supply side effects, while Panel B examines the labor-demand side effects of severe natural disasters. *Severe Disaster* is an indicator variable that equals one when a county has a Federal Emergency Management Agency (FEMA) declared natural disaster that exceeds the 90th percentile of local economic damages from 2010 – 2022. Specifications include lagged and contemporaneous county-level characteristics and direct FEMA assistance, as controls. I also include county fixed effects and calendar year fixed effects. Standard errors are reported in parentheses and clustered at the county level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Labor Supply

	log(LaborForce)	log(Employment)	Unemployment Rate
	(1)	(2)	(3)
Severe Disaster	-0.0918***	0.0083***	-0.0001
	(0.0354)	(0.0031)	(0.0007)
ΔGDP_{t-1}	0.1107	0.0164**	-0.0104***
	(0.0731)	(0.0067)	(0.0016)
Unemployment $Rate_{t-1}$	0.2090		
	(1.215)		
$Income_{t-1}$	0.6292***	0.2523***	-0.0160***
	(0.1775)	(0.0238)	(0.0041)
Δ Establishments	0.8415***	0.1660***	-0.0410***
	(0.2118)	(0.0210)	(0.0057)
FEMA, $K	0.0029*	-0.0000	-0.0000***
	(0.0017)	(0.0000)	(0.0000)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	13,412	13,412	13,412
R^2	0.49376	0.99932	0.90834
Within R^2	0.00418	0.09394	0.02930

Panel B: Labor Demand

	log(Job Postings)	Δ Establishments	Taxable Wages
	(1)	(2)	(3)
Severe Disaster	-0.0328	0.0019**	0.0335
	(0.0217)	(0.0009)	(0.0256)
ΔGDP_{t-1}	-0.0137	0.0076	0.0910*
	(0.0729)	(0.0047)	(0.0504)
Unemployment Rate_{t-1}	-1.001	-0.2421***	-1.149***
	(0.7182)	(0.0315)	(0.3746)
Income_{t-1}	0.5706***	0.0029	0.4688***
	(0.1391)	(0.0070)	(0.1259)
Δ Establishments	-0.0684		
	(0.2299)		
FEMA, $K	-0.0022***	-0.0001	0.0003
	(0.0008)	(0.0001)	(0.0006)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	10,763	13,412	13,412
R^2	0.96945	0.22917	0.92838
Within R^2	0.00721	0.01145	0.00266

Table 3: Dynamic Effects

This table studies the dynamics of the difference-in-differences estimates using Equation 3. The base period used to normalize the coefficients is the year before the severe natural disaster. *Severe Disaster* is an indicator variable that equals one when a county has a Federal Emergency Management Agency (FEMA) declared natural disaster that exceeds the 90th percentile of local economic damages from 2010 – 2022. Specifications include lagged and contemporaneous county-level characteristics and direct FEMA assistance, as controls. I also include county fixed effects and calendar year fixed effects. Unbiased estimators are obtained using the cohort methodology described in sun2021estimating. Standard errors are reported in parentheses and clustered at the county level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
(continued next page...)

	ln(Labor Force)	
	(1)	(2)
Severe Disaster$_{t=-3}$	-0.1134	-0.0645
	(0.0750)	(0.0779)
Severe Disaster$_{t=-2}$	-0.0330	-0.0138
	(0.0491)	(0.0503)
Severe Disaster$_{t=0}$	-0.0779*	-0.0877*
	(0.0442)	(0.0450)
Severe Disaster$_{t=1}$	-0.0536	-0.0833*
	(0.0452)	(0.0480)
Severe Disaster$_{t=2}$	-0.1264***	-0.1001**
	(0.0442)	(0.0495)
Severe Disaster$_{t=3}$	-0.1298***	-0.0767
	(0.0483)	(0.0581)
ΔGDP$_{t-1}$	0.2411***	0.2247***
	(0.0706)	(0.0716)
Unemployment Rate$_{t-1}$	-2.512***	-1.755*
	(0.7430)	(0.9209)
Income$_{t-1}$	0.8602***	0.8684***
	(0.1643)	(0.1531)
Δ Establishments	0.8905***	1.094***
	(0.2027)	(0.2102)
FEMA, \$K	0.0010	-0.0003
	(0.0014)	(0.0014)
County FE	Yes	Yes
Year FE	No	Yes
Observations	13,412	13,412
R^2	0.46240	0.46686

Table 4: Anticipation of Future Disasters

This table studies the anticipation of future severe disasters by local labor markets. Panel A evaluates the labor-supply side predictors, while Panel B examines labor-demand side predictors of severe natural disasters. *Severe Disaster* is an indicator variable that equals one when a county has a Federal Emergency Management Agency (FEMA) declared natural disaster that exceeds the 90th percentile of local economic damages from 2010 – 2022. Specifications include county-level characteristics , as controls. Standard errors are reported in parentheses and clustered at the county level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Labor Supply

	Severe Disaster		
	(1)	(2)	(3)
log(Labor Force)$_{t-1}$	-0.0111**		
	(0.0045)		
log(Employment)$_{t-1}$		0.3294***	
		(0.1184)	
Unemployment Rate$_{t-1}$	-0.5576		-0.2005
	(0.4464)		(0.4771)
ΔGDP$_{t-1}$	-0.0283	-0.0315	-0.0282
	(0.0347)	(0.0345)	(0.0347)
Income$_{t-1}$	0.1160	0.0431	0.1233
	(0.0926)	(0.0940)	(0.0921)
Δ Establishments$_{t-1}$	0.1806*	0.1342	0.1812*
	(0.0929)	(0.0904)	(0.0932)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	13,412	13,412	13,412
R^2	0.76612	0.76642	0.76580
Within R^2	0.00230	0.00358	0.00093

Panel B: Labor Demand

	Severe Disaster		
	(1)	(2)	(3)
log(Job Postings)$_{t-1}$	-0.0187**		
	(0.0094)		
Δ Establishments$_{t-1}$		0.1685*	
		(0.0928)	
Taxable Wages$_{t-1}$			0.0065
			(0.0051)
ΔGDP$_{t-1}$	-0.0202	-0.0308	-0.0314
	(0.0328)	(0.0347)	(0.0347)
Unemployment Rate$_{t-1}$	-0.0828	-0.5400	-0.5320
	(0.4427)	(0.4463)	(0.4463)
Income$_{t-1}$	-0.0061	0.1065	0.1034
	(0.0895)	(0.0925)	(0.0925)
Δ Establishments$_{t-1}$	0.0935		0.1701*
	(0.0959)		(0.0930)
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	10,763	13,412	13,412
R^2	0.78596	0.76589	0.76595
Within R^2	0.00096	0.00134	0.00157

Table 5: Establishment-Level Demand for Automation-Related Skills

This table examines cross-sectional shifts in automation labor skill demand following a severe natural disaster. *Severe Disaster* is an indicator variable that equals one when a county has a Federal Emergency Management Agency (FEMA) declared natural disaster that exceeds the 90th percentile of local economic damages from 2010 – 2022. The automation response variables are defined according to Section 2.2. Specifications include a suite of parent firm characteristics, as well as calendar year, firm, county, and firm × fixed effects. Standard errors are reported in parentheses and clustered at the establishment level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Automation Postings

	Number of Automation Postings			
	(1)	(2)	(3)	(4)
Severe Disaster	0.4660***	0.4398***	0.5150***	0.4001***
	(0.1511)	(0.1537)	(0.1699)	(0.1545)
Firm Controls	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes
Firm x County FE	No	No	No	Yes
Firm FE	No	Yes	Yes	No
County FE	No	Yes	Yes	No
Observations	490,962	490,962	490,962	490,962
Pseudo R^2	0.37395	0.03869	0.19725	0.37748

Panel B: Automation and Related Postings

	Number of Automation and Related Postings			
	(1)	(2)	(3)	(4)
Severe Disaster	0.2477***	0.2372***	0.1949**	0.2327***
	(0.0711)	(0.0737)	(0.0968)	(0.0754)
Firm Controls	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes
Firm x County FE	No	No	No	Yes
Firm FE	No	Yes	Yes	No
County FE	No	Yes	Yes	No
Observations	490,962	490,962	490,962	490,962
Pseudo R^2	0.38051	0.04020	0.17415	0.38103

Table 6: Parent Firm Financing Constraints

This table examines the automation labor skill demand response of establishments with constrained parent firms following a severe natural disaster. *Severe Disaster* is an indicator variable that equals one when a county has a Federal Emergency Management Agency (FEMA) declared natural disaster that exceeds the 90th percentile of local economic damages from 2010 – 2022. *Maturing LTD* is in an indicator equal to one when long-term debt to assets is over an established threshold (i.e. 5% or 15%) at the time of the severe natural disaster. The automation response variables are defined according to Section 2.2. Specifications include a suite of parent firm characteristics, as well as calendar year and firm × county fixed effects fixed effects. Standard errors are reported in parentheses and clustered at the establishment level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Automation Postings

	Over 5% of Total Assets		Over 15% of Total Assets	
	(1)	(2)	(3)	(4)
Severe Disaster × Maturing LTD (0/1)	0.0665	0.0450	0.0680	0.0574
	(0.2742)	(0.2787)	(0.2027)	(0.1942)
Severe Disaster	0.4202**	0.3617*	0.4184**	0.3682**
	(0.1876)	(0.1938)	(0.1655)	(0.1694)
Firm Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm x County FE	No	Yes	No	Yes
Observations	490,962	490,962	490,962	490,962
Pseudo R^2	0.21366	0.21770	0.02309	0.21836

Panel B: Automation and Related Postings

	Over 5% of Total Assets		Over 15% of Total Assets	
	(1)	(2)	(3)	(4)
Severe Disaster × Maturing LTD (0/1)	0.1366	0.1357	-0.0320	0.3687
	(0.1610)	(0.1618)	(0.3337)	(0.2590)
Severe Disaster	0.2121***	0.1968**	0.2119***	0.2179***
	(0.0756)	(0.0797)	(0.0769)	(0.0769)
Firm Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm x County FE	No	Yes	No	Yes
Observations	490,962	490,962	490,962	490,962
Pseudo R^2	0.33357	0.33413	0.01684	0.33411

Table 7: Production Flexibility

This table examines the automation labor skill demand of establishments with parent-firms with production flexibility following a severe natural disaster. *Severe Disaster* is an indicator variable that equals one when a county has a Federal Emergency Management Agency (FEMA) declared natural disaster that exceeds the 90th percentile of local economic damages from 2010 – 2022. The automation response variables are defined according to Section 2.2. Specifications include a suite of parent firm characteristics, as well as calendar year and firm × county fixed effects fixed effects. Standard errors are reported in parentheses and clustered at the establishment level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Automation Postings		Automation & Related Postings	
	(1)	(2)	(3)	(4)
Severe Disaster x Multiple Locations (0/1)	-1.746**	-0.9834	-1.043***	-1.002***
	(0.7039)	(1.110)	(0.1563)	(0.1394)
Severe Disaster	0.5063***	0.4182***	0.2338***	0.1669*
	(0.1689)	(0.1228)	(0.0701)	(0.0865)
Firm Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm x County FE	No	Yes	No	Yes
Observations	490,962	490,962	490,962	490,962
Pseudo R^2	0.09703	0.02571	0.33388	0.14252

Table 8: Labor Adjustment Costs

This table examines establishment-level automation labor skill demand subject to labor adjustment costs following a severe natural disaster. Panel A examines a firm's labor skill compatibility in relation to automation's current technological progress, while Panel B examines unionization as a friction to adopting new production technologies. *Severe Disaster* is an indicator variable that equals one when a county has a Federal Emergency Management Agency (FEMA) declared natural disaster that exceeds the 90th percentile of local economic damages from 2010 – 2022. The automation response variables are defined according to Section 2.2. Specifications include a suite of parent firm characteristics, as well as calendar year and firm × county fixed effects fixed effects. Standard errors are reported in parentheses and clustered at the establishment level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Labor Skill Compatibility

	Automation Postings		Automation & Related Postings	
	(1)	(2)	(3)	(4)
Severe Disaster × Low Skill (0/1)	0.7093*	0.7745**	0.4094***	0.4576***
	(0.4204)	(0.3569)	(0.1389)	(0.1622)
Severe Disaster	-0.2210	-0.3115	-0.1625	-0.2141
	(0.4451)	(0.3536)	(0.1571)	(0.1704)
Firm Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm x County FE	No	Yes	No	Yes
Observations	490,962	490,962	490,962	490,962
Pseudo R^2	0.04981	0.23661	0.07666	0.37962

Panel B: Unionization

	Automation Postings		Automation & Related Postings	
	(1)	(2)	(3)	(4)
Severe Disaster × High Union (0/1)	0.0536	0.0328	0.0159	0.0339
	(0.1952)	(0.1894)	(0.0631)	(0.0717)
Severe Disaster	0.3609*	0.4311**	0.2238***	0.2217***
	(0.2014)	(0.1947)	(0.0769)	(0.0790)
Firm Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm x County FE	No	Yes	No	Yes
Observations	490,962	490,962	490,962	490,962
Pseudo R^2	0.00316	0.21512	0.00233	0.33330

Table 9: Parent Firm Spillover Effects

This table explores the spillover effects on firms' unimpacted establishments where at least one establishment is subject to a severe natural disaster in a particular year. Panel A examines shifts in demand for automation postings, Panel B examines shifts in educational requirements, and Panel C examines shifts in required experience. *Impacted Establishment* is an indicator equal to one when a firm has at least one establishment impacted by a severe natural disaster. All specifications include parent firm characteristics controlling for profitability, leverage, investment, dividend payouts, cash and equivalents, and financial constraints. All specifications include firm and calendar-year fixed effects. Standard errors are reported in parentheses and clustered at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Panel A: Automation Postings

	One Disaster	Two Disasters	Over 3 Disasters
	(1)	(2)	(3)
Impacted Establishment (0/1)	0.6095*	0.8855***	0.9086***
	(0.3362)	(0.1319)	(0.1535)
Firm Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	20,219	20,219	20,219
Pseudo R^2	0.75132	0.91050	0.87835

Panel B: Minimum Educational Attainment

		One Disaster	
	High School	College	Graduate/Professional
	(1)	(2)	(3)
Impacted Establishment (0/1)	1.263***	1.195***	1.217***
	(0.1531)	(0.1785)	(0.2300)
Firm Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	20,219	20,219	20,219
Pseudo R^2	0.94287	0.94826	0.93044

Panel C: Required Experience

	One Disaster	
	Any	5-10 Years
	(1)	(2)
Impacted Establishment (0/1)	1.277***	1.139***
	(0.1494)	(0.1468)
Firm Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
Observations	20,219	20,219
Pseudo R^2	0.94810	0.94285

Appendix A Variable Descriptions

A.0.1 Variable Definitions

This appendix provides variable definitions used in the analysis.

- *Severe Disaster* is an indicator equal to one following the initial natural disaster over the 90th percentile of total NOAA damages. The indicator remains active throughout the remaining sample period.
- *Automation Postings* is the number of job postings directly related to labor-saving. For more information, see Section 2.0.2.1.
- *Automation and Related Postings* is a relaxed version of *Automation Postings* that expands the definition to include occupations indirectly related to automation. For more information, see Section 2.0.2.1.
- *Maturing LTD* is in an indicator equal to one when $\frac{DD3 + DD4 + DD5}{AT}$ is over an established threshold (i.e. 5% or 15%) at the time of the severe natural disaster. For more information, see [5, 11].
- *Multiple Locations* is an indicator equal to one when a firm has reported at least one job posting in multiple counties over the sample period.
- *Low Skill* is an indicator equal to one when the weighted average labor-skill index across a firm's establishments job postings in a county is below the median [24, 10] at the time of the severe natural disaster.
- *High Union* is an indicator equal to one when the firm is a member of an above-median union industry located in an above-median union state at the time of the severe natural disaster.
- *Impacted Establishment* is an indicator equal to one when a parent firm has at least one establishment in a county subject to a severe natural disaster.
- *High School* is the number of job postings that require at least a high school diploma.
- *College* is the number of job postings that require at least a college degree.

- *Graduate/Professional* is the number of job postings that require at least a graduate or professional degree.
- *Any* is the number of job postings requiring any level of previous work experience.
- *5-10 Years* is the number of job postings requiring previous work experience of 5-10 years.
- Parent-Firm Controls:

  All variables winsorized at the 1% level.
  - *Profitability* is defined as $\frac{EBITDA}{AT}$.
  - *Firm Size* is defined as $\frac{AT - TEQ - MKVALT}{AT}$.
  - *Leverage* is defined as $\frac{DLC + DLTT}{AT}$.
  - *Investment* is defined as $\frac{CAPX}{AT}$.
  - *Dividend Payouts* is defined as $\frac{DVC}{AT}$.
  - *Cash and Equivalents* is defined as $\frac{CHE}{AT}$.
  - *Financial Constraints (SA)* is a continuous measure of financial constraints based on firm age and firm size from [29].
- County-Level Economic Data:
  - *Labor Force* is the reported working-age population from the Bureau of Labor Statistics (BLS) in a particular year.
  - *log(Employment)* is the reported employment from the Bureau of Labor Statistics (BLS) in a particular year.
  - *Unemployment Rate* is the reported unemployment rate from the Bureau of Labor Statistics (BLS) in a particular year.
  - *log(Job Postings)* is the total number of unique job postings from EMSI Lightcast in a particular year.
  - Δ *Establishments* is the change in unique establishments from the US Census, County Business Patterns (CBP) in a particular year.
  - *Taxable Wages ($M)* is reported taxable wages from the Bureau of Labor Statistics (BLS) in a particular year.

- *FEMA ($K)* is the total Federal Emergency Management Authority (FEMA) direct assistance disbursed in a particular year.

Appendix B Measures from Previous Literature

B.1 Measures from Previous Literature

In this appendix, I examine alternative measures of occupational exposure to automation from the literature, in the context of declines in local labor availability after severe natural disasters. Due to varying labor demands among firms, heterogeneity exists in the availability and adoption of automation applications.

In [38], current automation technologies are categorized into three applications using the text of patents to train the classifier: software, robotics, and artificial intelligence. To account for this heterogeneity in my specifications, I decompose automation into related categories using the reported skills content of the associated job posting: information processing, physical tasks, and algorithmic/machine learning applications. Skill decomposition provides deeper insights into the specific tasks and skill requirements involved in firm automation. Patents are unique because following the exclusivity period (around 20 years), the innovation enters the public domain. This biases the train data towards patented innovations, rather than general technological progress.

Additionally, I compare my results to previous measures of job susceptibility to generalized automation [21, 22]. [21] uses PhD students to classify occupations by susceptibility to automation, while [22] creates a continuous measure of susceptibility to computerization. These classifications inherently incorporate the subjective bias of the reviewer into the measures.

These alternative measures from prior settings define automation as a continuous measure of posting's exposure to technological substitution. To create a discrete mapping of postings, I define an indicator equal to one when a posting belongs to an occupation above the 90 percentile of the continuous measure. I consider this the most conservative definition, as these occupations have the greatest exposure to automation. The underlying assumption of these previous studies are that firms with greater exposure to automation will increase demand for automation skills in the future. In untabulated results, I relax the percentile threshold cut-off. This adds noise to my estimates and attenuates the results.

B.1.0.1 Previous Measures: Skill Content Correlation

As firms have heterogeneous demand for labor skills, I decompose automation into three categories using the methodology described in [38] and compare two generalized automation indices ([22] and [21]). Table B1 details the correlations between the automation measures and Occupational Information Network (O*NET) job zones.

Within the decomposed measures capturing the types of automation, I find information processing and physical tasks are negatively correlated with O*NET job zone, suggesting these applications automate low-skill tasks. Machine learning/AI applications are positively correlated with O*NET job zone, suggesting these applications automate high-skill tasks. Additionally, I find information processing is positively correlated with both physical tasks, as well as machine learning/AI. This suggests that while the overall skill of information processing applications is low, job postings exist requiring attributes of both information processing and machine learning/AI skill sets.

As the generalized automation indices of [21] (column 4) and [22] (column 5) combine attributes of all three categories, I compare the methodologies to the decomposed measures, as well as O*NET job zone. I find the automation index proposed in [21] is positively correlated with O*NET job zone and information processing and machine learning/AI applications. This suggests that this methodology captures high-skill technological automation, such as software and AI implementation versus physical automation, such as robotics. Conversely, the [22] automation index is negatively correlated with O*NET job zone and machine learning applications. This suggests this index proxies for more traditional, low-skill automation applications, such as software and robotics.

B.1.1 Previous Measures: Baseline Results

To map continuous measures of automation exposure to occupations, I create an indicator based on the percentile of the universe of mappings. I report the most restrictive definition of automation tasks in Table B2, such that a posting is identified as related to automation if the associated occupational score is above the 90th percentile across occupations. Using the binary classification of continuous measures of occupational exposure to automation from previous literature, I find no economically significant change in demand for automation skills. Columns (1), (3), and (5) report coefficients indistinguishable from zero, while Columns (2) and (5) report statistically significant coefficients that contribute to an increase in automation posting of 5%. For an average firm, that results in an average increase of 0.28 and 0.22 postings, respectively.

I find similar effects for untabulated results relaxing the percentile threshold. As previous measures are not binary classifications of exposure to automation skills, the associated measures are noisy and do not identify occupations related to technological investment, but rather the potential for technological substitution.

The noise in measurement is introduced by occupations with indirect exposure to automation, such that associated skills may be related to automation, but have non-automation applications. Additionally, the absence of the effect is not concentrated in a particular type of automation. This suggests that the lack of effect is not driven by established low-skill automation applications versus emerging technologies that proxy for high-skill labor. Therefore, a labor-skill proxy of investment requires not only the associated occupation to be related to the current automation but also a direct link between the associated occupation and realized investment. The labor skill measures defined in Section 2.0.2.1 exploit a direct link between occupational responsibilities and skills with direct links to automation investment.

Table B1: Skill Content Comparison

This table compares the correlations between decomposed measures of automation, the automation indices, and the Occupational Information Network (O*NET) job zones. Automation variables are reported as a continuous measure of technological exposure. Job zones group similar occupations by education, related experience, and on-the-job training required to satisfy occupational requirements and range from 1 (low-skill) to 5 (high-skill). Skill content is the sign of the correlation with the automation measure, where low skill is negative and high skill is positive.

	Automation Decomposition			**Generalized Indices**	
	Information Processing	Physical Tasks	Machine Learning/AI	Technological Automation	Low-Skill Automation
	(1)	(2)	(3)	(4)	(5)
Information Processing	**1.00**				
Physical Tasks	0.58	**1.00**			
Machine Learning / AI	0.64	0.10	**1.00**		
Felten, 2018	0.26	-0.11	0.48	**1.00**	
Frey, 2017	0.16	0.45	-0.18	-0.54	**1.00**
O*NET Jobzone	**-0.13**	**-0.59**	**0.31**	**0.57**	**-0.71**
Skill Type	**Low**	**Low**	**High**	**High**	**Low**

Table B2: Establishment-Level Demand for Automation-Related Skills

This table examines cross-sectional shifts in automation labor skill demand following a severe natural disaster. *Severe Disaster* is an indicator variable that equals one when a county has a Federal Emergency Management Agency (FEMA) declared natural disaster that exceeds the 90th percentile of local economic damages from 2010 – 2022. The automation response variables are defined according to **??**. Specifications include a suite of parent firm characteristics, as well as calendar year, firm, county, and firm × fixed effects. Standard errors are reported in parentheses and clustered at the establishment level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Prior Measures of Technological Exposure

	Decomposition Measures			**Generalized Indices**	
	webb2019impact			felten2018method	frey2017future
	Information Processing	Physical Tasks	Machine Learning/AI	Technological Automation	Low-Skill Automation
	(1)	(2)	(3)	(4)	(5)
Severe Disaster	0.0349	0.0477*	0.0445	0.0281	0.0483***
	(0.0269)	(0.0259)	(0.0332)	(0.0349)	(0.0187)
Firm Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Firm x County FE	Yes	Yes	Yes	Yes	Yes
Observations	490,962	490,962	490,962	490,962	490,962
Pseudo R^2	0.50439	0.57817	0.55481	0.67219	0.74753

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