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ABSTRACT

The evolution of work is of emerging importance to advanced economies' growth. In this study, we develop a new semantic-distance-based algorithm to identify “new work,” namely the new types of jobs introduced in the US. We characterize how “new work” relates to task content of jobs and skill characteristics of workers and document its geographic distribution and association with employment growth. Then, we analyze whether local factors associated in the previous literature with agglomeration economies and productivity growth as well as local exposures to global shocks—technology, trade, immigration, and population aging—predict the creation of “new work.” We find local supply of college educated in 1980 as the strongest predictor of “new work.” Using the historical location of 4-year colleges, a strong instrument for local college share, we find a positive and significant causal effect of local supply of human capital on “new work.”

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1 Introduction

The nature of work is constantly changing in advanced economies. According to Autor, Chin, Salomons, and Seegmiller (2024), 63% of the employment in 2018 was found in roles that did not exist in the 1940s. Based on decades of job advertisements, Atalay, Phongthiengtham, Sotelo, and Tannenbaum (2020) find that the most commonly posted job titles within an occupation in 1990 did not even exist in the 1950s. An economy's capacity to create "new work"—tasks and functions that culminate into distinctly new types of jobs—and employ its labor force in these types of jobs is crucial for maintaining high levels of employment (Autor, 2015). "Data Warehouse Architect," "Internet Marketer," "Global Supply Chain Director," but also "Life Care Planner," "Sommelier," and "Barista" did not exist as job titles before 2000, and yet now these titles all together employ millions of people.

In addition, the creation of "new work" potentially serves as an essential mechanism that improves aggregate productivity. "New work" is similar (and related) to the introduction of new production processes, goods, and services—all of which have long been recognized as fundamental components of economic growth (Romer, 1990; Krugman, 1980). "New work" also closely relates to human capital—a crucial element for achieving productivity growth (Barro, 2001)—as the implementation and diffusion of "new work" importantly depend on the adequate supply of novel tasks and abilities, which in turn affects innovations and knowledge creation.

Recent papers formalize the idea of "new work" in models of technological change and employment as the *essential counterpart* to work replacement (e.g. Acemoglu and Restrepo, 2019, 2020). This literature focuses on the role of technologies in replacing a set of jobs while simultaneously creating opportunities for new ones, where the intensity of these two phenomena, in the long run, determines the level of employment growth (Acemoglu and Restrepo, 2022). Less is known about how local factors as well as exposure to other global shocks in local labor markets may play a role in generating "new work." Examples include local labor market characteristics such as industry structure, population density, and supply of human capital; increased access to new goods and services facilitated by globalization; and changes in the composition of local workers and customers due to the evolving demographic structure in terms of age, place of origin, and skill levels of the local population.

In this paper, we introduce a novel measure of "new work" constructed over multiple decades and across occupations and commuting zones in the US. We characterize how "new work" relates to task content of jobs and skill characteristics of workers and document its geographic distribution and association with employment growth. We then investigate whether local factors (especially human capital intensity and population density) and differential local exposures to global shocks—technology, trade, immigration, and population aging—serve as important predictors of local "new work" creation.

Our first contribution is to re-conceptualize and innovate on measuring "new work." The extensive literature on the changing content of work (Autor, Levy, and Murnane, 2003; Autor, Katz, and Kearney, 2008; Autor, 2015) mainly considers the shift in employment between occupations characterized by either task or skill intensities and abstracts away from examining changes in detailed job definitions. Our method importantly complements the task-based approach and defines an algorithm applicable to any list of job titles to measure distances, in meaning, between titles and identify sufficiently different jobs as "new."

In doing so, we build on the pioneering concepts introduced by Lin (2011) and further developed by Autor et al. (2024) that exploit additions to Census catalogs of job titles. Our contribution extends and validates the innovation from Kim (2024) that uses text analysis to integrate the meanings of job titles to evaluate whether the job content of a new job title is different from that of any pre-existing job titles. Our "new work" measure exploits the evolution of comprehensive lists of job titles in documents produced by US government agencies to reflect the universe of existing job types: the Dictionary of Occupational Titles (Fourth and revised Fourth editions), the Alphabetical Index of Occupational Titles, and O*NET relative to 1980, 1990, 2000, and 2010 respectively. Our key innovation lies in (i) homogenizing the *granularity* of job space between different data sources across decades, and (ii) identifying a common minimum distance to define "new work" relative to previously existing titles—which serve critical purposes in studying the evolution of "new work" over longer time horizons.

The core function of our algorithm uses text analysis that transforms job titles into multidimensional vectors to compare semantic similarity. Job title vectors are assigned by the Continuous Bag-of-Words algorithm (trained on online pages, reports, technical and scientific documents) based on the probability that words in a job title appear in similar contexts as words in another job title across the millions of training documents. Essentially, two words surrounded by similar words in most sentences are closer in meaning than a pair of words surrounded by very different words in most sentences. We first apply this algorithm to adjust the level of granularity of the job title space over time—an essential step given the important differences across data sources stemming from not only the introduction of new jobs but also more granular definitions between different sources. Using the granularity-adjusted data, we then quantify the dissimilarity in content (meaning) between a new job title and its closest pre-existing job title. For each job title, we calculate the vector-distance from all titles existing in the previous period and consider the most similar title (minimum distance). If this value is above a threshold parameter, we classify the added job title as "new." Aggregating at the occupation level, the share of job titles classified as "new" among the total number of job titles in a given occupation represents its "new work" intensity. This approach can be applied to identify "new work" using any complete list describing the set of jobs and occupations in any economy over time.

A recent paper, Autor et al. (2024), similarly innovates on the measurement of "new work" through applying fuzzy matching to identify new titles over decades (from 1940 to 2018) and connects those changes to augmentation and automation in technology, as well as to aggregate demand changes in the US. Our approach supplements their work by employing an algorithm that captures a semantic distance between "new work" and existing work. Therefore, our method allows for tuning for more or less stringent definition of innovative jobs based on semantic meaning rather than fuzziness based on character (or phoneme) tokens as in fuzzy matching methods.

The second contribution of this study is a detailed characterization of "new work" across occupations, US commuting zones, and relative to prior analyses. We demonstrate the correlation of "new work" with the task content of jobs and skill characteristics of workers across occupations, connecting with the literature on the evolving task content of work (Autor et al., 2003; Autor, 2015, 2019; Atalay et al., 2020). We then transform the "new work" measure into a commuting zone level measure to study its evolution across US local labor markets. The limitation of the geographical measure is that it captures local "new work" based on the local level of occupational employment and the national content of "new work" within those occupations. However, the local labor market approach allows us to explore local spillovers and connect the phenomenon with local exposure to global shocks (as extensively studied in previous work examining their impacts on the labor market) and other local factors such as the availability of human capital, population density, and industrial composition (e.g. Diamond, 2016; Moretti, 2013, 2012).

This brings us to the third contribution of this study: we analyze how exposure to global shocks and the presence of local factors correlate with the emergence of "new work" across commuting zones between 1980 and 2010—an era marked by important departures from the stable labor market structures and wage distributions in the preceding decades (Autor et al., 2008). During this period, the share of manufacturing employment, which began to decline in the mid-1970s, continued its downward path (Charles, Hurst, and Schwartz, 2019; Feyrer, Sacerdote, Stern, Saiz, and Strange, 2007); inequality across cities grew (Diamond, 2016; Moretti, 2013; Ganong and Shoag, 2017); inequality across skills, especially between more and less educated workers, expanded significantly (Katz and Murphy, 1992), followed by a polarization with high- and low-skilled workers outperforming intermediate-skilled workers in the 1990s and 2000s (Autor, Katz, and Kearney, 2006). We add to this important strand of work investigating deep changes affecting local labor markets post-1980s by examining the evolution of "new work" creation.

Additionally, we contribute to the urban literature that analyzes the role of local factors—

especially human capital and population density—in generating growth, innovation, and agglomeration economies (Moretti, 2004a,b; Ciccone and Hall, 1996; Iranzo and Peri, 2009); and further connect “new work” with the numerous studies that have measured the impact of exposure to technology, trade, immigration, and demographic change on local labor markets. We follow several strands of the economic literature to construct measures of local exposure to technology (Autor et al., 2003; Autor, Dorn, and Hanson, 2015; Acemoglu and Restrepo, 2019, 2022), trade (Autor, Dorn, and Hanson, 2013; Batistich and Bond, 2023; Eriksson, Russ, Shambaugh, and Xu, 2021), immigration (Ottaviano and Peri, 2005, 2006), and population aging (DellaVigna and Pollet, 2007) from 1980 to 2010. We are the first, to the best of our knowledge, to homogenize a coherent set of local exposure measures for these four types of global shocks—and further add them to local factors—to simultaneously investigate their relationships to the evolving geography of labor markets and “new work.”

The study produces several main findings. First, we establish that our “new work” measure—strongly validated by comparing it to other measures available from Lin (2011) and O*NET; and robust to the choice of threshold, covering 50-75% of possible parameter range—is significantly correlated to the share of college educated workers and non-routine cognitive-analytical intensive tasks across occupations. It is also significantly associated with employment growth across occupations and, more strongly, across commuting zones, which implies positive spillovers from “new work” stemming from the local structure of occupation co-location and forces of co-agglomeration economies.

Second, we find that the local share of college educated population in the initial period is the most statistically significant and economically important (positive) predictor of “new work” in the following decades. High population density and low share of manufacturing employment in 1980 are the next important predictors. A one standard deviation higher share of college educated between commuting zone populations in 1980 is associated to a difference of 0.6 standard deviations more “new work” over each decade. This result highlights the role of human capital and local density in generating innovation, employment, and productivity growth (Moretti, 2004a,b; Ciccone and Hall, 1996; Iranzo and Peri, 2009).

Given the clear importance of the local college share, we sharpen the analysis by exploring the causal role of the local supply of human capital. Specifically, we exploit the historical presence and density of local colleges to identify exogenous variation in the local college educated share. We confirm a statistically and economically significant positive causal effect of human capital supply on local “new work” intensities.

Third, our analysis of exposure to global shocks in predicting “new work” reveals that the correlation is weaker compared to local factors. In fact, population aging is the only shock with a strong average association with “new work” in the long run, which seems especially driven by the predicted share of retirees—suggesting an important role of this group in stimulating demand for new services. Exposure to other global shocks, however, does not show significant correlations, on average, with "new work."

Finally, the importance of both local factors and global shocks reveals important heterogeneity by occupation types and regions. Exposure to technology has a positive predictive power when we focus on "new work" in high non-routine cognitive-analytical occupations. We also find stronger positive correlations for cognitive-intensive "new work" with local human capital and local density. In terms of heterogeneity by regions, we find that only in locations with high "new work" potential, which we call "high-skilled cities," exposure to trade shocks encourage higher creation of "new work." Exposure to high-skilled immigration, instead, is associated to more "new work" only in areas that are not "high-skilled cities"—high-skilled immigration potentially supplies important skills in generating "new work" where the local supply of high-skilled workers is low.

In summary, while all these results are important, we see the central contribution of our paper as empirically investigating the important role of local human capital in stimulating "new work" and mediating the role of global shocks on the capacity of local labor markets to create "new work" and sustain employment growth.

The rest of the paper is organized as follows. Section 2 describes the data and construction of "new work" measures. Section 3 characterizes its main features and geographical distribution. Section 4 shows the correlation with employment growth. Section 5 introduces the measures of local factors and local exposure to shocks; and Section 6 discusses the results. Section 7 analyzes important extensions. Section 8 examines the causal effect of local supply of human capital on "new work." Section 9 concludes.

2 Data Sources and the Construction of New Work

2.1 Data Sources for New Work and Explanatory Variables

We obtain job titles data, the finest classification of jobs available, from three primary sources: the Dictionary of Occupation Titles (DOT, 1977 and 1991, which respectively serve as a proxy for 1980 and 1990), the Census Bureau's Classified Index of Industries and Occupations (2000), and the Sample of Reported Titles and Alternate Titles in the O *NET database (2016, which serves as a proxy for 2010). Note that our choice of using detailed titles in O*NET for the post-2000s implies a more radical change in the source of job titles relative to the previous years. It is, however, a necessary choice because O*NET, which replaced DOT in the early 2000s, produced a comprehensive list of job titles starting in 2016. Our algorithm for constructing measures of "new work" adjusts for this change.

After calculating the job-title-specific "new work" intensity scores using our algorithm, the data is aggregated to the occupational level using the time-consistent 3-digit IPUMS *occ1990* definition, which includes roughly 350 detailed occupation codes. These aggregated measures are then merged with the 5 percent sample of the Decennial Censuses for 1980, 1990, and 2000, and the American Community Surveys (ACS) for 2010 (Ruggles, Flood, Goeken, Grover, Meyer, Pacas, and Sobek, 2020) where we obtain individual sociodemographic and economic characteristics that we aggregate to the occupational and local labor market levels. We also use earlier decades (1950, 1960 and 1970) to obtain pre-existing levels and trends in employment.[1]

Our first technology-related measure follows Autor and Dorn (2013) to capture local exposure to computerization. This construction exploits past shares in routine-intensive occupations that are likely to be replaced by computers. As in Autor et al. (2003), occupation-specific routine intensities are constructed from job task requirements using the DOT (1977). Further combined with the Decennial Censuses for 1970, we obtain local labor market shares of routine jobs that are likely automated in the following decades.

Our second technology-related measure follows Acemoglu and Restrepo (2020) to capture local exposure to industrial robots. We use the International Federation of Robotics (IFR) data to obtain country-industry-level stock of robots. Due to limited data availability for the US, we use data from the five European countries at the technology frontier (Denmark, Finland, France, Italy, and Sweden) for 1993, 2000, and 2010 to construct the industry-level penetration rate of robots.[2] We next use country-industry-specific employment and output from EU KLEMS data to aggregate the measure at the industry level. We then apportion these measures to US local labor markets using the 1970 local industry structure obtained from the County Business Patterns (CBP) data.

Our globalization-related measures follow Autor et al. (2013) to construct local exposure to import competition. We use UNComtrade data to obtain product-level import flows from Japan, the four Asian countries often referred to as Asian Tigers (South Korea, Taiwan, Singapore, Hong Kong), and China to the US and six other high-income countries (Australia, Denmark, Finland, New Zealand, Spain, and Switzerland) for 1980, 1991, 2000, and 2010.[3] We map 6-digit HS products to SIC industries using the crosswalk by Pierce and Schott (2012). For 1980, the data is only available in SITC (Rev.2) codes, so we map SITC to SIC industries using a crosswalk shared by the Center for International Data (Feenstra,

[1]For 1970, the 1% Form 1 & 2 Metro samples are combined and equally weighted down for a more rich sample for that decade.

[2]Industry-level data for the US is available only from 2004 and they include the overall stock of robots in all countries in North America.

[3]Similar to Batistich and Bond (2023), in order to be consistent with our definition of high-income countries when constructing the shift-share instruments for import competition from China, Japan, South Korea, Taiwan, Singapore, and Hong Kong, we do not include Japan (for obvious reasons) and Germany (due to lack of consistent collection of data in before 1990s) in our instruments.

Romalis, and Schott, 2002).[4] We then combine with initial local industry compositions constructed using the CBP Data (1975) as weights to apportion industry-level shocks to local labor markets.

Our population-related measures follow Ottaviano and Peri (2005) and DellaVigna and Pollet (2007) to construct local exposures to immigration and demographic changes, respectively. Here, we use the same Decennial Census and ACS samples as outlined above for constructing measures of "new work." Since immigration shock measures a labor supply shock, the samples are restricted to working ages 16 and older and further separated into high and low education groups.[5] The age shock sample is restricted to ages 6 and older in the prior decade to calculate the predicted age structure, and ages 16 and up to measure the actual age structure. Mortality data is sourced from an US Social Security Administration's Actuarial Study (Bell and Miller, 2002).

Finally, we construct human capital supply instruments using the historical presence of colleges. Specifically, we borrow data on college counts by county as collected by Currie and Moretti (2003), which we crosswalk and merge to our commuting zone level dataset to create college density measures for 1960 and 1980. As a third alternative instrument, we consider land-grant institutions in the spirit of Moretti (2004a); Ehrlich, Cook, and Yin (2018) as a source of exogenous variation in the college-educated share in 1980. The data is obtained through U.S. Department of Education, National Center for Education Statistics (1980) as land-grant status is indicated in the institutional characteristics section of IPEDS.[6]

2.2 Definition and Measurement of New Work

The fundamental idea underlying our "new work" measure originates from the pioneering work of Lin (2011) which leverages the emergence of new job titles over time. Kim (2024) generalizes the approach by implementing text analysis methods to examine job titles across decades to identify whether or not there exists an identical or *contextually* very close job title observed in the previous decade. Job titles for which a very close match does not exist are considered as "new work." Our measurement approach builds on Kim (2024), yet makes important procedural improvements to: (i) homogenize the *granularity* of job space between different data sources across decades, and (ii) identify a common minimum distance to define "new work" relative to previously existing titles—which serve critical

[4] The crosswalk can be downloaded from the following websource: https://cid.econ.ucdavis.edu/usix.html

[5] We use the variable *educ* in IPUMS Decennial Censuses and ACS to construct education groups: 1 or more years of college versus all others everywhere except in Section 8 where we refine the measure to 4 or more years versus all others to better capture

[6] We further adjust the IPEDS land-grant indicator from 1980 using the Wikipedia page for "List of land-grant institutions" as in Ehrlich et al. (2018).

purposes in studying the evolution of "new work" over longer time horizons.[7]

The core function of our algorithm lies in measuring the pairwise distance between job titles, which is achieved by implementing one of the widely used Word2Vec algorithms: the Continuous Bag of Words (CBOW) model.[8] The CBOW model is trained using an extensive sample of text (Google news, scientific and technical documents, Wikipedia articles, and other online sources) and generates word-specific vectors. Each word in our sample of job titles is assigned a 300-dimensional vector, which is produced by predicting the appearance of the target word based on their surrounding words in the context of these large texts. For multi-word job titles, we aggregate the CBOW-generated vectors at the job title level by computing the average of the word-specific vectors of all the words comprising a job title.

The model demonstrates advantages in quantitatively detecting semantic similarity, as words with similar meanings appear in similar contexts, and thus are assigned similar vectors. Therefore, the model allows us to recognize job titles associated with the same type of job yet relabeled across sources or over time (e.g., custodian vs. janitor; stewardess vs. flight attendant) by producing for them *similar* vector values.

We proceed in the following three steps to construct our measures. First, we adjust the level of granularity of the job title space for 1990, 2000, and 2016 to that of 1980. The value-added of this refinement process is high given the important differences we observe across data sources over time. For example, the number of job titles increases around five-fold from 11,120 in the 1977 DOT to 59,800 in the 2016 O*NET; and the number of job titles per occupation code increases by the same factor from 22 to 113 (Table 1). Part of this proliferation is genuinely due to new job titles, but another part stems from more varied wording or more granular definitions between the different job title sources.

Specifically, we use the job titles data from DOT 1977 and calculate the minimum vector distance between each job title and its closest match within the same occupation code. These distances provide information on the granularity of within-occupation job space, each indicating the minimum difference required to meaningfully discern titles within an occupation code in 1980. We further take the minimum of these occupation-specific granularity measures to define a threshold value,

$$\min_{occ_{1980}}\left[1-\max_{y\in occ_{1980}}\left(\frac{f(x)\cdot f(y)}{\|f(x)\|\,\|f(y)\|}\right)\right], \tag{1}$$

[7] Kim (2024) focuses on studying the adoption of "new work" in the post-2000s period examining the causal effects of import competition from China.

[8] Before applying the algorithm, we edit job-titles by correcting spelling errors, standardizing hyphenations, and removing unnecessary source documentation to improve the precision of the model. We also utilize legacy crosswalks (maintained by and for government statistical agencies, WIDCenter, 2024) that allow us to make gains relative to Lin (2011) in linking DOT titles to IPUMS occupations. Furthermore, we adjust the sources to account for differences in their granularity, namely our method addresses the concern that a longer list of job titles may contain both genuinely new titles and existing titles but labeled in a more detailed way.

which reflects the minimum granularity of job space in 1980—the minimum difference required to meaningfully distinguish job titles in 1980.

We then apply this threshold value to homogenize the granularity of job space in 1990, 2000, and 2016. Specifically, for each period, we iterate the procedure above to estimate within-occupation granularity (the minimum distances with its closest match within occupation code) and identify the set of job title pairs with distances that are smaller than or equal to Equation (1). For these job titles that are very similar, we collapse the vector values $f(x)$ into single observations taking the average vector. This refinement ensures that, within an occupation code, job titles are different enough (i.e. the distance with its closest match within occupation code is above the specified threshold based on the 1980 data) and addresses concerns related to differences in granularity of the job title space across sources.

Second, we use the granularity-adjusted job titles data and construct "raw new work intensities," which measures how different a job title is from its closest match in the previous period. Formally, for each job title $x \in X_t$ (the set of all granularity-adjusted job titles observed in period t), we use the job-title-specific vector $f(x)$ and compute pairwise distances between that job title and all job titles in the past decade, $\forall y \in X_{t-10}$:

$$RNWI_t(x) = 1 - \max_{y \in X_{t-10}} \left(\frac{f(x) \cdot f(y)}{\|f(x)\| \, \|f(y)\|} \right) \tag{2}$$

If for a specific title, $x \in X_{t-10}$ and $x \in X_t$, i.e. the exact same title also appears in the source document of period $t-10$ and t then $RNWI_t(x) = 0$, which implies that x is not "new work" based on an exact string match, nesting the procedure in Lin (2011). In the case of non-exact match of a title $x \in X_{t-10}$ with the closest title in $x \in X_t$, the algorithm generates values of $RNWI_t(x)$ very close to zero for virtual synonyms and larger positive values for those that significantly differ. Thus, the algorithm helps identify cases of non-exact matches and generates a "new work" intensity. For brevity in notation, we use $RNWI$ to indicate "raw new work intensities."

Finally, we refine $RNWI$ by applying a homogenized criterion of what meaningfully distinguishes a job title as new. That is, we construct NWI: a binary indicator that assigns to each job title a value of 1 when $RNWI$ is greater than a particular threshold value and 0 otherwise. Here, the threshold value is constructed based on analogues of Equation (1) where we define p^{th} percentile threshold values using the distribution of these occupation-level minimum distances in 1980. In our main exercises, the baseline measure of "new work" intensity scores $NWI^{\mathrm{p}25}$ is based on the 25th percentile threshold. Thus, for a job title to be recognized as new, the distance with its closest match should be at least larger than the 25th percentile value of occupational granularity measured in 1980. For ease of notation, we refer to our preferred baseline measurement NWI^{p25} as NWI.[9]

Hence, our measure of "new work" at the job title level (NWI) in period t is defined as a binary indicator of new job titles that emerged between periods t and $t+10$. As we aggregate NWI to the 3-digit census occupation level, this measures the *share* of new job titles in each occupation in a given period, which we denote with NWI^o. Note that we follow Lin, 2011 and assign equal weights to job titles observed within each occupation to compute NWI^o.[10]

2.3 Validation of Measurement: Comparisons with Lin (2011) and N&E

This section presents two validation exercises to benchmark our measure of "new work." The first exercise involves understanding its comparability with the measure proposed in Lin (2011) for the 1980s, which leverages the list of "New Definitions in the DOT" in "Section 3 of the 1991 Conversion Table" to identify new job titles.[11] Given the vast resources and efforts involved to periodically update the DOT, it is plausible that this basis is an accurate accounting of title-level "new work." Therefore, the extent of overlap between the new titles based on our algorithm and the DOT list serves as an informative check for the decade in which both of them are available. Table 3 reports the share of titles that (i) our method classifies as new but the DOT list does not (i.e. false positives) and (ii) the DOT classifies as new but our method does not (i.e. false negatives). We report results using NWI constructed at different thresholds from no threshold to the 25th percentile.[12]

There are three important takeaways. First, our algorithm and the DOT list produce the same classification for the vast majority (85 to 90 percent) of job titles. Second, our misclassifications are almost exclusively false positives; however, implementing higher thresholds reduces this error. Table A.3 presents an illustrative list of these job titles sorted by $RNWI$ in ascending order, with the intensity listed along with a title's closest match assigned by our algorithm and indicators of "new work" by varying thresholds. Job titles with minimal values of $RNWI$ are likely misclassified—differences between titles and their closest matches are mainly due to small variations in wording and terminology. Note, however, increasing

[9]As for more inclusive definitions, we define NWI^{Min}, NWI^{p5}, NWI^{p10} using the minimum, 5th, and 10th percentile thresholds, respectively. $RNWI \geq \{0.01283,\ 0.05583,\ 0.06625.\ 0.10190\}$ is the set of minimum, 5th, 10th, and 25th percentile numerical thresholds (see Section 3 for context).

[10]Table 2 summarizes the notations, definitions, and interpretations of our new work measures prepared at different levels (job title, occupation, and CZ).

[11]There are two alternative measures that Lin (2011) provides for the 1990s. One identifies titles with any update since DOT 1977. The other is the most conservative version based on the "discussion in the 1991 DOT that indicates that titles added during the last of a series of inter-revision reviews," which focuses on 89 titles.

[12]As an overall comparison of our measures to Lin (2011), we examine the correlations between our basic measure of NWI and the measures constructed by Lin (2011) at the occupational level and find a clear positive and very significant correlation in each decade (Figure 2). Also, we find a dispersion around the line of perfect correlation, indicating that there does not seem to be a systematic tendency of our method to overestimate or underestimate "new work" intensities relative to Lin (2011) at different levels of innovative intensity.

the threshold value mitigates this concern.[13] Some job titles with larger values of $RNWI$, however, are genuinely different from their closest match (e.g. "slaughter religious rituals" versus "director of religious activities" or "sales representative bottling equipment" versus "sales representative bottles and jars"). Finally, false negative are extremely rare—our method does not miss new job titles. Overall, the exercise demonstrates the effectiveness of our algorithm in identifying "new work" for the 1980s and provides validity in implementing it to obtain "new work" measures for the following decades.

The second exercise tests how our measure compares with the "New & Emerging" occupations (N&E) defined by O*NET for the 2000s. While the idea of identifying "new work" is related in spirit, the measure has some key differences. The criteria O*NET imposes for an occupation to be classified as new are more demanding than our algorithm, that is, an occupation needs to be large and growing. Also, the unit of classification is detailed occupations (8-digit Standard Occupational Classification code), which are more aggregate than job titles.[14] Despite these differences, comparing the N&E measure is still informative in assessing the performance of our algorithm.

Table 4 presents correlations between the two measures. For comparability, within each 6-digit SOC occupation code, we aggregate the counts of new job titles identified using our algorithm in our sample of O*NET data and the number of occupation titles (corresponding to 8-digit O*NET SOC codes) listed as N&E. Column (1) uses these counts of new titles aggregated at the 6-digit occupation level. Columns (2) and (3) normalize these counts to construct comparable intensity measures. Given the different levels of aggregations between the two data sources (job titles versus 8-digit SOC), we check this in two ways. Specifically, for each 6-digit SOC occupation code, Column (2) uses the aggregated counts relative to the total number of job titles, and Column (3) uses that relative to the total number of 8-digit occupations. We find that the correlations are statistically significant but not close to one, which we consider an affirming check given a significant relation is detected despite the expected imperfect overlap with this "New *and Emerging*" measure that combines a notion of "new work" with other considerations.

In sum, the two validation exercises support the validity of our algorithm in measuring "new work" when tested against the best decade-specific measures we have available from DOT and O*NET.[15]

[13]This threshold parameter is thus an important component of our analysis, which we adjust to check the robustness of our results.

[14]O*NET defines a list of occupation titles associated with 8-digit O*NET-SOC occupation codes, which (i) reflect changes in technology, society, law, or business practices; (ii) involve significantly different work yet not adequately reflected in the current taxonomy; and (iii) show enough current and high projected employment.

[15]As an additional robustness check in our main analysis, we define and use a "benchmark" index of new work, which combines the new work measures constructed based on the DOT new title-based measures for the 1980s and 1990s and the O*NET N&E-based measure for the 2000s.

3 Characterization of New Work

This section provides descriptive patterns and statistics of our measurements of "new work" to achieve three goals: (i) illustrate the nature of "new work" through examples; (ii) connect our new measures with previous studies about the characteristics of "new work" post-1980s; and (iii) show correlations of "new work" with skill/task intensities and a description of its geographic distribution.

3.1 Examples of New Work Intensive Occupations and New Job Titles

We begin by presenting examples of "new work" intensive occupations, namely those with highest values of NWI^o for each decade (Table 5). In the 1980s, occupations related to teaching, healthcare, and health technologies ("Post-secondary Teachers," "Health Technologists and Technicians," and "Health Assessment and Treating") appear among some of the highest in NWI^o. Teaching-related occupations, in particular, are continuously observed as occupations with high NWI^o, which are suggestively related to new knowledge and techniques and the proliferation of specialties. "New work" in healthcare likely reflects the various technological advances in pharmaceuticals, cancer care, and biotechnology.

In the 1990s, "Mathematical and Computer Scientists" enter the top occupations with high NWI^o, in addition to those related to teaching and health.[16] As the use of computers and information technology becomes increasingly important for modern work and life, "new work" emerges in occupations closely related to technological change. Several other occupations related to sales and different types of services (retail, finance, recreation) show high NWI^o, which is possibly explained by a combination of technological applications, more demands for them, and the increased diversity of services provided.

In the 2000s, occupations such as "Librarians" and "Social Scientists" that relate to evolving use of data in more aspects of economic and social life and the growth of human capital intensive services appear among those with very high NWI^o. Occupations in healthcare and health technologies continue to be among those experiencing high "new work" intensities. Across all decades, technology seems clearly an important factor related to "new work" (e.g. occupations in computer science, healthcare, and engineering); however, other factors such as the growth in diversity of demand, variety of people, and new needs may also be critical channels to "new work" creation as implied by the intensity measured in other occupations like teachers, therapists, lawyers, librarians, and urban planners. This reinforces our motivation to study drivers of "new work" beyond technological change alone.

[16]Occupations in information technology and medicine are those with largest intensity of "new work" in the 1980s and 1990s according to Lin (2011), Table 1.

Next, we present examples of new job titles within occupations with high NWI^o, namely the computer and mathematical occupation category. Given the rapid technological change that has deeply modified the nature of work, investigating new job titles in this occupation group over time importantly reflects the trajectory of the information technology revolution. Not surprisingly, this occupation group continues to show a significant share of new job titles in each of the decade—a good illustration of the types of new job titles emerging in each decade and of how our algorithm identifies them in comparison to existing job titles in the previous period. Table 6 presents examples of the newest titles within this occupation in the first column. The second column shows the "closest" matched job title from the previous decade, and the third column reports the $RNWI$ capturing the degree of newness using the vector distance between the new job title and its closest pre-existing title.[17]

In the 1980s, titles such as "Computer Programmer," "Code Inspector," and "Computer System Hardware Analyst" are identified as new job titles with the distance from its closest match significantly larger than our baseline threshold (0.1). These jobs are related to an important part of computer operations in this period, such as coding and programming. Clearly, the closest job titles from the previous decade do not match the new job titles, neither in wording nor meaning. An "Electrical Inspector" does not perform the same job as a "(Computer) Code Inspector." A "Computer Operator" performs a more generic function than "Computer Programmer." The values of $RNWI$, ranging between 0.16 and 0.27 as shown in the third column, imply that the two job titles in each pair are clearly distinct.

In the 1990s, new job titles are related to the (World Wide) Web and computer networks reflecting the importance of these two innovations in shaping how firms organize tasks and production. Jobs like "Webmaster" and "Network Support" are substantially new relative to the closest ones in the previous decade ("Web Pressman" and "Customer support," respectively), with significantly high $RNWI$ (0.55 and 0.37, respectively).

In the 2000s, new job titles involve tasks based on the internet related to e-commerce strategies, online marketing, and transactions. For instance, a "Pay-per-click Strategist" engages in tasks related to planning and optimizing the effectiveness of online advertising campaigns. The closest match from the previous period, a "Price Economist" is quite distant in terms of tasks performed and the content of the pre-existing job is not directly oriented towards online search functions. Similarly, a "Search Engine Optimization Strategist" is a role relevant to the increasing use of online platforms to attract consumers, which again, is clearly distinct from the work of a "Database Design Analyst." In these examples, $RNWI$ ranges between 0.44 and 0.5, indicating a significant dissimilarity with jobs in the past.

Examining the new job titles across three decades reveals how the subsequent phases

[17] Due to the refinement process we implement, a distance measure of 0.1 is the 25^{th} percentile in the job title distance of 1980 representing our baseline threshold to define a new job title.

of the Information and Communication Technology (ICT) revolution have shaped and redefined the skill set and jobs within the computer and mathematical occupation category. With the advent of the personal computer and its increased utilization in the 1980s, ICT exhibited further expansion through the diffusion of the Web and networks of computers collecting and processing information in the 1990s. Finally, the massive expansion of online markets in the 2000s connecting firms and consumers through online platforms revolutionized traditional business models and further induced the demands for e-commerce management, data analytics, cybersecurity, etc.

Other examples of new job titles in occupations with high NWI^o such as "Health Technologists and Technicians" and "Teachers, except Post Secondary" are shown in Tables A.1 and A.2 respectively. Among "Health Technologists and Technicians," new job titles such as "Head of Cytogenetics" and "Perfusionist" mostly link to new technologies that appeared in the 1990s and 2000s. In the "Teachers, except Post-secondary" category, new titles over the 1980s include teachers oriented towards various impairments while the newest job titles in 2000s are various types of "interventionists," which reflect (especially in contrast to their closest match) increased awareness of societal issues and higher demands for effective interventions. However, "new work" in this category also reflects rapid diversification and specialization of teachers towards topics like "skilled trades" and "television repair" teachers as seen in the 1990s portion. [18] Our examples of new job titles collectively confirm that our algorithm captures "new work" related to new production methods, emerging technologies, new demands for services, as well as new and evolving abilities of workers.

3.2 Characterization of New Work: Occupation-Level Analysis

As discussed earlier, our baseline "new work" intensity measure is indexed at the 3-digit census occupation codes—the level at which we observe employment information in the Decennial Censuses and ACS. Table 7 provides employment-weighted summary statistics of NWI^o by threshold value (from minimum to 50th percentile threshold) for each decade. The decade averages for our default measure (implementing the 25th percentile threshold) imply that around 21 percent, 14 percent, and 41 percent of the job titles are classified as "new work" in the 1980s, 1990s, and 2000s, respectively.

The notably larger share of "new work" in the 2000s relative to the other decades may be a residual consequence of the more granular 2016 O*NET data left over after our algorithm. While an important feature of our sample, this holds little relevance to our main analysis in the following sections. That is, average changes in "new work" in each decade do not identify any of our findings, but instead are absorbed by decade fixed effects. What is more

[18] These titles may be consequence of the formalization of career and technical education over this period.

relevant is the variation of NWI^o across occupations in each decade. Note that the standard deviation of NWI^o across occupations is much more stable across decades with a value of 15, 15 and 12 percentage points (ppts) for each consecutive decade, respectively. An occupation experiencing 10 to 15 ppts higher NWI^o than the average represents a highly innovative occupation.

To help characterize the nature of "new work" and connect it with the existing literature, Figure 1 shows the average values of NWI^o for 10 broad occupation categories for each decade. We follow Autor and Dorn (2013) to construct these categories and array them from left to right in descending order of the average wage in 1980. The first three occupational groups represent high-wage occupations associated with high intensity in cognitive and analytical skills (Managers, Professionals, and Technicians). The next four groups are intermediate-wage occupations, which are routine-intensive in both manual and cognitive areas (Sales, Office/Administrative Work, Production, and Laborers). The last three groups include low-wage occupations in manual, personal service areas (Protection, Food, and Personal Care), which several studies have identified as jobs not easily replaced by technology and whose employment has increased substantially, especially from the 1990s to the post-2000s period (Autor, 2015, 2019).

The partition of workers into these broad occupational categories has been used to demonstrate the growing "polarization" of the US labor market from the 1990s to the 2000s period (Autor and Dorn, 2013). The set of occupations at the top and bottom ends of the distribution have grown more in employment and (to a lesser extent) in wages than those in the middle.[19] As shown in Figure 1, the pattern for the *average* NWI^o calculated for these occupational groups also features a U-shape for all decades, which is more pronounced in the 2000s decade (green bars) compared to the 1980s (blue bars) and 1990s (red bars). In particular, the high-wage occupation group shows greater intensity of "new work" than other groups. Low-wage occupations are also strong performers. However, intermediate-wage occupations, especially "Production" and "Laborers" consistently show lower "new work" intensities while "Sales" and "Office" occupations experience some intense periods.

We also characterize "new work" through the correlation of NWI^o with occupational skill intensities and task characteristics.[20] Table 8 shows results for various OLS correlations. Each result represents separate bivariate regressions for a single decade using 3-digit occupation as the unit of observation. Panel A considers (i) occupational share of workers with any years of college education, (ii) average years of schooling, and (iii) average age.

[19] In fact, a plot of employment growth in each decade for those occupations would show the three groups on the left with large positive growth, negative values for the four middle groups, and small positive values for the three right groups. See Autor and Dorn (2013) for a detailed discussion.

[20] The exercise extends Kim (2024) that demonstrate features of "new work" focusing on the post-2000s by combining information across three decades.

Panel B examines the 6 different types of task intensities constructed following Acemoglu and Autor (2011).[21]

Panel A shows that occupations with greater share of college-educated workers have significantly higher NWI^o in each decade. Similarly, average years of schooling in an occupation is associated with a higher NWI^o. Specifically, an occupation with 10% more workers with a college degree experiences 1.1, 1.7 and 4.1 ppts more "new work," respectively, in the considered decades (recall that the standard deviation of "new work" across occupations is between 12 and 15 ppts). Age is negatively correlated with "new work" only in the early decades and the coefficient is rather small. There is no strong evidence that the presence of younger or older workers in the occupation as of 1980 was associated with the more or less introduction of new job titles in an occupation in the subsequent decades.

Panel B shows that "new work" creation is stronger in occupations that are intensive in non-routine cognitive-analytical and non-routine interpersonal tasks. In contrast, occupations intensive in physical and routine tasks have significantly lower "new work" intensities. Consistent with the growing labor demand for jobs using cognitive-analytical tasks (Autor, 2015, 2019; Autor et al., 2003), high "new work" intensities in these occupations are not surprising. The important role of interpersonal tasks (both cognitive and manual) resonates with the recent literature that emphasizes the growing demand for these tasks in labor markets (Deming, 2017). It is also consistent with the pattern shown in Figure 1 where occupations in personal care and protective services, likely intensive in interpersonal tasks but not in analytical tasks, show high levels of "new work" intensities across our sample period. These occupations are typically not limited to college-educated workers, hence "new work" in these jobs may also have a positive impact on less educated workers—an important dimension in which "new work" is not the same as, nor fully explained by, (skill-biased) technological innovation.

3.3 The Geography of New Work: Local Labor Market Analysis

We now turn to our discussion of the geographic variation of "new work" across local labor markets, which is motivated by three considerations. First, the pattern of co-location and co-agglomeration of occupations (e.g. health technicians and doctors; librarians and teachers) implies that "new work" intensities in certain jobs may affect employment in other occupations; and these spillovers are likely to concentrate locally. Second, the existing urban literature indicates that cities and their local characteristics, such as population density, human capital intensity, and industrial diversity, are essential determinants of innovation

[21] The skills (degree, schooling, and age) are measured at the beginning of the period of analysis (1980); the task intensity is first constructed at 6-digit SOC occupations are then aggregated at the 3-digit IPUMS occupations using employment in 1980 as weights.

(Glaeser, 2013) and "new work" (Lin, 2011). Third, the extensive literature on the impact of global shocks on employment—including automation (Autor, 2019; Acemoglu and Restrepo, 2020), import competition (Autor et al., 2013), and immigration (Peri and Sparber, 2009)—all takes a local labor market approach. Therefore, conducting a regional analysis to investigate the importance of "new work" in employment growth and its relationship to local factors and economic shocks helps connect to existing studies on other economic phenomena in a clearer and more comparable way.

To proceed with the regional analysis, we construct our local measure of "new work" at the commuting zones (CZ) level using the value of the NWI^o in period t weighted by the local occupational composition,

$$NWI_t^c = \sum_o Sh_{t+10}^{o,c} \times NWI_t^o. \tag{3}$$

As our analyses in the rest of this section and the following sections importantly leverage variations in time, we specify the time information in our notations. Thus, NWI_t^o captures occupational "new work" intensities in period t constructed based on new job titles that emerge between period t and $t+10$; and $Sh_{t+10}^{o,c}$ is the within-CZ occupational shares in period $t+1$. There are two important features of NWI_t^c. First, the geographic variation in "new work" intensities is driven by variation in occupational compositions across CZs. Second, we use the occupational compositions at time $t+10$. Given the interpretation of NWI_t^o as the probability of "new work" emerging in each occupation between t and $t+10$, a regional aggregation of NWI_t^o weighted by the local employment in $t+10$ captures the predicted "new work" intensity generated as a result of the evolution of work in the considered decade.[22] Thus, CZs with large shares of occupations with high NWI_t^o exhibit larger values of NWI_t^c.

Panel B of Table 7 reports the CZ-level summary statistics for employment growth (and college and non-college employment growths separately) and "new work" intensities by threshold value (from the minimum to 50th percentile). The aggregation from occupations to CZs leaves the average NWI^c across decades relatively unaffected, but its variation reduces by one order of magnitude. This is due to the fact that, while differentiated, CZs do not specialize only in occupations generating high values (or low values) of "new work." The standard deviation increases from 0.8 ppts in the 1980s to 1.2 ppts in the 1990s and 1.4 ppts in the 2000s. This implies that a 1 ppt difference in "new work" in a decade between two locations was large and roughly equal to the difference between the average and the top quartile. A natural and immediate question is whether these seemingly small differ-

[22]Note that both the occupational shares in the initial period (at t) and the changes over time (between t and $t+10$) will contribute to the share at $t+10$.

ences possibly carry economic significance. In Section 4, we show how CZ-level variations in "new work" are associated with significant differences in net employment growth.

Figure 3 shows the geographic distribution of "new work" across CZs for each decade—darker shades correspond to areas with greater "new work" intensities. The maps suggest two features. First, there is significant persistence in the geographical patterns of "new work" creation over the decades; this is also confirmed by the significant correlation coefficients reported in Table A.4. Several areas in California, Texas and Northeast/Mid-Atlantic are persistently large "new work" creators.[23] On the other hand, local labor markets in Southern states, for example, Alabama, Arkansas, Tennessee) show lower intensities of "new work" in each decade.[24] Second, urban areas in general are among the biggest "new work" creators, showing greater concentrations not only in the Bay Area, New York City, but also Denver, Austin, and Chicago—which is consistent with role of agglomeration forces highlighted in Lin (2011).

These areas also show important connections with regional intensities in innovation activities—which is not surprising given how "new work" potentially relates to innovation in products, processes, and techniques. Specifically, Table A.6 reports the OLS correlations between local "new work" intensities and patents per capita where patent activities are assigned based on where the inventor's location when the patent is issued.[25] In a pooled panel regression where we regress local "new work" intensities on patents per capita (standardized) controlling for decade fixed effects, the coefficient estimate implies that a location with a standard deviation more patents per capita would also experience 0.43 ppts more "new work" in the same decade.[26] This difference is equal to roughly one half standard deviation of "new work" across CZs. This relationship is economically and statistically significant—a location with higher intensity of product and technological innovation correlates with higher "new work" intensities.[27]

4 New Work and Employment Growth

This section highlights the importance of "new work" by establishing its connection with employment growth. It is evident that "new work" by definition positively contributes to the creation of jobs. However, it may not necessarily foster employment growth—new titles

[23]e.g. Baltimore-Washington, D.C.; Austin, TX; College Station, TX; San Jose, CA.

[24]See Table A.5 for the list of CZs at the top and bottom of "new work" intensities.

[25]See Section A.2 for further details on the data and measure construction.

[26]The SE is 0.06. These coefficients are shown in Column (1) of Table A.6. The other columns show the coefficients of regressions when the variables are cumulative average over the 1980-1990, 1980-2000 and 1980-2010 periods. See the following analyses for explanation of these other specifications.

[27]Table A.10 shows the robustness of the patent-NWI panel correlations to different ways of constructing the "new work" intensities, using different thresholds.

may represent a small share of employment and their emergence can potentially accompany (disproportionate) job title destruction in the same occupations or crowding out from other jobs. Thus, we investigate whether "new work" is significantly associated with employment growth using occupation-level analysis. Since occupations co-located with "new work" can contribute to stronger regional employment growth, we also explore possible local job multiplier effects through co-location and co-agglomeration of occupations (Ellison, Glaeser, and Kerr, 2010) using CZ-level analysis.

4.1 Occupation-Level Analysis

Table 9 shows the OLS correlations between employment growth and "new work" examining more than 300 occupations across three decades. Column (1) uses a pooled panel regression where we regress log changes in occupation-level employment between time t and $t+10$ on "new work" intensities (NWI_t^o), which is constructed based on new job titles that appear between t and $t+10$; we include decade fixed effects in this specification. Note that the regression is in changes—the outcome variable is changes in log employment and the independent variable NWI_t^o captures changes by construction. Thus, occupation fixed effects are not included.

Columns (2) to (4) separately examine the correlations over different time horizons. For periods 1980 to 1990, 1980 to 2000, and 1980 to 2010, we regress the corresponding average log change in employment on *cumulative* "new work" intensities, which we construct by taking the average of "new work" intensities in these periods. For example, Column (3) shows how employment growth between 1980 and 2000 is correlated with the average of "new work" intensities constructed based on new jobs that emerged in 1980s (1980 to 1990) and 1990s (1990 to 2000). Panel A uses total employment growth as dependent variables. Panels B and C iterate the exercise focusing on employment growth of workers with at least 1 year of college education and those with a high school degree or less, respectively.

Three informative features emerge from the estimates. First, the correlation of "new work" with log changes in total employment is positive and statistically significant across all specifications. Column (1) shows that occupations with 1 ppt more new job titles in the average decade experience 0.67 log points faster employment growth. Column (4) further reveals that the effects accumulate into a higher growth by 1.23 log points (per each 1 ppt more new job titles) over the 30-year period. Together with the progression of larger coefficients considering longer intervals from Columns (2) to (4), our results suggest that the association of "new work" with employment growth is persistent and has a cumulative effect.

Second, occupations with high "new work" intensities experience employment growth for both the college-educated as well as the non-college-educated. A comparison of Panels B and C for Column (1) shows that employment growth associated with 1 ppt more "new work" in the average decade associates with a 0.52 log points higher employment growth of college-educated and 0.42 log points higher growth for the non-college group. This finding suggests that the margin of "new work" in transforming the job space is certainly associated with skill-intensive jobs in which college-educated workers show comparative advantage but also with others that do not require any college education. Albeit at a slower rate, jobs for non-college workers represent an important margin of employment growth associated with "new work." This is consistent with the patterns shown in Figure 1, which demonstrates how "new work" intensive occupations are also, to a significant extent, in broad occupational categories such as "Protective Services" and "Personal Care," which often do not require any post-secondary education.

Finally, in the long run, "new work" is a strong predictor of employment growth, especially for college-educated workers. A comparison between Panels B and C for Columns (2) to (4) reveals how the correlations between "new work" and employment growth become stronger over time, especially for the college-educated. Namely, 10 ppts more "new work" over 30 years is associated with 8.3 log points and 5.4 log points higher employment for those with college education and without, respectively.

Overall, the occupation-level evidence shows that the emergence of "new work" corresponds to faster growth in employment. These findings are not sensitive to the thresholds we implement in the construction of NWI.[28] Table A.8 shows the results for the panel regressions using a wide range of thresholds as well as the benchmark index (using external DOT sources and O*NET N&E) and confirms the robustness in the connection between "new work" and employment growth.[29]

4.2 Local Labor Market Analysis

To further assess the role of "new work" in possibly generating local spillovers in employment growth, namely "new work" in one job fostering the creation of other co-located jobs, we repeat the exercise above at the CZ level. If the correlation between employment growth and "new work" is stronger at the CZ level than at the occupation level, then there must be

[28]See Section 2.2 for a detailed discussion.

[29]The estimates show that for any index up to p75, including the benchmark, correlation with employment growth is positive and significant between 0.63 and 1.2, and stable up to p50. Similarly, they show a larger correlation with college employment growth, around 0.5 to 0.6, and a smaller but usually significant correlation with non-college employment growth, around 0.4. In both cases, up to a threshold of p75, the results are consistent and stable. Only choosing an extremely demanding threshold at p90 or above results become very imprecise. A threshold at such a high level will classify most "different" job titles as not new, likely missing an important share of "new work."

“new work” induced local co-agglomerations and positive spillovers across occupations. If we find smaller correlations instead, this would possibly imply that “new work” systematically crowds out employment in other co-located occupations.

Table 10 shows the OLS correlations between local employment growth and “new work” by CZs across three decades. We run the same regressions as in Table 9 but at the CZ level using local “new work” intensities defined in Equation (3) as the explanatory variable. Again, to examine the relationship over different time horizons, we construct an analogous version of the *cumulative* “new work” intensities at the CZ level.

Two features emerge. First, the coefficients on employment growth are two to three times larger than the occupation-level regressions, which suggests strong local spillovers (or job multiplier effects) where employment growth is not only directly in the “new work,” but growth is also generated in co-located occupations complementing the “new work.” Second, the correlations are stronger for employment growth of college-educated workers than non-college workers, which is consistent with the occupation-level evidence; however, here both the magnitudes and significance of the estimates are more similar to their college-educated counterparts relative to the findings at the occupation level.

“New work” is clearly associated with greater employment growth for all workers across cities. We confirm that the panel regression correlations between local “new work” intensities and employment growth are robust to different threshold choices when defining new job titles (Table A.9).[30] Our findings imply that spillovers from “new work” stemming from the local structure of occupation co-location are potentially important in fully capturing the impact of “new work” on labor. This importantly motivates our analyses in the following sections, which take a local labor market approach using CZs and explore relationships between “new work” and local factors and locally varied exposure to global shocks.

5 Post-1980 Global Shocks: Technology, Trade, Immigration, and Population Aging

Deep structural economic forces have changed the labor markets in the US and the rest of the developed world, especially since the 1980s. After decades of growth in the manufacturing sector, relatively stable wage distribution, and relatively low levels of exposure to import competition and immigration through the 1950s, 1960s, and 1970s, a series of remarkable

[30] The correlation with employment growth are larger than for occupation-level regressions, positive significant for all thresholds from minimum to p50 and for the benchmark definition. The correlation with college-educated employment growth is positive and significant and larger than the correlation with non-college employment growth across all thresholds. Even in this case, for very high thresholds, the correlations with NWI become imprecise and unstable. A broad range of thresholds around p25, which is our baseline, produce the same qualitative and similar quantitative correlations.

changes took place starting in the 1980s—marked by an important departure from the stable labor market structures and wage distributions in the preceding decades (Autor et al., 2008).

First, new general-purpose technologies related to computers, telecommunications, and rapidly accelerating capacity for data storage and processing began to permeate the workplace during the 1980s. In the 1990s and 2000s, the expansion of the internet and the World Wide Web revolutionized businesses and their practices, while other more specialized technologies such as robots further expanded this industrial transformation. Second, the sizable broadening of import competition was initially marked by Japan in the 1980s, Taiwan, Korea, Singapore, and Hong Kong in the 1980s and 1990s, and China in the 2000s. These countries accelerated the integration of both the final and intermediate goods markets, which not only shifted global trade patterns, but also induced substantial labor market effects in many countries including the US. Third, the characteristics of the US population changed substantially due to increased immigration. A large inflow of non-college workers from Mexico first emerged in the late 1970s and became a prominent force in the 1980s and 1990s, followed by a substantial inflow of college-educated from China and India in the 2000s. Finally, the demographics of the US population changed due to aging of the labor force, especially with the baby boomers entering retirement age in the 2000s.

Although several studies address the consequences of and possible connections between some of these shocks, this is the first study, to the best of our knowledge, to harmonize and bring together the ten different shocks in a single context for across US CZs from 1980 to 2010. Our analysis investigates whether local labor markets adjust to these economic forces at the margin of "new work" creation, which serves as a quintessential question for understanding the potential of these forces on the long-term future of work in the US.

5.1 Construction of Global Shocks

We focus on these four important shocks—technology, trade, immigration, and population aging—and examine their importance in predicting the intensity of "new work" creation across US local labor markets. The construction of each of these shocks follows the well-established approaches in existing studies. We bring together and homogenize these shocks in our context to analyze their connection to "new work." This section describes an overview of these shocks. See Section A.3 for further details related to the construction.

5.1.1 Technology: Computers and Robots

We focus on computerization (Autor and Dorn, 2013) and robotization (Acemoglu and Restrepo, 2020) as important technology shocks, which have been extensively studied in the literature examining the polarization of labor markets (e.g. Autor et al., 2003, 2006) and the displacement of tasks and jobs (Acemoglu and Restrepo, 2020).

For exposures to computerization, we follow Autor and Dorn (2013) to construct CZ-level routine task intensities in the pre-1980s that capture the extent of jobs replaced by computers. Specifically, our main measure of exposures to computerization is,

$$\widetilde{RSH_c} = \sum_{j}^{J} E_{j,c,1970} \times R_{j,-c,1970}, \tag{4}$$

where $E_{j,c,1970}$ is the employment share of industry j in CZ c in 1970; and $R_{j,-c,1970}$ is the routine occupation share of industry j excluding the CZs in the state that includes CZ c. By construction, this shock does not vary with time.

For exposures to robotization, we follow Acemoglu and Restrepo (2020) and first construct the industry-level penetration rate of robots in countries at the technology frontier (Denmark, Finland, France, Italy, and Sweden) for years 1993, 2000, and 2010. We then weight changes in these industry-level measures of robot adoption ($\Delta\overline{APR}_{j,t}$) by the 1970 industry shares in the CZs ($\frac{L_{cj,1970}}{L_{c,1970}}$), creating a local measure of exposure as follows:

$$\Delta\text{Exposure to Robots}_{c,t} = \sum_{j \in J} \frac{L_{cj,1970}}{L_{c,1970}} \times \Delta\overline{APR}_{j,t}. \tag{5}$$

By construction, this shock covers periods 1990 to 2000, and 2000 to 2010.

5.1.2 Import Competition: Three Trade Shocks

We include exposure measures to three episodes of import competition experienced since 1980: the rise of Japanese exports mostly in the early 1980s, the emergence of Hong Kong, Taiwan, Singapore, and South Korea as strong exporters during the 1980s and 1990s and the rise of China as world exporter starting in the 1990s with substantial growth in the 2000s.[31]

The construction of exposures to import competition from China follows Acemoglu, Autor, Dorn, Hanson, and Price (2016) and Autor et al. (2013) and leverages variations in the pre-1980 local industry structure and industry-specific imports from China. Our main measure of local exposures to the China shock is,

$$\Delta IP_{ct}^{ch,oth} = \sum_{j \in J} \frac{L_{cj,1975}}{L_{c,1975}} \Delta IP_{jt}^{ch,oth} \tag{6}$$

[31] A number of studies since Autor et al. (2013) have analyzed the labor market effects of increased import competition in the US and other developed countries (e.g. Autor et al., 2013; Costa, Garred, and Pessoa, 2016; Edmonds, Pavcnik, and Topalova, 2010; Hakobyan and McLaren, 2016; Hasan, Mitra, and Ural, 2006; Hasan, Mitra, Ranjan, and Ahsan, 2012; Kondo, 2018; Kovak, 2013; Dix-Carneiro and Kovak, 2017; McCaig, 2011; Topalova, 2010, etc.)

where $\Delta IP_{jt}^{ch,oth}$ is the change in imports of high-income countries from China in industry j over a decade t (1991 to 2000 and 2000 to 2010) adjusted by the absorption value in 1988.[32] And $\frac{L_{cj,1975}}{L_{c,1975}}$ is the 1975 CZ's employment share in industry j.[33] By construction of the UNComtrade data, the shock is activated for 1990 to 2000 and 2000 to 2010.

A similar approach is used to construct local exposures to import competition from Japan and the four Asian countries:

$$\Delta IP_{ct}^{jp,oth} = \sum_{j \in J} \frac{L_{cj,1975}}{L_{c,1975}} \Delta IP_{jt}^{jp,oth}, \quad \Delta IP_{ct}^{tg,oth} = \sum_{j \in J} \frac{L_{cj,1975}}{L_{c,1975}} \Delta IP_{jt}^{tg,oth} \tag{7}$$

where $\Delta IP_{jt}^{jp,oth}$ and $\Delta IP_{jt}^{tg,oth}$ are changes in imports of the high-income countries from Japan Asian Tigers, respectively, in industry j over a decade t adjusted by the absorption value. Here, our shocks cover periods 1980 to 1990, 1990 to 2000, and 2000 to 2010.

5.1.3 Immigration and Population Aging

To capture the dynamics of local populations, we focus on (i) immigration, which affects the availability of foreign-born (Ottaviano and Peri, 2012) and diversity of skills (Ottaviano and Peri, 2005); and (ii) population aging, which affects the size of cohorts entering and exiting the workforce (DellaVigna and Pollet, 2007). These are important determinants of labor supply, as well as of demands for local goods and services.

Our construction of the immigration shift-share variable follows (Goldsmith-Pinkham, Sorkin, and Swift, 2020). We use the pre-1980 origin-specific distribution of immigrants across CZs interacted with the origin-specific changes in immigrants post-1980. This variable proxies CZ-level variations in exposures to immigrants driven by the change in the supply of immigrants. We construct measures separately for high-skill (with some college or more) and low-skill (high school degree or less) immigrants as follows:

$$\frac{\Delta \widehat{H_{c,t}^{Foreign}}}{Pop_{c,1980}} = \frac{\sum_{n=1}^{N} S_{nc}^{1970} \cdot H_{t+10}^{n} - \sum_{n=1}^{N} S_{nc}^{1970} \cdot H_{t}^{n}}{Pop_{c,1980}}, \tag{8}$$

$$\frac{\Delta \widehat{L_{c,t}^{Foreign}}}{Pop_{c,1980}} = \frac{\sum_{n=1}^{N} S_{nc}^{1970} \cdot L_{t+10}^{n} - \sum_{n=1}^{N} S_{nc}^{1970} \cdot L_{t}^{n}}{Pop_{c,1980}}, \tag{9}$$

[32]To be consistent with our construction of the instrument variable across different types of import shocks (Japan, Asian Tigers, and China), we focus on imports of Australia, Denmark, Finland, New Zealand, Spain, and Switzerland. As discussed in Batistich and Bond (2023), the instrument excludes Japan for obvious reasons and Germany for the reliability of trade data before its reunification.

[33]The level of industry aggregation for the CBP data in 1970 is broader than the subsequent periods. Thus, we use data for the closest alternative period with the 4-digit SIC codes.

In Equations (9) and (8), the variable S_{nc}^{1970} is the share of all foreign born in working age (16 and older) from country of origin n in CZ c in 1970 relative to the total number of foreign-born working age from country n in the US in 1970; H_t^n (L_t^n) is the population in working age with college education (no college education) from country n residing in the whole US in year t for $t = 1980, 1990, 2000$.

Finally, our population aging shock follows DellaVigna and Pollet (2007), which captures variations in local age structures by constructing shares of the adult population for three age groups—young workers (18 to 45), old workers (46 to 65), and potential retirees (66 and over)—as predicted by the demographic structure in the CZ a decade earlier. For each age group a, we construct,

$$\Delta sh_{c,t}^{a} = \widehat{sh^{a}}_{c,t} - sh_{c,t-10}^{a} \tag{10}$$

$$\text{where} \quad sh_{c,t-10}^{a} = \frac{Pop_{t-10,c}^{a}}{Pop_{t-10,c}^{adult}} \quad , \quad \widehat{sh^{a}}_{c,t} = \frac{Pop_{t-10,c}^{a-10}(1 - mort_{t-10}^{a-10})}{\sum_{a \in adult} Pop_{t-10,c}^{a-10}(1 - mort_{t-10}^{a-10})}$$

where $Pop_{t-10,c}^{a}$ measures the population age-group a residing in CZ c in $t-10$ and it is adjusted by the expected morality rate for that age group, namely, the term $(1 - mort_{t-10}^{a-10})$. Note that this measure predicts local aging independently of internal mobility, which can be more responsive to labor demand forces.

5.2 Aggregation of Post-1980 Global Shocks and Correlations

In this section, we describe our construction of aggregate measures of these shocks capturing the underlying global forces of technology, trade, immigration, and population aging, and we characterize how the shocks co-vary across labor markets using both the ten and aggregated measures of our shocks.

5.2.1 Aggregation of Post-1980 Global Shocks

For the technology shock, we combine our measures for computerization and robotization, namely Equations (4) and (5) constructed for each decade by taking the first principal component. Due to the positive correlation between its components, the aggregate technological shock is an average of computer and robot exposure with roughly equal weight. For the trade shock, we construct a measure that aggregates import penetration from Japan, the four Asian Tigers, and China. Specifically, we use Equation (7) but with aggregate import flows from these countries. For the immigrant shock, we sum the exposure to high- and low-educated immigrants, as they are both expressed as a proportion of the total local population. Finally, for the population aging shock, the approach is similar to the technology shock, where we combine our measures for each age group using Equation (10) by taking the first principal component. The first principal component is positively correlated with the change in older workers and retirees, and negatively correlated with the share of younger workers—thus capturing aging. For ease of interpreting our results in Section 6, we standardize the four shocks by their own standard deviation for each decade.

5.2.2 Correlations in Post-1980 Global Shocks

To understand whether CZs exposed to one type of shock are systematically exposed to other shocks and further examine which shock exposures are most correlated with each other, we proceed with two exercises. Table 11 presents the matrix of pairwise correlation coefficients for all ten shocks using the full panel variation.[34] Table 12 repeats the exercise, but using the aggregates of the four global shocks.[35]

As shown in Table 11, the highest and most significant correlations are those observed within the categories of immigration and aging shock. High- and low-skilled immigration shocks have a very high and significant positive correlation (0.797). The share of old and young are also highly negatively correlated (-0.948). In comparison, computerization and robot shocks are less positively correlated (0.137). This is due in part to the different timing of those shocks; robot adoption started only in the 1990s and thus is zero in the 1980s. It also reflects potential differences in sectors that are hard-hit by computerization versus robotization, which corresponds to the weak correlations across CZs.

Among trade shocks, the China shock has significant and negative correlations with the other two shocks, originating from the four Asian Tigers (-0.220) and Japan (-0.040), while the correlation between the last two is strong and positive (0.395). These patterns likely arise from important differences in the structure of comparative advantages across these country groups. Specifically, import competition from Japan mainly affected the car, motor-vehicle, photographic, optical, electro-medical and related equipment sectors. In contrast, Chinese imports concentrated more on household video and audio equipment, games, toys, luggage, footwear, handbags, purses, leather, and sheep-lined clothing. Consistent with these substantial differences in industries, Eriksson et al. (2021) highlights that US local labor markets with high exposures to imports from Japan and China differ significantly.

Table 12 shows that the correlations between global shocks tend to be smaller in magnitude compared to the correlations derived by examining individual shocks, especially between shocks in the same group. Only one correlation coefficient in Table 12 is quantitatively large (0.332, between technology and aging), while all other coefficients are smaller

[34] The variables "Computer" and "Robot," represent the technology shocks; "China," "Tigers," and "Japan" are the trade shocks; "Immigrant high-" and "Immigrant low-skilled," the immigration shocks; and the share of "retired", "old," and "young," the age shocks.

[35] The maps for each of the global shocks in each decade are shown in Figures A.1, A.2, and A.3.

than 0.3 (and most below 0.1). The global shocks do not show large correlations neither between trade and immigration shocks, nor between trade and aging shocks. This implies that CZs hard-hit by one of these types of shocks were not necessarily affected by other shocks during this period.

There are two notable correlations between technology and other shock groups. First, the correlation with aging shock is significant and positive (0.332). Examining individual shocks (Table 11), we see that the aggregate correlation is produced by the positive correlations between both computerization and robot adoption with the growth in the share of older and retired workers; and the negative correlations with growth in the share of young workers. This is consistent with the hypothesis that locations with faster aging adopt more technological replacements for workers, as proposed in (Acemoglu and Restrepo, 2022).

Our results suggest that in locations with faster aging of the labor force, machines partially replaced younger workers during this period.[36] Note that the positive correlation between computerization and high-skilled immigrants provides empirical support for the complementarity between the two—high-skilled immigrants facilitate computerization (Peri, Shih, and Sparber, 2015) and computerization creates demand for their skills (Basso, Peri, and Rahman, 2020). However, low-skilled immigration and its negative correlation with computerization prevail in the aggregate.

Second, technological exposure shows a significant correlation with trade exposure (0.229). Examining individual shocks (Table 11), we see a significant correlation especially between the China shock and robotization, on the one hand; while on the other, trade shocks from Asian Tigers, Japan are correlated with computerization. Openness to import competition may have coincided with sectors most under pressure to adopt new technologies and thereby accelerated the technology adoption process (Bustos, 2011; Bloom, Draca, and Van Reenen, 2016); and/or the adoption of new computer-driven technologies may have induced the fragmentation of production processes and increased exposure to imports of intermediate goods (Fort, 2016).

6 Predictors of New Work: Local Factors and Global Shocks

This section examines the likely predictors of "new work" after 1980 by leveraging CZ-level variation in exposures to global shocks and differences in local factors. Motivated by the literature on agglomeration economies that analyzes local factors associated with productivity and growth, we consider the following local characteristics in 1980 as potentially related to

[36] An alternative replacement mechanisms for young workers in the labor force could be represented by new (younger) immigrants. This mechanism, however, does not appear to be at work: the correlation between aging and immigration shocks is not significant (0.007).

the creation of "new work."

First, population density is strongly related to the frequency of interactions—an important input in the generation and cross-fertilization of ideas (Jacobs, 1961)—and therefore, fosters innovation and learning that potentially generate "new work" (Lin, 2011). As a second consideration, the intensity of human capital is a driver of economic success, innovation, and growth for local labor markets (Diamond, 2016; Moretti, 2013), and thus, may facilitate the creation of "new work." Third, the presence of a large manufacturing base in 1980 is instead a predictor of strong declines in employment post-1980s (Gagliardi, Moretti, and Serafinelli, 2023), and possibly hampers the potential for "new work." In contrast, greater diversity in industry compositions can contribute to innovation and growth (Glaeser, Kallal, Scheinkman, and Shleifer, 1992; Moretti, 2012) and may contribute to "new work." These are the important local factors that produce (or capture) agglomeration economies and therefore of interest in our analysis.

The primary empirical specification adds these local factors to the local exposure to global shocks explained in Section 5. All explanatory variables are standardized for ease of coefficient interpretation.[37] Specifically, we estimate the following equation:

$$\begin{aligned} y_{ct} =&\beta_1(\text{Technology}_{ct}) + \beta_2(\text{Trade}_{ct}) + \beta_3(\text{Immigration}_{ct}) + \beta_4^s(\text{Aging}_{ct}) + \\ &\gamma_1 \ln(\text{Pop/area})_{c,1980} + \gamma_2(\text{College/Pop})_{c,1980} + \gamma_3(\text{1-HHI}_{c,1980}) + \\ &\gamma_4(\text{Share Manuf.})_{c,1980} + \Delta \ln(\text{Emp})_{c,1970-1980} + \eta_t + \epsilon_{ct}. \end{aligned} \tag{11}$$

The dependent variable is the "new work" intensities for CZ c in time t constructed using Equation (3) multiplied by 100.[38] Specifically, the key explanatory variables include the global shocks—technology (Technology_{ct}), trade (Trade_{ct}), immigration (Immigration_{ct}), and population aging (Aging_{ct})—as described in Section 5.2.1. The local factors measured in 1980 include: log of working age population density ($\ln \text{Pop/area}_{c,1980}$: persons per square mile); college share ($\text{College/Pop}_{c,1980}$: the adults with any post-secondary education relative to the working age population); industry diversity ($\text{1-HHI}_{c,1980}$: the Herfindahl-Hirschman Index (HHI) of employment share across IPUMS *ind1990* industry codes subtracted from 1 to capture diversity instead of concentration); and manufacturing employment share ($\text{Share Manuf.}_{c,1980}$: employment in manufacturing industries, as defined by IPUMS *ind1990* industry codes 100 through 392, relative to total employment).

While these explanatory variables are predetermined, their distribution across CZs in

[37]Throughout this paper, population is measured as working age individuals (16 and above).

[38]As discussed in Section 4, our baseline measure uses the 25th percentile threshold for the job-title-level construction of NWI. In Table A.11 we show the coefficients of the same panel estimation using different thresholds to define new job titles in NWI, namely p0, p5, p10, p20, p25, p50, p75, p90, p95 and the benchmark definition.

the pre-1980s period is not random. To alleviate concerns that the post-1980s correlation between agglomeration factors and "new work" may simply be a continuation of pre-existing (omitted) trends, we add the prior trend in employment growth from 1970 to 1980, $\Delta \ln(\text{Emp})_{c,1970-1980}$, as a control. We also add period fixed effects to control for macroeconomic time trends. Finally, we cluster standard errors at CZs to capture within CZ's correlation of residuals.[39]

To facilitate our understanding of whether the role of these local factors and global shocks in predicting "new work" is stronger in the long run, we also consider alternative specifications. Here, the dependent variables are the *cumulative* "new work" intensities. Similarly to Section 4.2, the cumulative measures capture averages of NWI_t^c across decades for the periods considered.[40] The global shock variables are adjusted similarly so that we capture the average exposure to shocks for the same periods (1980 to 1990; 1980 to 2000; 1980 to 2010). Local factors are measured using information from 1980 in all specifications. The past trends in employment growth are measured commensurately to the horizon of each specification: 1970 to 1980, 1960 to 1980, and 1950 to 1980 for periods of analysis 1980 to 1990, 1980 to 2000, and 1980 to 2010, respectively.

6.1 The Role of Local Factors

Table 13 presents our main results from Equation (11). We begin by discussing the role of local factors related to agglomeration forces as measured in 1980 (shown in the 5th through 8th rows). Column (1) shows the pooled panel estimates including decade fixed effects. Columns (2) through (4) show the regression coefficients for progressively longer cumulative "new work" intensities as dependent variables. We discuss results for each of the four local factors in turn.

First, population density is very strongly and significantly correlated with "new work." A standard deviation[41] denser CZ in 1980 implies 0.5 ppts more new job titles per decade over the following 30 years, as shown in Columns (1) and (4). This is a substantial predictive power relative to the standard deviation of "new work" intensities across CZs (1.2 ppts) in the 1990s. Our finding also corroborates the findings from Lin (2011) that occupations more concentrated in highly populated labor markets are more likely to generate "new work"

[39]This is equivalent to the standard heteroskedasticity robust standard errors in the cumulative specifications.

[40]For example, the *cumulative* "new work" intensities constructed for 1980 to 1990 is equivalent to NWI_{1980}^c, which is constructed based on new jobs that emerged in 1980s (1980 to 1990), while the outcome variable constructed for 1980 to 2010 would be the average of "new work" intensities combining information on new jobs observed in the 1980s (1980 to 1990), 1990s (1990 to 2000) and 2000s (2000 to 2010).

[41]A s.d. in log pop. density is about 147 log points; equal to a fourfold increase.

through intense interactions among workers, with customers, and with innovators.[42] It is also possible that the correlation captures occupations with high interactive tasks becoming increasingly concentrated in cities (Michaels, Rauch, and Redding, 2018).

Second, the local intensity of human capital is even more strongly associated with "new work." A standard deviation[43] greater share of college-educated in 1980 is associated with 0.57 ppts more "new work." This is substantial and close to half of one standard deviation of "new work" intensities across CZs in the 1990s (1.2 ppts) and to nearly three quarters of the standard deviation in the 1980s (0.8 ppts). Moreover, this implies that a CZ with around 50% of its workers being college-educated (e.g. San Francisco or San Jose, CA) differs from a CZ with about 15% (e.g. Stockton or Modesto, CA) by an average of 2.9 ppts of "new work" per decade, which is equal to more than twice its standard deviation in the average decade considered.

There are at least three explanations for this correlation being positive and impressively strong. First, occupations that tend to require college education are more likely to create "new work" as also suggested by the correlations in Section 3.2. Second, cities with high human capital intensity in 1980 experienced productivity growth and innovation at a faster rate than the others after 1980 (Moretti, 2012). If new ideas and their implementation are at the core of the emergence of "new work," then this correlation corresponds to this important mechanism. Finally, college-dense cities continued to attract more college-educated workers during this period (Diamond, 2016) and this virtuous cycle may have increased the attractiveness of the city for people in occupations experiencing large "new work" creation.

Third, the share of manufacturing employment shows a very significant and stable correlation with local "new work" intensities. However, this relationship is negative. A CZ with a standard deviation[44] more manufacturing employment in 1980 correlates with 0.31 ppts lower intensity of "new work," equal to more than one third of its standard deviation in the 1980s. The decline in manufacturing negatively affected several US locations and was associated with a net decline in employment (Gagliardi et al., 2023), a significant share of which were occupations intensive in routine and manual tasks and are unlikely to generate "new work." The departure of skilled workers from these areas accelerated deindustrialization, further contributing to this negative correlation. Altogether, high concentration of manufacturing in 1980 appears to hinder any subsequent generation of "new work."

Finally, the degree of industrial diversity does not reveal a consistent and statistically significant correlation with "new work" intensities. While diverse industry composition[45] is recognized as an important factor associated with economic growth and productivity across

[42]See Table 5 of Lin (2011) for further details.

[43]A s.d. in college share is about 6.7 ppts of the local CZ population.

[44]A s.d. in manufacturing share is about 10 ppts of local employment.

[45]A s.d. in industry diversity is about 0.01 in the diversity index.

cities in prior work (Glaeser et al., 1992; Lin, 2011), especially when analyzing the 1980s, our results do not show a significant correlation overall and the estimates weaken to insignificance over longer horizons following 1980. Industry diversity may have played some role in stimulating "new work" at the local level, but this characteristic appears much less relevant than the other factors related to agglomeration economies.

6.2 The Role of Global Shocks

We now turn to discussing the relationship between "new work" and local exposures to global shocks. We discuss results using the aggregated measures of our four shocks constructed in Section 5.2.1 and further investigate the correlations between the individual components of the shocks and "new work" to deepen our understanding of how exposure to global forces relates to "new work."

6.2.1 Aggregated Global Shocks

Table 13 (1st through 4th rows) presents results. We standardize the four shocks for each decade, and thus, the estimated coefficients capture how an increase in one standard deviation in a given shock was correlated to the outcome variable, measured in percentage points. It is important to control for local characteristics (described above), as some of these shocks are strongly correlated with those (for instance, a very high correlation exists between manufacturing share in 1980 and exposure to trade).[46]

The first row of coefficients shows that local exposure to technology does not have a significant correlation with the creation of "new work" on average, both in the panel estimate and in the 30-year cumulative specification. The shock combines exposure to computers and robots, where the former affected labor markets in the 1980s and 1990s (Autor et al., 2003), while the latter instead began in the 1990s and grew more intense in the 2000s. We will study these shocks separately in the following section.

The second row of coefficients shows that the intensity of trade exposure was not significantly related to "new work" on average in the panel specification or across various horizons. This result deserves two comments. First, if one examines the correlation of trade shocks with "new work" *without* controlling for local labor market characteristics, one finds a significant negative association between trade exposure and "new work" in each decade (Table A.7). Hence, the inclusion of local characteristics, especially the manufacturing share in 1980, absorbs the negative association between "new work" and trade. Other studies (Eriksson et al., 2021) show that the negative effects of import competition were stronger

[46] For completeness of the exercise, we show in Table A.7 that estimate our baseline specification without the local characteristics significantly differs from our main results in Table 13.

in locations that were previously specialized in traditional manufacturing that are already on the decline. Therefore, it may be difficult to isolate the impact of import competition if one does not properly control for the decline in manufacturing. Second, it is important to analyze whether the null effect masks different impacts from specific trade shocks across locations. We study this in the next section.

Our results for immigration show an insignificant relationship with "new work" on average in the panel analysis, though there is a borderline positive correlation over the long run. The dynamics reflect an increase from a negative relationship in the 1980s to a positive association over longer time horizons. A CZ with one standard deviation higher exposure to immigrants over 30 years experiences 0.03 ppts higher "new work" intensity per decade from 1980 to 2010. This average effect is quite small. Notice that, similar to trade shocks, the immigration shocks have a much stronger correlation with "new work" without controlling for local characteristics. As immigrants are attracted to high human capital and high density areas, it is important to control for these related local characteristics.

Finally, our findings for population aging show a large and significant relationship with "new work" intensities that strengthen over longer time horizons. As this aggregate measure captures increases in the share of older workers and expected retirees (and is negatively correlated to the change in share of younger workers) the pooled regression estimate implies that a CZ with one standard deviation faster aging experiences 0.11 ppts more "new work" intensity on average in each decade; and the average cumulative effect is marginally higher at 0.13 ppts per decade over the 30-year period. The role of population aging becomes statistically and economically significant throughout the 1990s and beyond.

At the local level, a larger share of older and retired people may generate the demand for more differentiated services in healthcare, entertainment, house care, and personal care. This may stimulate new job titles related to services and new technologies accommodating the demands of an aging population (e.g. therapist, health technicians, but also personal trainer). Previous studies show that demographic change is a very important predictor of demand shifts for several industries (DellaVigna and Pollet, 2007). In particular, the increase in non-tradeable local services demanded by older people can be a strong stimulus to local diversification of those services and therefore likely generates "new work" related to them.

6.2.2 Unpacking Global Shocks

We next unpack these global shocks to study the correlations between the individual components of the shocks and "new work." Figure 4 represents the coefficients and the 95% confidence intervals from the regression of "new work" on the individual components of the global shocks: technology (top 2 rows), trade (next three), immigration (next two), and population aging (last two rows).[47] The estimated coefficients represented in navy marks are from the panel specification that includes all controls; and those shown in light blue marks are obtained using the 30-year cumulative specification. The results correspond to Columns (1) and (4) of Table 13 but using disaggregated shocks.

The first two rows show the coefficients on the local exposures to robotization and computerization, respectively (as described in Section 5.1.1). Neither of the two shocks are significantly associated with more (or less) "new work." While there is strong empirical support for computerization replacing routine tasks (Autor et al., 2003), locations with greater degree of exposures to this shock do not show stronger responses by creating more "new work." Similarly, robotization—a technology aimed at replacing complex manual functions performed by humans—is not associated to higher "new work" intensity. Both coefficients imply that being exposed to technological pressure in local labor markets did not automatically spur the creation of "new work." Our finding can be consistently interpreted with previous work showing how locations exposed to technological change, which replaced specific functions of labor with technology, resulted in lower employment growth and job losses for most types of workers (Autor, 2015; Acemoglu and Restrepo, 2020).

The third through fifth rows of Figure 4 show the coefficients examining local exposures to each of the three episodes of import competition (as described in Section 5.1.2). Exposure to the rise of Chinese competition shows no significant correlation with "new work" intensity; Japanese competition, instead, reveals significant and negative correlations; and finally, the competition from the Asian Tigers shows a positive yet borderline significant correlation with "new work," especially in the cumulative specification. Japan was a strong technological competitor in advanced sectors to the US, especially in the 1980s and 1990s, and now it is one of the most advanced producers of industrial robots. Thus, it is possible that innovation-related work in locations that competed with Japanese imports in these high-tech sectors were negatively affected, thereby reducing local "new work" creation. On the other hand, trade competition from less advanced countries in more traditional sectors may have modest impacts on "new work."[48]

Rows six and seven of Figure 4 show the coefficients for exposures to high-skilled and low-skilled immigrants (as described in Section 5.1.3). Our results show that the inflow of

[47] The full set of coefficient estimates are reported in Table A.12.

[48] Kim (2024) shows a positive and significant impact of import competition from China on the local generation of "new work" intensities focusing on post-2000s and the results are primarily driven by within-CZ changes in the occupational compositions (shifting towards high-skilled professional occupations with high NWI^o) between 2000 and 2010. Note that the main focus of Kim (2024) is to use "new work" measures to capture a broader definition of innovation, and thus, the outcome variable of interest in the main specification uses *changes* instead of levels for local occupational shares combined with NWI^o, which also speaks to nuanced differences in the results.

high-skilled immigrant workers is not positively associated with "new work." One possible explanation for this is that areas with a large share of high-skilled immigrants also have a local supply of domestic high-skilled workers, for example, through local colleges. Hence, any possible positive correlation between high-skilled immigration and "new work" is absorbed into the correlations with the local share of college-educated. We show in Section 7.1 that only areas with insufficient supply of local high-skilled workers reveal a positive correlation between local exposures to high-skilled immigration and creation of "new work."

Finally, the last two rows of Figure 4 show the correlation with aging shocks separating the increase in the share of older workers (45 to 65) and that of retirement age (65 and older) in a labor market (as described in Section 5.1.3). Both shocks have a positive correlation with "new work" on average. In the cumulative specification, in particular, the correlation with the share of retirees is strongest and more significant. Our results do not suggest that fewer young workers in the workforce depress "new work" creation. Instead, it suggests that more experienced workers in the labor market and the demand for services from retirees may be an important ingredient for "new work." As the generation of baby boomers (born between 1945 and 1965) started to retire during the 2000s, a more prominent share of retirees affecting local demand for services (health care, hospitality, travel) may have induced the creation of new types of services, consequently leading to the emergence of "new work" to cater to these evolving and diverse demands.

6.3 Summary and Robustness Checks

Throughout this section, the results indicate a consistent finding: local college-educated share and population density are the strongest predictors of the post-1980s local "new work" intensity; and the inclusion of these factors in the analysis substantially reduces the importance of global shocks in predicting "new work." This aligns with extensive evidence on large cities with highly educated population experiencing higher productivity, innovation, and rapid economic growth, especially in the recent past decades (Ciccone and Hall, 1996; Duranton and Puga, 2004; Glaeser and Gottlieb, 2009; Diamond, 2016; Card, Rothstein, and Yi, 2023).

Note that our results on the predictive power of these local factors in 1980 on the post-1980s "new work" are based on regressions including past trends in employment growth.[49] As shown in Table 13 (9th row), past employment growth is only marginally (negatively) correlated with "new work" intensities post-1980s. This is possibly because local growth in the 1970s was associated with traditional technologies, capital accumulation, the expansion

[49]The pre-trends in employment growth are measured commensurately to the horizon of each specification: one decade from 1970 to 1980 for the panel and the one decade horizon; across two decades from 1960 to 1980 for the two decade horizon; across three decades from 1950 to 1980 for the three decade horizon.

of manufacturing and construction sectors, and their local spillovers on traditional office and business services. In contrast, the economy post-1980s experienced substantial disruptions stemming from the advent of new technologies, new patterns in trade, and increased immigration—all causing significant changes in the geography of jobs. These results show that the role of local factors related to agglomeration forces in the 1980s on the post-1980s "new work" is not just a continuation of pre-existing trends in employment.

Finally, we check the baseline results are robust relative to the choice of threshold value in defining new job titles. Table A.11 shows the panel regression coefficients (as in Column (1) in Table 13) across a range of thresholds (from min. to p90, plus the benchmark measure of NWI described in Section 2.3). The estimated coefficients for all local factors and the aging shock are very stable and consistent for all thresholds up to p50. Population density, share of college educated, and share of manufacturing are consistently and strongly predict the creation of "new work" across locations. The coefficients on the exposure to all other global shocks confirm that there is no significant correlation with technology, trade, and immigration on average.

7 Heterogeneity Analysis

Given the clear importance of the local share of college-educated workers and population density—both central features affecting local productivity (Glaeser, 2010; Moretti, 2013) and now the strongest predictors of "new work"—this section focuses on understanding the role of human capital in constructing dimensions of heterogeneity in the response to shocks and the type of "new work."

7.1 High-Skilled Cities versus Standard Commuting Zones

Large and dense CZs with high human capital—which for brevity we will call "high-skilled cities"—may be better positioned to respond to an increase in import competition, to absorb changes in labor-replacing technology, and capitalize on their comparative advantages by generating "new work." To explore this possibility, we define "high-skilled cities" as the CZs in the top quartile of the distribution of predicted "new work" intensities based on the four initial local factors included in our regressions.[50] We refer to all other CZs as "standard." In Figure 5, we show that "high-skilled cities" include large dynamic urban centers such as San Francisco CA, Los Angeles CA, New York City NY, Boston MA, as well as other cities with important supply of high-skilled workers such as Denver CO, Austin TX, Santa Barbara CA

[50]While we include manufacturing share and industry diversity, given the predictive power of initial population density and human capital share, the name "high-skilled cities" accurately captures this group.

in the West and South of the US.[51]

In our empirical exercise, we extend the panel regressions of Equation (11) by including a binary indicator for the "high-skilled cities" as well as its interaction terms with each of the shocks. Figure 6 presents the point estimates and 95% confidence intervals for the coefficients (aggregate, not differential, association for "high-skilled cities") estimated using the panel regression.[52] The estimates for the "high-skilled cities" are in blue while those for the standard CZs are in orange.

This analysis reveals interesting differences in the relationship between shocks and "new work" intensity across those two types of local labor markets. The associations to the technological shocks are presented at the top of the figure and show that standard CZs experience a negative correlation with "new work" intensities, while "high-skilled cities" seem to absorb those shocks without reducing "new work" intensity. We also find a notable difference in the correlations of "new work" with trade shocks between the "high-skilled cities" and standard CZs. While trade shocks are not correlated with "new work" in standard CZs, there is a large and significantly positive association with trade shocks in "high-skilled cities."

Given the extensive evidence on trade-induced restructuring in which manufacturing firms evolve both in scope and nature, focusing on core competencies (Bernard and Fort, 2015) and switching towards services (Bernard, Smeets, and Warzynski, 2017; Bloom, Handley, Kurmann, and Luck, 2019; Ding, Fort, Redding, and Schott, 2022), our results suggest "new work" as an additional dimension of response. However, it seems a strong potential for agglomeration economies is required for trade competition to generate "new work." Similarly, Kim (2024) also emphasizes the importance of adjustments at the extensive margin through "new work" adoption in response to import competition, which is importantly driven by the supply of high-skilled workers.[53]

Another important aspect of heterogeneous responses is that high-skilled immigration shocks have a positive correlation with "new work" in standard CZs, while this relationship is insignificant and imprecisely estimated (negative point estimate) in "high-skilled cities." High-skilled migration is often larger in dense and high human-capital cities (e.g. Peri, 2016); thus, once we control for those local features, its additional correlation to "new work" may be much reduced. However, in locations with lower local potentials, the abilities of high-skilled immigrants can be a fundamental factor in generating "new work." When immigrants flow into locations where human capital is scarce, they may be contributing to

[51] See Table A.13 for the top 10 cities and their ranking in these local characteristics.

[52] Table A.14 reports the coefficients on the interaction terms to isolate the differential correlations and their significance with the corresponding shock for "high-skilled cities."

[53] There is also a substantial literature emphasizing the impact of trade on innovation (product, process) through several channels (including competition, comparative advantages, and knowledge spillovers) See Melitz and Redding (2021) for a comprehensive review.

"new work" in a more substantial way. Low-skilled immigration, on the other hand, does not have a significant correlation with "new work" in either location type. Lastly, the correlation with aging is similar in "high-skilled cities" relative to other locations. This further affirms the relevance of older workers and the demand from retirees in generating "new work."

Overall, this section suggests that creative and destructive forces such as technology and trade competition may be mediated in their impact on "new work" by the local ability of workers to respond to them. We find that areas particularly characterized by high human capital and frequent interactions are better equipped to turn these dynamic challenges into "new work." High-skilled immigration, in addition, seems to serve as input that complements local supply of human capital, and thereby facilitates the creation of "new work" in locations with low agglomeration potential.

7.2 Cognitive-Analytical versus Manual-Interpersonal NWI

Our analysis in Section 3.2 shows that a large share of "new work" emerged from occupations intensive in non-routine tasks, which include two distinct types of occupation groups: high-wage occupations intensive in cognitive-analytical tasks and lower wage occupations intensive in manual-interpersonal tasks.

In this section, we separately analyze the correlates of "new work" oriented towards these two groups. We attempt to identify distinctly different types of "new work" that we expect to correspond to these two groups. This is possible by isolating NWI derived only from certain titles—or specifically in this exercise, titles belonging to occupations based on their task intensity.

The first group includes occupations in the top tercile of non-routine cognitive-analytical intensities, exemplified by "Management Analysts," "Economists," or "Aerospace Engineers." The second group includes occupations in the top tercile of non-routine manual-interactive intensities, like "Social Workers," "Vocational and Educational Counselor," and "Clergy and Religious worker."[54] For brevity, we refer to the resulting two measures as cognitive-analytical and manual-interpersonal "new work" (or NWI), respectively. Figure 7 shows the estimated coefficients and 95% confidence intervals separately examining the panel regression of Equation (11) for "new work" in cognitive-analytical (in blue marks) and in manual-interpersonal "new work" (in orange marks). The changes in explanatory variables, as elsewhere, are standardized for ease of interpretation and comparability with each other.

Several important findings emerge. As for local factors, population density and the share of college-educated have strong predictive power for "new work" in both groups,

[54]See Table A.15 for more example occupations that contribute to these more specific NWI measures."

but with greater magnitude for the cognitive-analytical than for the manual-interpersonal "new work." Cognitive-analytical occupations and related "new work" are more intensive in abstract, quantitative, and mathematical skills that are mainly supplied by the college-educated and, therefore, thrive in large cities with human capital-rich environments. Although showing a smaller predictive power—in terms of the magnitude of the coefficients and statistical significance—the manual-interactive type of "new work" is also positively predicted by density and human capital. "High skilled cities" are the places where "new work" with cognitive-analytical content is created, but also "new work" in the interactive content thrives given the high density of people and social interactions. Many of these jobs also originate in metro areas, which may be due to co-location and agglomeration forces discussed in Section 4.2.

We next turn to discussing global shocks. First, exposure to technology is significantly correlated with cognitive-analytical "new work," which likely corresponds to the strong complementarities of technology to work that implements and leverages accelerating computing power and advanced robotics. In contrast, it is only marginally (yet positively) correlated with "new work" in manual-interpersonal occupations. Second, exposure to trade has a positive non-significant relationship to "new work" in cognitive-analytical occupations and negative non-significant coefficient on "new work" in manual-interpersonal ones. This is weakly consistent with the results shown by Kim (2024) where trade exposure induces the adoption of "new work" in "Managerial and High-Skill Professional" occupations. Third, exposure to immigration does not show any average significant correlation with "new work" in either group. Finally, exposure to population aging is strongly associated with "new work" in cognitive-analytical occupations, but not in manual-interpersonal ones. On-the-job experience enriches cognitive skills[55] and may be crucial in translating general innovation into "new work." In addition, an aging population may demand new types of cognitive-intensive services in health care and personal services.

Overall, we notice that both human capital, population density, and the intensity of shocks have a lower predictive power for "new work" in high manual-interpersonal jobs than in cognitive-analytical ones. One possible explanation for the weak or null estimates is that the geographically diffused nature of the underlying occupations might mask the factors driving innovation in these more nuanced NWI measures in a CZ-level analysis.

[55] See for instance Hertzog, Kramer, Wilson, and Lindenberger (2008).

8 The Causal Role of Local Supply of Colleges

Our results in the previous sections consistently suggest the critical importance of human capital in relation to "new work." At the occupation level, "new work" is generated at higher intensity in high-skill/high-wage occupation categories (Figure 1); and "new work" intensity is further correlated with more years of schooling, having any post-secondary education, and having a college degree (Table 8).

At the CZ level, the local share of college-educated workers has the largest and most significant predictive power on local "new work" intensities (Table 13). Moreover, a large CZ's share of college-educated workers is a fundamental factor in distinguishing "high-skilled cities," which appear to generate "new work" as a response to import shocks and labor-substituting technologies (Figure 6); while in standard CZs, high-skilled immigration predicts more "new work." Clearly, "new work" and human capital have an important relationship, but the nature of this relationship is still largely unexplored.

This section investigates one causal direction—the effect of the local *supply* of human capital on the creation of "new work." To do this, we use measures of the local supply of college-educated workers as instruments, namely the historical presence and density of 4-year college institutions in the CZ. These instruments isolate supply-driven variations in the college-educated share across CZs from potentially confounding demand forces (such as the local industrial composition and local adoption of emerging technologies) that otherwise preclude a causal interpretation of the initial college share on "new work." Also note that the distribution of 4-year colleges across CZs is by no means exogenously determined, that is, the openings of these colleges follow policy decisions that respond to local needs and opportunities. Our strategy importantly isolates college supply driven by decisions and events that are progressively further in the past and, hence, increasingly weakly related to post-1980 economic trends.[56]

We consider three instruments for our analysis. First, we measure the density of 4-year colleges per capita (standardized) across CZs in 1980 as a contemporaneous instrument for baseline comparison. Second, we only consider the standardized density using 4-year institutions existing by 1960. Finally, we use only an indicator for the presence of an early-wave land-grant college established and designated before 1920. These progressively more exogenous variations in local college supply across these instruments relative to economic forces of the post-1980s allow us to estimate coefficients that are more informative on the causal role of local college-educated populace on "new work."

Note that the instrument using land-grant colleges is not just a third similar instrument determined by a more distant past. Land-grant colleges generally *evolved* into prominent

[56]Our strategy and data construction follow (Currie and Moretti, 2003; Moretti, 2004a; Ehrlich et al., 2018).

institutions, but these institutions are not simply the prominent universities of early American post-secondary education. Many institutions opened shortly before (e.g. Penn State University, University of Maryland) or after (e.g. Cornell University, University of California, Texas A&M) their land-grant designation. Thus, this instrument largely identifies the quasi-random spatial variations in human capital supply generated by the federal Morrill Land-Grant Acts of 1862 and 1890.

We integrate these instruments into our analytic dataset from different sources. The measures of local colleges density in 1980 and 1960 are constructed using data from Currie and Moretti (2003), which contains information on the number of 4-year colleges in each US county measured from 1960 to 1990. We aggregate these county-level college counts to construct the number of 4-year colleges per capita in each CZ for 1980 and 1960.[57] For the land-grant indicator, we use information on institutional characteristics obtained from the U.S. Department of Education, National Center for Education Statistics (1980) IPEDS to derive whether a CZ had a land-grant institution before 1920. We supplement our IPEDS-based indicator with the information available on Wikipedia to account for historical nuances.[58] We further adjust a small number of cases where IPEDS data in 1980 is inaccurate in capturing earlier land-grant status.[59]

We re-estimate the panel regression of Equation (11) using measures of local supply of colleges as IVs for the local share of working-age people with 4+ years of college education. The results are shown in Panels A and B of Table 14. Panel A shows the estimates when only controlling for local factors. Panel B shows the estimates when including the full set of controls, namely local factors, exposure to aggregate global shocks, and the pre-1980 employment growth. The bottom three rows of each panel include the F-statistics for the first stage and the p-values for the Anderson-Rubin statistics, testing for consistency under weak instruments. The F-statistics are equal to or above 10 for the 1960 college density IV and it is very large for the land-grant IV; the AR test always rejects the null of weak IV at the standard confidence level. These diagnostic tests indicate that variation in college density in both decades and land-grant universities effectively predict a CZ's college share in 1980

[57] We use the dataset variable that captures 4-year colleges with the minor refinement that the institution must grant at least an associate degree.

[58] We use 1980 data to preempt inclusion of land-grant institutions from the Improving America's Schools Act of 1994. Some land-grant institutions were designated after legislation enactment and before the institution was established, e.g. University of California was founded in 1868 but designated a land-grant university in 1866 based on the legislation enacted in 1862. Therefore, we apply a rule based on land-grant status as of 1920 to cover all institutions from the first two rounds of land-grant legislation.

[59] Namely, West Virginia State University lost its designation in the 1950s amid the desegregation era, and it was restored in 2001; thus, this IPEDS dataset did not indicate land-grant status here. We manually override land-grant indicator for West Virignia State. University of the District of Columbia is also omitted from the 1980 IPEDS dataset, likely due to name changes around that time. We manually add this to the corresponding CZ for Figure A.4, but the CZ already contains University of Maryland and thus its indicator is unaffected.

and, in turn, the explanatory variable predicts ”new work” post-1980.

The coefficient in Column (1) of Table 14 shows the OLS estimate for the standardized share of college graduates in a CZ. An increase by one standard deviation in this college educated proportion of the working age population increases “new work” by about 0.6 ppts, which is half of its standard deviation in the 1980s and one third of its deviation in the 2000s.[60] For Columns (2) to (7), the odd and even columns show the two-stage least squares and reduced-form coefficients, respectively. The instruments are presented from least to most plausibly exogenous: Columns (2) and (3) use 4-year college density in 1980; Columns (4) and (5) use 4-year college density in 1960; and Columns (6) and (7) use the pre-1920 land-grant indicator. While the standard errors increase significantly relative to the OLS estimates, especially in Columns (2) and (4), the coefficients are still similar and significant at the 5 or 10% level. Focusing on the sequence of 2SLS estimates in Panel B, we see a robust and significant series of effects ranging between 0.47 and 0.74 ppts more “new work” given a standard deviation change in college share.

Finally, the specification with the most exogenous IV shows that a one standard deviation change of college share driven by the land-grant instrument leads to almost 0.6 ppts higher “new work” in the post-1980 decades. As shown in Column (7), the reduced form implies that the presence of a land-grant college in a CZ produces 0.84 ppts more “new work” in the post-1980s decades—a difference larger than one standard deviation in local “new work” intensities across CZs in 1980.

Altogether, these results confirm that differences in the historical presence of 4-year college institutions significantly affected college education in the 1980s and, in turn, stimulated the creation of “new work” in the following three decades. Our results highlight the quintessential importance of human capital supply for the creation of “new work.” The likelihood of introducing new technologies and new knowledge is tightly connected to the knowledge stock that prominent post-secondary institutions cultivate. The supply of high-skilled workers with comparative advantages in performing new tasks—part of which may be attributed to these local institutions being more adaptive to the evolving demands for skills—facilitates the implementation and the diffusion of “new work.” Understanding the relative importance of each channel in the creation of “new work” constitutes important avenues for future research.

[60] This corresponds to the *College Share* estimate shown in Table 13, however the estimate is slightly larger here given we turn to the share of people with four or more years versus at least one year of college education in the prior table.

9 Conclusion

In this paper, we develop and implement a novel measure of "new work" identified from the emergence of new job titles to capture innovations in job types. Our measure is based on the idea that each job title signals its job nature, which can be summarized by a vector using text analysis algorithms that quantify semantic meaning. Based on this, two vectors that are sufficiently distant from one another represent different jobs; a job different from all pre-existing jobs captures "new work." We apply the method to construct "new work" intensity measures across occupations and commuting zones for each decade between 1980 and 2010, extending the seminal work of Lin (2011) into the new millennium.

A key advantage of our method is that the algorithm does not rely in pre-determined classifications of skills or technologies used, but rather measures *novelty* in content relative to existing jobs. As such, the paper is complementary to recent papers analyzing the emergence of new types of work using data on job postings (Atalay and Sarada, 2020) and on "new work" related to new technologies (Hanson, 2021; Autor et al., 2024). Our method can be applied to constructing "new work" measures for any period and country for which detailed job titles exist from the Census.

Using our measure of "new work," we provide various descriptive patterns and statistics—importantly connecting to the literature on the evolving task content of work (Autor et al., 2003; Autor, 2015, 2019; Atalay et al., 2020). We show that occupations with higher college education and with larger intensities in non-routine cognitive-analytical and non-routine manual-interactive skills experience more "new work." We also show a significant correlation between "new work" intensities and employment growth across occupations and, more strongly, across local labor markets.

We systematically analyze how local factors as of 1980 and local exposure to global shocks—trade, technology, immigration, and population aging—predict "new work" intensity from 1980 to 2010. We document the importance of the initial local share of college educated and log population density as the two most significant predictors of "new work" across CZs and decades. High manufacturing share in 1980 also strongly (yet negatively) predicts "new work." Additionally, we find that exposure to technology, trade, and immigration does not predict, on average, more or less "new work" across CZs, but population aging shows a strong positive association with "new work."

We further demonstrate important heterogeneity in the role of local factors and global shocks by occupation types and regions. We find that cognitive-analytical oriented "new work" (which is found in jobs mostly employing college educated) has a strong positive correlation with technological change, suggesting that those types of new jobs are likely related to applications of new technologies. They are also more positively affected by local human capital and local density, thus likely more responsive to local agglomeration economies. However, it is less clear what predicts manual-interpersonal oriented "new work" beyond local agglomerations. As for the heterogeneity analysis by regions, we find clear patterns where "high-skilled cities" suggestively leverage "new work" in a response to global shocks. This differential relationship between region types indicates a critical role of local human capital supply, which is further supported by a uniquely positive association of high-skill immigration only found in standard CZs where local human capital supply is lower.

To delve into the relevance of human capital (which relates to mechanisms of agglomeration economies) in generating "new work" and mediating the local impact of exposure to possibly adverse global shocks such as technological change and import competition, we investigate the causal impact of local supply of human capital on the creation of "new work." Specifically, we use the historical presence of 4-year college institutions in the CZ as an instrument for the local supply of college educated. We establish significant 2SLS estimates of the impact of college share on post-1980 "new work" intensity—consistent with a causal link from human capital to "new work."

We consider these findings as the first comprehensive exploration of the local and global determinants of "new work." We expand implications from regional, trade, immigration, and various labor topics studying the evolution of employment in the US since 1980; and further inform the active literature on the changing nature and future of work.

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Tables

Table 1: Job Titles Data; Summary statistics and Sources

Period	Source	No. Titles	Avg Titles (per Occ)	SD Titles (per Occ)
1980	Dictionary of Occupation Titles (1977)	11120	22.479	37.945
1990	Dictionary of Occupation Titles (1991)	11677	21.825	37.139
2000	Classified Index of Industries and Occupations (2000)	30304	60.008	102.566
2010	O*NET Alternate Titles (2016)	59800	113.982	100.456

Notes: This table summarizes the data sources for each period, the number of job titles included in each of these sources, the average number of titles observed per occupation code, and the corresponding standard deviations.

Table 2: Definition and Notation of New Work Intensities

Notation	Definition	Interpretation
$RNWI$	minimum distance from the closest match	job-title-specific degree of newness
NWI^p	1 if $RNWI$ exceeds threshold p; 0 otherwise	new job title if 1; otherwise 0
NWI^o	(unweighted) average of NWI^p	share of new job titles of an occupation
NWI^c	(within-CZ occupation share) weighted average of NWI^o	average new work intensities of a CZ

Notes: This table provides the definitions and interpretations of our "new work" measures that we use at the job title level ($RNWI$ and NWI^p), occupation level (NWI^o), and CZ level (NWI^c). For brevity, we omit the period subscript. For example, NWI_t^p indicates new job titles emerged between periods t and $t+1$.

Table 3: Validation Exercise I– Comparisons with Lin (2011)

Thresholds Applied	Share of False Positives	Share of False Negatives
None	0.134	0.006
Min	0.131	0.007
5th	0.129	0.007
10th	0.126	0.007
25th	0.109	0.010

Notes: This table presents validation exercises to benchmark our measure of "new work" by examining its comparability with the measure proposed in Lin (2011) for the 1980s, which leverages the list of "New Definitions in the DOT" in "Section 3 of the 1991 Conversion Table" to identify new job titles. The share of false positives indicates the number of titles Lin (2011) classifies, yet CBOW classifies as new relative to the total number of titles. The share of false negatives indicates the number of titles Lin (2011) classifies as new, yet CBOW classifies as existing relative to the total number of titles.

Table 4: Validation Exercise II–Comparisons with N&E–

Thresholds Applied	(1)	(2)	(3)
None	0.389***	0.149***	0.157***
Min	0.434***	0.141***	0.157***
5th	0.435***	0.142***	0.160***
10th	0.439***	0.145***	0.162***
25th	0.437***	0.139***	0.156***

Notes: This table presents validation exercises to benchmark our measure of "new work" by examining its comparability with the O*NET's "New & Emerging" occupations (N&E) for the 2000s. Column (1) examines correlations between CBOW-based and N&E-based "new work" using the number of new titles within each 6-digit occupation codes. Column (2) examines correlations using the number of new titles relative to total number of job titles within each 6-digit occupation codes. Column (3) examines correlations using the number of new titles relative to total number of job titles within each 6-digit occupation codes for CBOW-based; the number of new titles relative to total number of 8-digit occupation titles within each 6-digit occupation codes for the N&E-based approach.

Table 5: Top 10 Occupations in New Work Intensity by Decade

Decade	Occupations	NWI^o
2000s	Teachers, Postsecondary	.745
	Librarians, Archivists, and Curators	.647
	Social Scientists and Urban Planners	.643
	Lawyers and Judges	.629
	Teachers, Except Postsecondary	.579
	Engineers, Architects, and Surveyors	.576
	Therapists	.576
	Health Assessment and Treating Occupations	.552
	Health Technologists and Technicians	.551
	Firefighting and Fire Prevention Occupations	.55
1990s	Teachers, Postsecondary	.91
	Teachers, Except Postsecondary	.541
	Sales Workers, Retail and Personal Services	.345
	Mathematical and Computer Scientists	.323
	Therapists	.301
	Health Service Occupations	.267
	Sales Representatives, Finance and Business Services	.259
	Social, Recreation, and Religious Workers	.235
	Health Diagnosing Occupations	.205
	Technicians, Except Health, Engineering, and Science	.201
1980s	Firefighting and Fire Prevention Occupations	.515
	Teachers, Postsecondary	.477
	Librarians, Archivists, and Curators	.419
	Secretaries, Stenographers, and Typists	.408
	Information Clerks	.401
	Health Technologists and Technicians	.396
	Health Assessment and Treating Occupations	.392
	Social Scientists and Urban Planners	.392
	Precision Woodworking Occupations	.389
	Motor Vehicle Operators	.368

Notes: This table lists the ten occupations with highest share of titles classified as "new work" (NWI^o) calculated by our algorithm for each decade. We use the 25th percentile threshold value to construct the new title identifier for each job title (NWI^p or simply NWI), which is aggregated at the 3-digit occupation codes.

Table 6: Example New Job-titles in Computer and Mathematical Occupations

Decade	Job Title	Closest Title (previous period)	RNWI
	pay per click strategist	price economist	0.49
	lotus notes developer	developer	0.456
2000s	search strategist	economist	0.451
	emerging solutions executive	business management consultant	0.447
	search engine optimization strategist	database design analyst	0.444
	webmaster	web pressman	0.556
	database support	database management system specialist	0.383
1990s	unix system administrator	ibm operator computer console	0.383
	network support	customer support	0.372
	chat room host monitor	dining room host	0.369
	data base administrator	supervisor data control clerk	0.383
	user support analyst	maintenance data analyst	0.302
1980s	technical support specialist	technical coordinator	0.292
	user support analyst supervisor	maintenance data analyst	0.291
	quality assurance analyst	inspector quality assurance	0.249

Notes: This table provides examples of new job titles within an occupation category "Computer and Mathematical Occupations," the "closest" matched job title in the prior decade, and the Raw New Work Intensity ($RNWI$) scores–the minimum distance from the closest match in the previous decade—for each decade.

Table 7: Summary Statistics for Employment Growth and New Work Intensity Measures

	1980			1990			2000		
	count	mean	sd	count	mean	sd	count	mean	sd
Panel A: 1990 IPUMS Occupation Code Level									
Employment Growth	364	0.110	0.309	334	0.003	0.486	325	0.007	0.262
College Emp. Growth	364	0.511	0.301	334	-0.103	0.479	325	0.163	0.287
High School Emp. Growth	364	-0.199	0.354	334	0.020	0.593	325	-0.142	0.313
NWI (Threshold Min)	364	0.238	0.156	334	0.168	0.177	325	0.480	0.148
NWI (Threshold p25)	364	0.210	0.146	334	0.137	0.149	325	0.405	0.124
NWI (Threshold p50)	355	0.149	0.116	334	0.099	0.118	325	0.291	0.102
NWI Benchmark	355	0.079	0.127	334	0.035	0.068	325	0.047	0.074
Panel B: Commuting Zone Level									
Employment Growth	722	0.163	0.117	722	0.105	0.092	722	0.055	0.088
College Emp. Growth	722	0.511	0.115	722	0.066	0.095	722	0.182	0.082
High School Emp. Growth	722	-0.125	0.120	722	0.151	0.119	722	-0.091	0.111
NWI (Threshold 0)	722	0.245	0.007	722	0.194	0.014	722	0.561	0.014
NWI (Threshold Min)	722	0.244	0.007	722	0.190	0.014	722	0.510	0.015
NWI (Threshold p25)	722	0.218	0.008	722	0.158	0.012	722	0.433	0.014
NWI (Threshold p50)	722	0.156	0.007	722	0.114	0.010	722	0.313	0.011
NWI Benchmark	722	0.080	0.004	722	0.046	0.011	722	0.051	0.006

Notes: This table provides summary statistics for employment growth and "new work" intensities across 3-digit occupations (Panel A) and CZs (Panel B). In each panel, the first row reports total employment growth, and the second and third rows reports employment growth specific to education groups: college (any years of education beyond high school) and high school (any educational attainment up to and including a high school diploma). The "new work" intensities are defined as in Section 2.2 and 3.3, ordered from the least to most conservative in classifying "new work." The average value and the standard deviation are listed respectively for each variable for each decade. The statistics are weighted by employment in 1980 to approximate national aggregate statistics.

Table 8: Correlation of NWI with Occupational Skill & Task Composition

	1980	1990	2000
Panel A: Skills			
Any college	0.107***	0.167***	0.412***
	(0.0389)	(0.0256)	(0.0176)
B.A. or more	0.108***	0.154***	0.296***
	(0.0383)	(0.0226)	(0.0167)
Years of Schooling	0.0158***	0.0226***	0.0486***
	(0.00549)	(0.00336)	(0.00243)
Age	-0.00428*	-0.00221	0.00116
	(0.00254)	(0.00176)	(0.00167)
Observations	367	336	330
Panel B: Tasks			
NR Cog. Anal.	0.0202	0.0361***	0.0909***
	(0.0131)	(0.00795)	(0.00629)
NR Cog Interp.	0.0134	0.0364***	0.0776***
	(0.0133)	(0.00806)	(0.00698)
NR Man. Interp.	0.0128	0.0467***	0.0862***
	(0.0123)	(0.00721)	(0.00584)
NR Man. Physc.	-0.0208*	-0.0344***	-0.0768***
	(0.0123)	(0.00746)	(0.00628)
R Cog.	0.0225*	-0.0326***	-0.0361***
	(0.0132)	(0.00811)	(0.00801)
R Man.	-0.0198	-0.0460***	-0.0944***
	(0.0121)	(0.00713)	(0.00528)
Observations	305	306	306

Notes: This table shows results for various OLS correlations examining the correlation of NWI^o with skill intensities and task characteristics of occupation. Each result represents separate regressions using 3-digit occupation as the unit of observation. Panel A shows the OLS correlations of the NWI^o with the share of workers with any years of post-secondary education (first row), 4-years or more of post-secondary education (second row), the average years of schooling (third row), and average age (fourth row). The skills (schooling and age) are measured at the beginning of the period of analysis, which is 1980. Panel B shows the correlations with 6 different types of task intensity. The definition of task intensities follows Acemoglu and Autor (2011). The construction of the measure uses O*NET (2016) for each 6-digit occupation, and they are aggregated at the three-digit level using 1980 weights. Parentheses contain robust standard errors (*** p<0.01, ** p<0.05, * p<0.1).

Table 9: Correlation between Occupation-level Employment Growth and New Work Intensity

	(1) Panel	(2) 1980-1990	(3) 1980-2000	(4) 1980-2010
Panel A: Aggregate Employment				
NWI	0.674***	0.313***	0.729***	1.235***
	(0.109)	(0.121)	(0.180)	(0.165)
Panel B: College Employment				
NWI	0.519***	0.183*	0.530***	0.827***
	(0.108)	(0.105)	(0.185)	(0.163)
Panel C: High School Employment				
NWI	0.417***	0.122	0.317	0.537***
	(0.141)	(0.162)	(0.234)	(0.194)
Observations	1031	365	332	327

Notes: This table shows the OLS correlations between the change of employment (as log changes) and "new work" intensity NWI^o as the explanatory variable across 3-digit occupation codes. We use *occ1990* in IPUMS for the occupation definitions; the exact number of occupations observed varies across IPUMS samples. Panel A reports estimates with total employment growth as the dependent variable, and Panels B and C report employment growth specific to education groups: college (any years of education beyond high school) and high school (any educational attainment up to and including a high school diploma). Column (1) uses a pooled panel regression where we regress log changes in occupation-level employment between time t and $t+10$ on new work intensities NWI_t^o, which is constructed based on new jobs that appear between t and $t+10$. We include decade fixed effects. Columns (2) to (4) separately examine the correlations over different time horizons. For periods 1980 to 1990, 1980 to 2000, and 1980 to 2010, we regress the corresponding log changes in employment on *cumulative* "new work" intensities, which we construct by taking the average of new work intensities in these periods. Parentheses contain robust standard errors clustered at the occupational level (*** p<0.01, ** p<0.05, * p<0.1).

Table 10: Correlation between CZ-level Employment Growth and New Work Intensity

	(1)	(2)	(3)	(4)
	Panel	1980-1990	1980-2000	1980-2010
Panel A: Aggregate Employment				
NWI	2.450***	4.434***	3.954***	3.714***
	(0.243)	(0.631)	(0.418)	(0.306)
Panel B: College Employment				
NWI	1.601***	1.621**	2.517***	2.158***
	(0.273)	(0.752)	(0.465)	(0.342)
Panel C: High School Employment				
NWI	1.066***	-1.023	2.060***	2.068***
	(0.289)	(0.662)	(0.440)	(0.336)
Observations	2166	722	722	722

Notes: This table shows the OLS correlations between the change of employment (as log changes) and "new work" intensity NWI^c as the explanatory variable across CZs. Panel A reports estimates with total employment growth as the dependent variable, and Panels B and C report employment growth specific to education groups: college (any years of education beyond high school) and high school (any educational attainment up to and including a high school diploma). Column (1) uses a pooled panel regression where we regress log changes in occupation-level employment between time t and $t+10$ on new work intensities NWI_t^c, which is constructed based on new jobs that appear between t and $t+10$. We include decade fixed effects. Columns (2) to (4) separately examine the correlations over different time horizons. For periods 1980 to 1990, 1980 to 2000, and 1980 to 2010, we regress the corresponding log changes in employment on *cumulative* "new work" intensities, which we construct by taking the average of new work intensities in these periods. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

Table 11: Correlations Across Individual Global Shocks (All Periods)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) China	1.000									
(2) Japan	-0.040*	1.000								
(3) Asian Tigers	-0.220***	0.395***	1.000							
(4) Computers	0.064***	0.206***	0.154***	1.000						
(5) Robots	0.435***	-0.052**	-0.030	0.137***	1.000					
(6) Immigration (L)	-0.012	-0.101***	-0.060***	-0.104***	-0.026	1.000				
(7) Immigration (H)	0.046**	-0.121***	-0.053**	0.047**	0.086***	0.797***	1.000			
(8) Aging (Retirees)	0.167***	0.067***	0.022	0.234***	0.115***	0.000	0.031	1.000		
(9) Aging (Old)	0.275***	-0.340***	-0.195***	0.132***	0.569***	0.038*	0.234***	-0.022	1.000	
(10) Aging (Young)	-0.316***	0.303***	0.179***	-0.200***	-0.580***	-0.036*	-0.234***	-0.296***	-0.948***	1.000

Notes: This table shows the matrix of correlation coefficients between the shock variables related to trade, technology, immigration, and aging constructed for local labor markets across all periods. The first three variables "China," "Japan," and "Asian Tigers" represent the trade shocks; the next two, "Computer" and "Robot" represent the technological shocks; the next two, "Immigration (L)" and "Immigration (H)" represent the immigration shocks for low-skilled and high-skilled immigrants, respectively; and the final three, "Aging (Retirees)," "Aging (Old)," and "Aging (Young)" capture the age shocks (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 12: Correlations Across Aggregated Global Shocks (All Periods)

	(1)	(2)	(3)	(4)
(1) Trade	1.000			
(2) Technology	0.229***	1.000		
(3) Immigration	-0.083***	-0.098***	1.000	
(4) Aging	0.022	0.332***	0.007	1.000

Notes: This table shows the correlation across the aggregates of the shock variables related to trade, technology, immigration, and aging constructed for local labor markets across all periods. For the technology shock, we combine our measures for computerization and robotization, namely Equations (4) and (5) constructed for each decade by taking the first principal component. Due to the positive correlation between its components, the aggregate technological shock is an average of computer and robot exposure with roughly equal weight. For the trade shock, we construct a measure that aggregates import penetration from Japan, the four Asian Tigers, and China. Specifically, we use Equation (7) but with aggregate import flows from these countries. For the immigrant shock, we sum the exposure to high- and low-educated immigrants, as they are both expressed as a proportion of the total local population. Finally, for the population aging shock, the approach is similar to the technology shock where we combine our measures for each age group, namely Equation (10) constructed separately for each age group, by taking the first principal component (*** p<0.01, ** p<0.05, * p<0.1).

Table 13: New Work Intensity on Global Shocks and Local Factors

	(1)	(2)	(3)	(4)
	Panel	1980-1990	1980-2000	1980-2010
Technology	-0.0358	0.0161	-0.0375	-0.0262
	(0.0239)	(0.0252)	(0.0279)	(0.0286)
Trade	0.0228	-0.0369	-0.00698	0.0248
	(0.0244)	(0.0286)	(0.0268)	(0.0257)
Immigration	0.0244	-0.0458***	0.0459***	0.0321*
	(0.0190)	(0.0171)	(0.0152)	(0.0188)
Aging	0.111***	-0.0184	0.0948***	0.130***
	(0.0257)	(0.0241)	(0.0270)	(0.0350)
Log Pop. Density	0.502***	0.313***	0.458***	0.515***
	(0.0286)	(0.0225)	(0.0265)	(0.0317)
College Share	0.565***	0.456***	0.528***	0.568***
	(0.0341)	(0.0311)	(0.0359)	(0.0371)
Industry Diversity	0.00798	0.0781***	0.0306	0.00815
	(0.0217)	(0.0278)	(0.0225)	(0.0218)
Manufacturing Share	-0.308***	-0.254***	-0.304***	-0.317***
	(0.0354)	(0.0367)	(0.0369)	(0.0377)
Emp. Trend	-0.151	-0.0411	-0.113	-0.136**
	(0.121)	(0.124)	(0.0958)	(0.0612)
Constant	21.14***	21.11***	17.89***	25.96***
	(0.0385)	(0.0374)	(0.0384)	(0.0305)
Year FEs	Yes	No	No	No
Observations	2166	722	722	722

Notes: This table shows the OLS correlations between "new work" intensities NWI^c and the following explanatory variables: four aggregate proxies for the global shocks "Technology," "Trade," "Immigration," and "Aging" as defined in Sections 5; and the local factors measured in 1980: the log of population density, the share of local population (age 16+) with any college education , the index of industrial diversity (the complement of the employment-based Herfindahl-Hirschman index based on IPUMS industry codes (*ind1990*), and employment share in manufacturing; and the trend of employment growth over a number of decades prior to 1980: one decade in Columns (1) and (2), two decades in Column (3), and three decades in Column (4). All explanatory variables are standardized. Column (1) uses a pooled panel regression where we regress log changes in occupation-level employment between time t and $t+10$ on new work intensities NWI_t^c, which is constructed based on new jobs that appear between t and $t+10$. We include decade fixed effects. Columns (2) to (4) separately examine the correlations over different time horizons. For periods 1980 to 1990, 1980 to 2000, and 1980 to 2010, we regress the corresponding log changes in employment on *cumulative* "new work" intensities, which we construct by taking the average of new work intensities in these periods. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

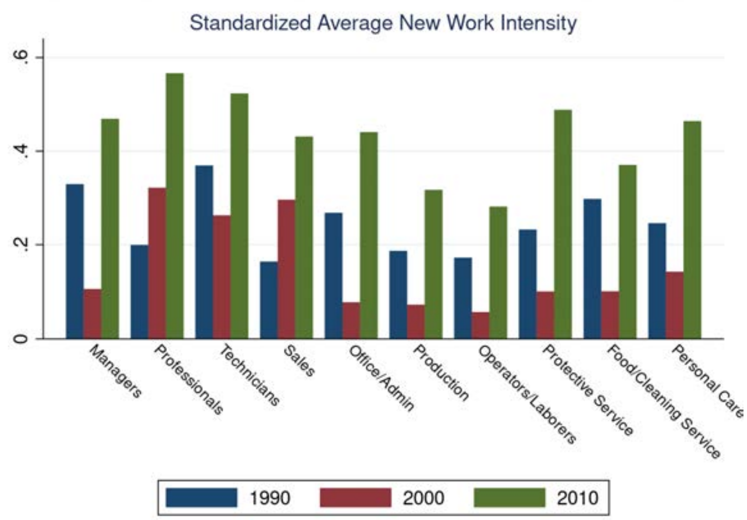
Table 14: New Work Intensity on Human Capital Supply

	(1) OLS	(2) IV (1980)	(3) RF (1980)	(4) IV (1960)	(5) RF (1960)	(6) IV (< 1920)	(7) RF (< 1920)
Panel A: Local Factors Only							
College Share	0.623***	0.881**		0.725**		0.927***	
	(0.0319)	(0.344)		(0.308)		(0.0770)	
Colleges (per capita)			0.0824***		0.105***		
			(0.0262)		(0.0296)		
Land Grant							1.031***
							(0.101)
SW F Stat		6.087		12.39		97.95	
AR F Stat		9.923		12.45		104.6	
AR F p-value		0.0017		0.0004		< 0.0001	
Panel B: Full Specification							
College Share	0.626***	0.747*		0.473*		0.588***	
	(0.0384)	(0.389)		(0.281)		(0.0725)	
Colleges (per capita)			0.0765***		0.0782**		
			(0.0235)		(0.0350)		
Land Grant							0.844***
							(0.101)
SW F Stat		6.102		15.96		116.2	
AR F Stat		11.41		12.57		168.8	
AR F p-value		0.0008		0.0004		< 0.0001	
Observations	2166	2166	2166	2166	2166	2166	2166

Notes: This table presents OLS (column 1) and 2SLS (columns 2, 4, 6) coefficients for CZ share of working age persons with 4-years or more of post-secondary education; reduced form estimates are also shown (columns 3, 5, 7) for the instrumental variables: 1980 college density (4-year universities per capita), 1960 college density (same definition), and an indicator for a land-grant university. The underlying data and construction of these variables is described in Section 8. Panel A reports coefficients from a specification only controlling for local factors measured in 1980: the log of population density, the share of local population (age 16+) with any college education , the index of industrial diversity (the complement of the employment-based Herfindahl-Hirschman index based on IPUMS industry codes (*ind1990*), and employment share in manufacturing. Panel B reports coefficients from the full specification, which includes four aggregate proxies for the global shocks "Technology," "Trade," "Immigration," and "Aging" as defined in Sections 5 and the trend of employment growth over the decade prior to 1980. All explanatory variables are standardized. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

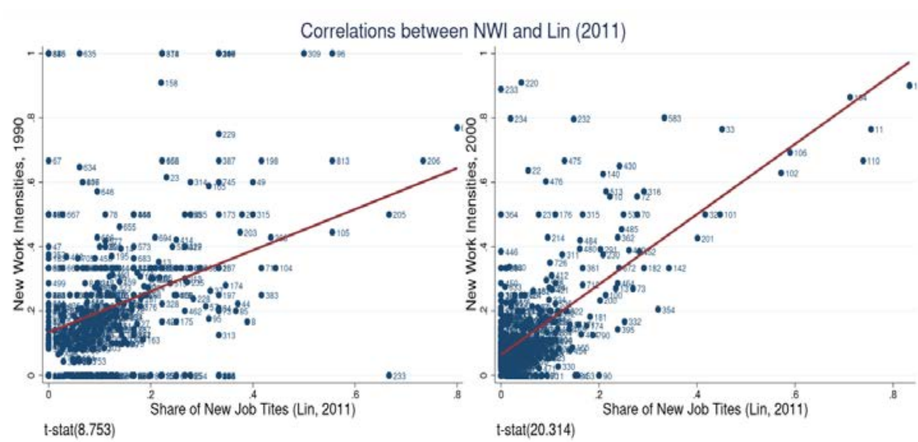
Figures

Figure 1: New Work Intensities by Broad Occupation Groups



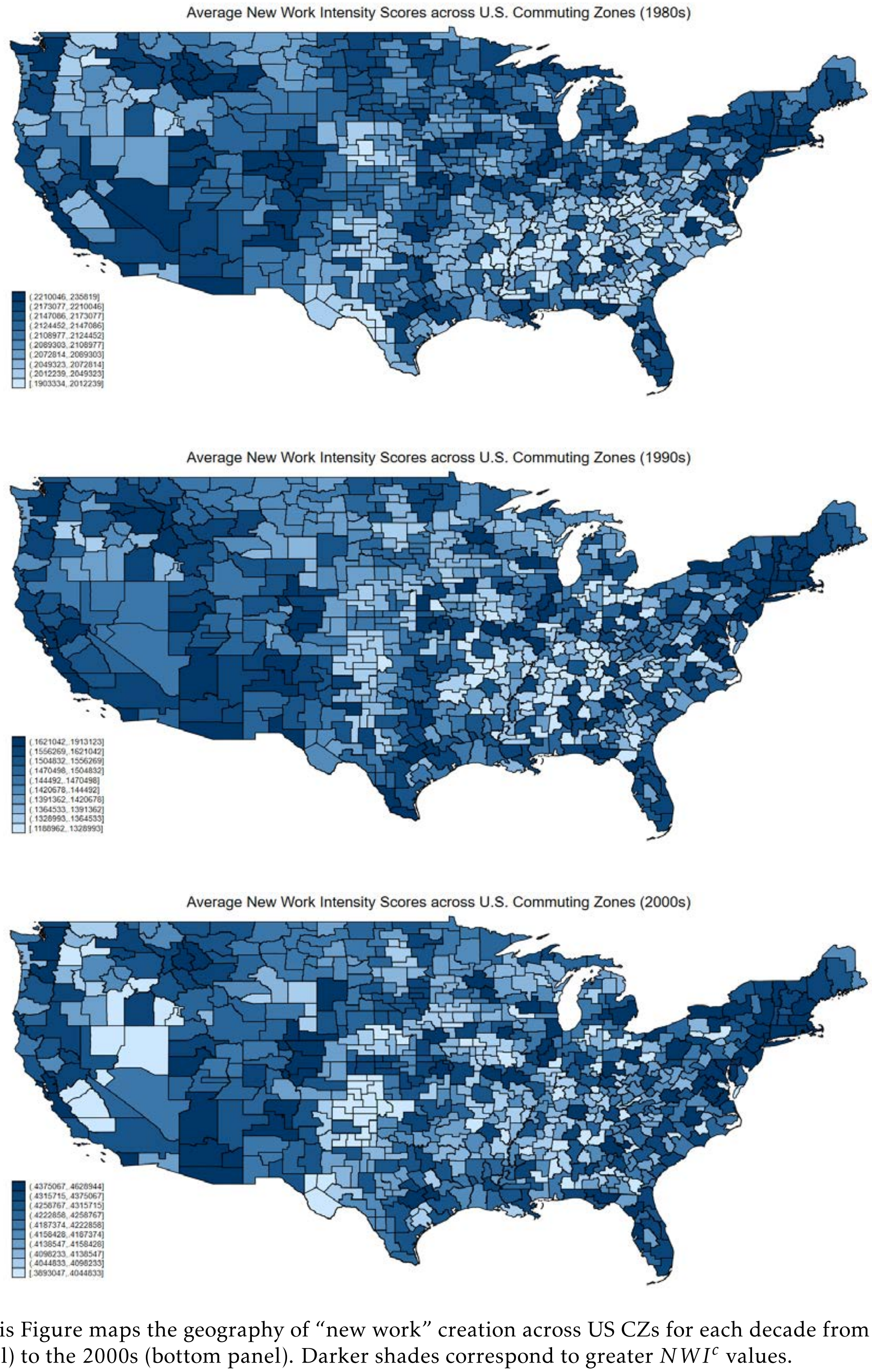
Notes: This Figure shows the average values of NWI^o for 10 broad occupation groups for each decade. Occupations are aggregated following Autor and Dorn (2013) and we array them from left to right in decreasing order of average wage in 1980. In doing so, the three occupational groups to the left-side of the range represent high-wage occupations using more cognitive and analytical type of skills (Manager, Professional, Technicians). The four groups in the middle of the range use more routine intensive jobs, both in the manual and cognitive areas (Sales, Office, Production Occupations, and Laborers). The three groups at the right end of the range include those low-wage occupations in the manual, personal service areas (Protection, Food, Personal Care) intensive in manual and inter-personal skills.

Figure 2: Correlations of Occupation-level NWI with measure in Lin (2011)



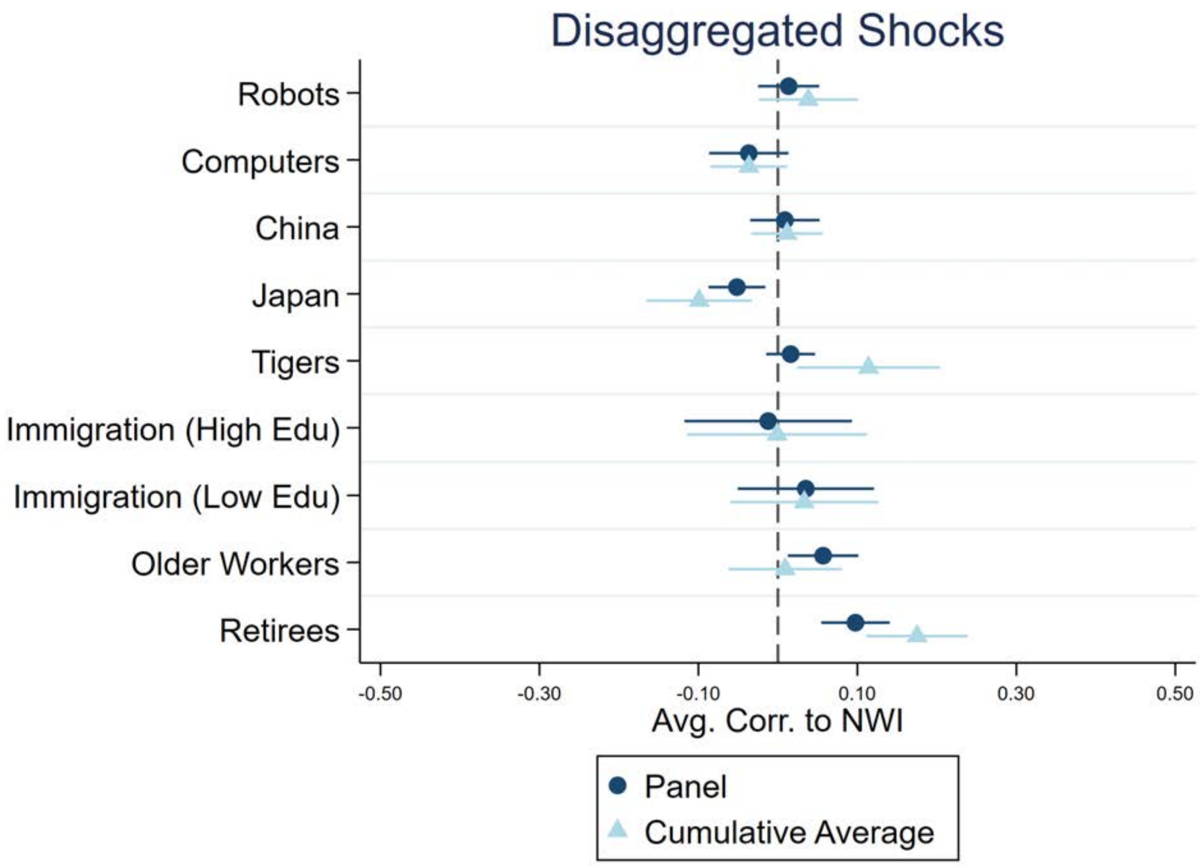
Notes: This Figure shows the correlations between our basic measure of NWI^o and the measures constructed by Lin (2011) at the occupational level for the 1980s (left) and 1990s (right).

Figure 3: New Work Intensities across US CZs



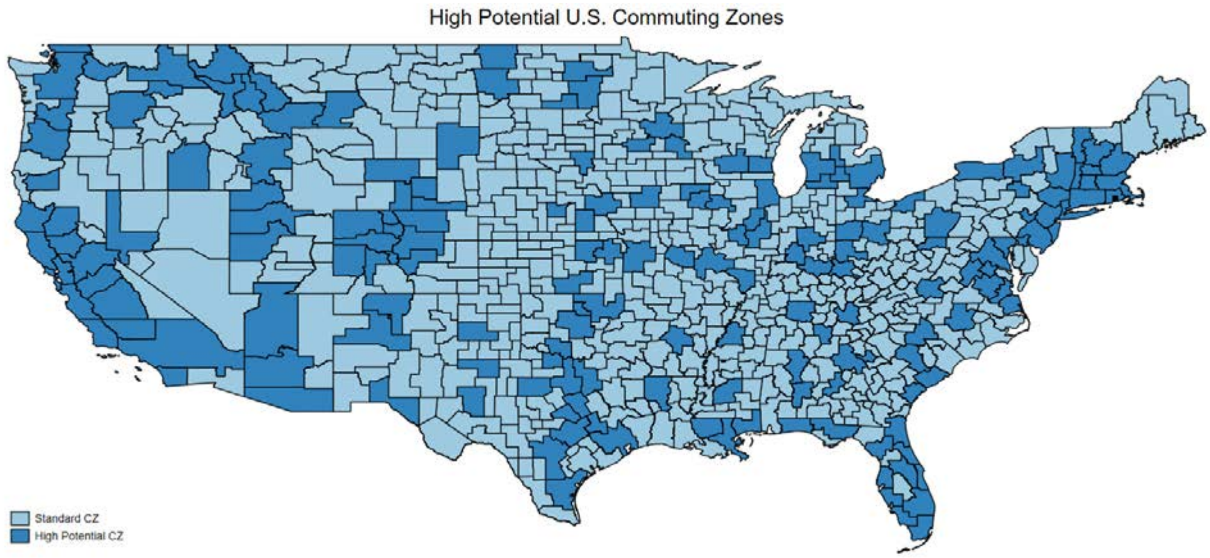
Notes: This Figure maps the geography of "new work" creation across US CZs for each decade from the 1980s (top panel) to the 2000s (bottom panel). Darker shades correspond to greater NWI^c values.

Figure 4: New Work Intensity on Disaggregated Global Shocks



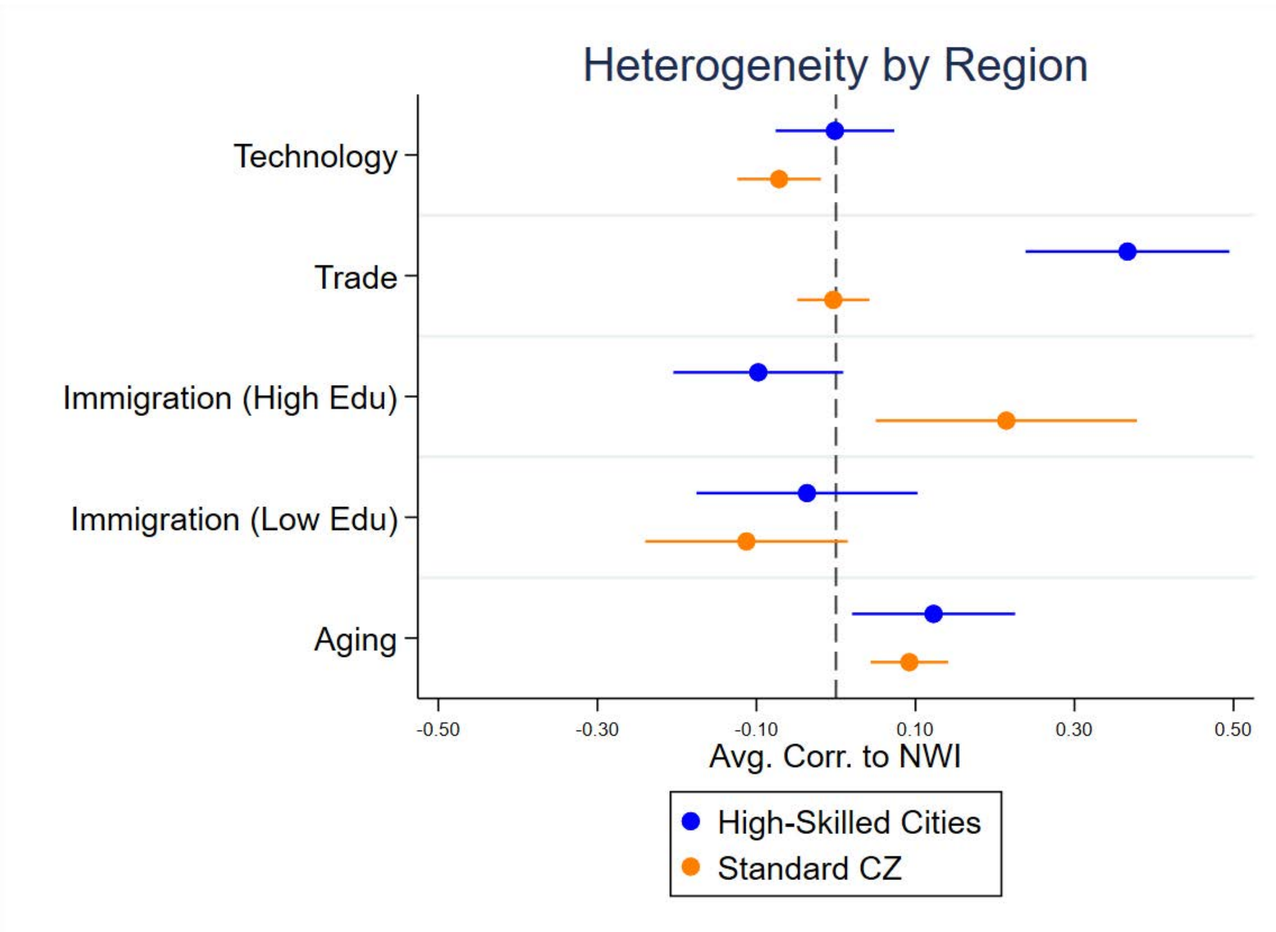
Notes: This figure presents OLS regression results examining the correlations between the individual components of the shocks and "new work." The coefficients and the 95% confidence intervals in navy marks are from the panel specification of Equation (11) but including disaggregated shocks instead of the aggregate ones; and those shown in light blue marks are obtained using the 30-year cumulative specification. Robust standard errors clustered at CZs.

Figure 5: High-Skilled Cities vs. Standard Commuting Zones



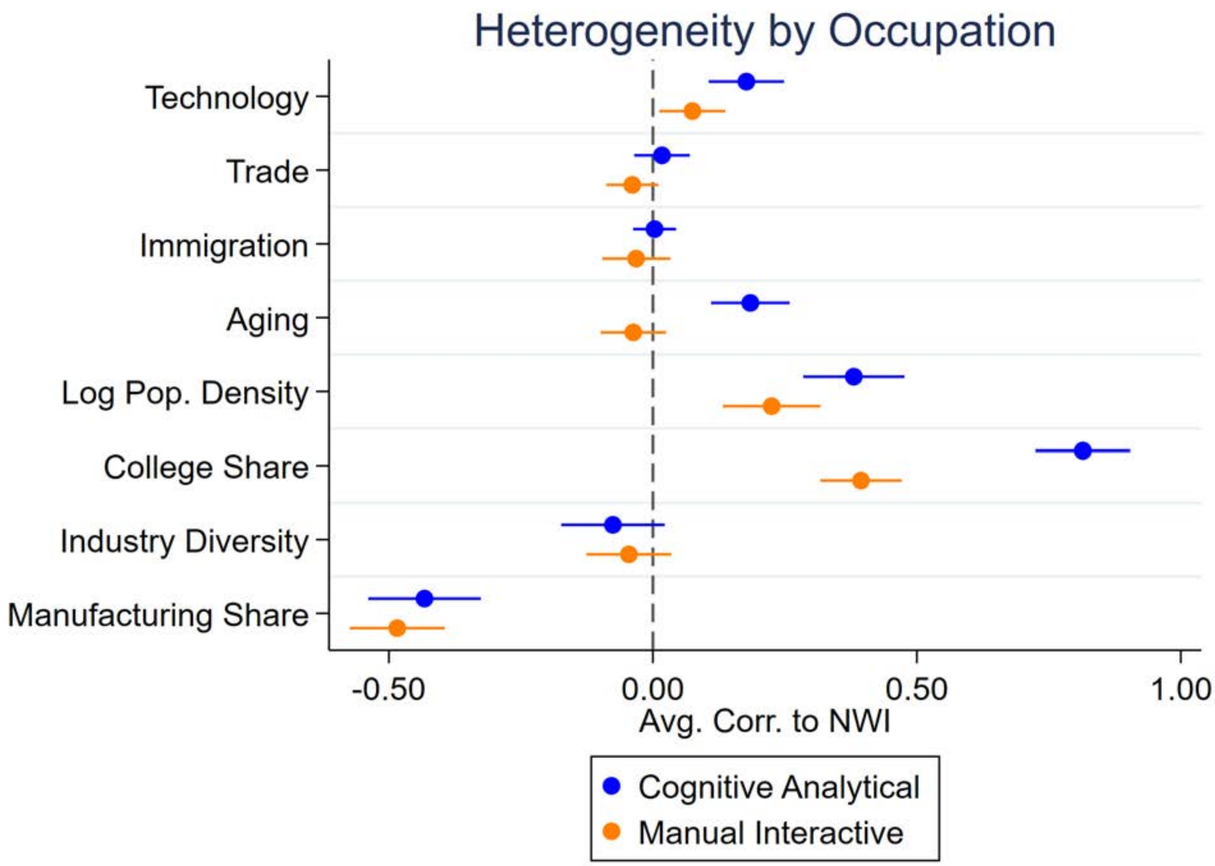
Notes: This figure provides the geographic distribution of ”high-skilled cities” and standard CZs. We define ”high-skilled cities” as areas in the top quartile of the distribution of predicted “new work” intensity based on initial (1980) local factors: the log of population density, the share of local population (age 16+) with any college education , the index of industrial diversity (the complement of the employment-based Herfindahl-Hirschman index based on IPUMS industry codes (*ind1990*), and employment share in manufacturing. We define all other CZs as “standard.”

Figure 6: New Work Intensity and Exposure to Global Shocks: High Skilled Cities and standard CZs



Notes: This figure presents OLS regression results examining the heterogenous patterns in the results across "high-skilled cities" and standard CZs. Here, we define "high-skilled cities" as areas in the top quartile of the distribution of predicted "new work" intensity based on initial (1980) local factors: the log of population density, the share of local population (age 16+) with any college education , the index of industrial diversity (the complement of the employment-based Herfindahl-Hirschman index based on IPUMS industry codes (*ind1990*), and employment share in manufacturing. We define all other CZs as standard. We extend the panel regression of Equation (11) by including a binary indicator for "high-skilled cities" as well as its interaction terms with each of the shocks. The estimated coefficients and 95% confidence intervals report the results of the interaction terms. The results are in blue marks for the "high-skilled cities" and in orange marks for the standard CZs. Robust standard errors are clustered at the CZ-level.

Figure 7: New Work Intensity on Global Shocks and Local Factors by Occupational Tasks



Notes: This figure presents OLS regression results separately analyzing the correlates of "new work" for jobs in non-routine cognitive-analytical and non-routine manual-interactive occupation groups. For each group, we construct a binary indicator for occupations in the top tercile of these task intensities. The estimated coefficients and 95% confidence intervals separately examining the panel regression of Equation (11) for "new work" deriving from cognitive-analytical (in blue marks) and from manual-interpersonal occupations (in orange marks). The changes in the explanatory variables are standardized to have standard deviation of one, so as to be more comparable with each other. Robust standard errors are clustered at the CZ-level.

Appendix

FOR ONLINE PUBLICATION

Measuring and Predicting "New Work" in the United States: The Role of Local Factors and Global Shocks

Gueyon Kim   Cassandra Merritt   Giovanni Peri

A Appendix: Data and Construction of Measurements

A.1 Data and Sample Construction

The following two tables provide a technical summary of analytic dataset by outlining the underlying samples and definitions of key variables. The global shocks are excluded here and described in the following subsections.

Technical Summary of Samples

Decade	Sample	Sample Geographic Unit	Crosswalk to CZs	Notes
2010	ACS	2000 PUMA	Dorn	
2000	5%	2000 PUMA	Dorn	
1990	5%	1990 PUMA	Dorn	
1980	5%	1980 County Group	Dorn	
1970	Metro (Form 1 + Form 2)	1970 County Group	Dorn	Sample weights divided in half given two national samples
1960	5%	1960 PUMA	Rose	
1950	1%	1950 SEA	Rose	

Notes: The crosswalks “Dorn” and “Rose” reference Autor and Dorn (2013) and Rose (2023).

Technical Summary of Variables

Variable	IPUMS Source Variable(s)	Definition	Technical Definition/Restriction
Panel A: IPMUS Based Variables			
Working Age Population (*pop*)	*age*, *gq*, *statefip*	All persons age 16 or more, living in CONUS households.	$age \geq 16$, $gq \notin \{0,3,4\}$, $statefip \notin \{AK, HI\}$
Employment	*empstat*	Employed persons.	$empstat = 1$
College Employment	*empstat*, *educ*	Employed persons with any postsecondary education	$empstat = 1$, $educ \geq 7$
High School Employment	*empstat*, *educ*	Employed persons with no postsecondary education.	$empstat = 1$, $educ < 7$
Employment Growth/Trend	*empstat*, (*educ*)	The difference in log of employment between decades.	e.g. $ln(emp_t) - ln(emp_{t-1})$
College Share	*educ*	Persons with any postsecondary education	$educ \geq 7$
Industry Diversity	*ind1990*	The complement of the sum of squares of industry employment shares.	$1 - \Sigma_{j \in ind1990} (\frac{emp_j}{emp})^2$
Manufacturing Share	*ind1990*	Employment share in manufacturing industries.	$\Sigma_{j=ind1990} \in [100, 392] \frac{emp_j}{emp}$
Panel B: Variables dependent on other data sources			
Area	*area* from EGLP	CZ land area crosswalked & aggregated from county land area (square meters converted to square miles)	
Log Pop Density		Log of population from IPUMS (as above) divided by land area	$\ln(pop/area)$

Notes: "EGLP" refers to the crosswalk corresponding to Eckert, Gvirtz, Liang, and Peters (2020).

A.2 Patent Data

Patent Data is sourced from PatentsView (U.S. Patent and Trademark Office, 2021), which provides bulk download of world wide patenting activity. Our analysis leverages patent, inventor, and location datasets to assemble an intermediate dataset of all inventor-linked patents across our analysis period (1980 to 2010) with an identified state-county fips code (based on the inventor's location at issue). After indicating unique patents and inventors at the state-county level, this data is collapsed to the state-county-decade level to get a sum total of inventors and patents per county each decade. This county-level data is then cross-walked to the commuting zone (CZ) level, and then standardized by CZ-decade for our analysis.

A.3 Construction of Exposure to Global Shocks

A.3.1 Computerization

We follow Autor and Dorn (2013) to measure the degree of exposure to computerization using local routine task intensities in the 1980s. Given how computers have replaced easily codifiable and routine tasks, CZ-level exposures to the introduction of computer technologies differ based on the share of routine intensive occupations in 1980.

The relative routine task intensity (RTI_k) for each occupation k is measured as the difference between the intensity of routine tasks ($T^R_{k,1980}$), and the intensity of manual ($T^M_{k,1980}$) and analytical tasks ($T^A_{k,1980}$), in the same occupation, namely:

$$RTI_k = ln(T^R_{k,1980}) - ln(T^M_{k,1980}) - ln(T^A_{k,1980}). \tag{12}$$

The CZ-specific measure, $RSH_{c,1980}$, is the share of routine-intensive occupations in each CZ c in 1980, where routine-intensive occupations are those in the top third of routine intensities, RTI_k.

$$RSH_{c,1980} = \sum_{k\in\Omega} \frac{L_{ck,1980}}{L_{c,1980}} \quad \text{where} \quad \Omega = [k|RTI_k > RTI^{P66}] \tag{13}$$

To construct exposure measures based on pre-1980 local employment structure, we infer the occupations in a CZ based on its industrial composition in 1970, namely:

$$\widetilde{RSH}_c = \sum_j^J E_{j,c,1970} \times R_{j,-c,1970}, \tag{14}$$

where $E_{j,c,1970}$ is the employment share of industry j in CZ c in 1970; and $R_{j,-c,1970}$ is the routine occupation share of industry j in the US excluding the CZs in the state that includes CZ c. We use Equation (4) as our main measure of exposures to computerization.

A.3.2 Robotization

We follow Acemoglu and Restrepo (2020) and construct the industry-level "Adjusted Penetration Rate" of robots, $\overline{APR}_{j,t}$, using robotics-industry data from the five European countries at the technology frontier (Denmark, Finland, France, Italy, and Sweden; stylized $EUR05$) for years 1993, 2000, and 2010:

$$\Delta\overline{APR}_{j,t} = \frac{1}{5}\sum_{n\in \text{EUR05}}[\frac{\Delta M_{jn,t}}{L_{jn,1990}} - g_{jn,t}\frac{M_{jn,t}}{L_{jn,1990}}]. \tag{15}$$

For each country n, we construct the change in the number of robots in industry j per worker, $\frac{\Delta M_{jn,t}}{L_{jn,1990}}$), adjusted by the initial level of robots per worker, $\frac{M_{jn,t}}{L_{jn,1990}}$), augmented by industry's growth rate in outputs, $g_{jn,t}$. The second term corrects for the predicted growth of robotic inputs driven simply by the sector value-added growth.

We then apportion these industry-level measures of robot adoption to each CZ in the US using the 1970 industry shares in the CZs from the CBP data. This construct captures the local potential for exposure to robotization,

$$\Delta\text{Exposure to Robots}_{c,t} = \sum_{j\in J}\frac{L_{cj,1970}}{L_{c,1970}} \times \Delta\overline{APR}_{j,t}. \tag{16}$$

Using 1970 as a baseline for industry composition helps capture only pre-1980 local characteristics. We use Equation (5) as our main measure of exposures to robotization.

A.3.3 Import Competition from China

As in Acemoglu et al. (2016), Autor et al. (2013), and Autor, Dorn, and Hanson (2019), we define local labor market exposures to the China shocks as,

$$\Delta IP_{ct}^{ch,us} = \sum_{j\in J}\frac{L_{cj,1990}}{L_{c,1990}}\Delta IP_{jt}^{ch,us}, \tag{17}$$

where $\Delta IP_{jt}^{ch,us}$ is the change in US imports from China in industry j over a decade t (1991-2000 and 2000-2010) adjusted by the absorption value, the sum of industry shipment and net exports ($Y_{j,t} + IM_{j,t} - EX_{j,t}$) in 1991. We then use CZ-level local industry structures in 1990 as weights to aggregate industry-level measures and calculate local average exposures to Chinese imports.

To further isolate the Chinese-driven part of the shock and the pre-1980 industrial structure of the CZ, we construct,

$$\Delta IP_{ct}^{ch,oth} = \sum_{j \in J} \frac{L_{cj,1975}}{L_{c,1975}} \Delta IP_{jt}^{ch,oth} \tag{18}$$

where $\Delta IP_{jt}^{ch,oth}$ is the change in other high-income countries' (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) imports from China in industry j over a decade t (1991-2000 and 2000-2010) adjusted by the absorption value in 1988. This term identifies the supply-driven component of the growth in Chinese imports. The index also uses the industry structures observed in 1975 as weights.[61] We use Equation (6) as our main measure of exposures to the China shock, which is, by construction of measure, activated only in the 1990s and 2000s decades.

A.3.4 Import Competition from Japan and Asian Tigers

We take a similar approach to construct measures of import competition from Japan and the four Asian countries (Hong Kong, Taiwan, Singapore, and South Korea) or the Asian Tigers during the 1980s and 1990s and distribute across CZs using pre-1980 local industry structure. Again, we identify the supply-driven component of the growth in imports from Japan (the Asian Tigers) by using changes in imports to high-wage countries (Australia, Denmark, Finland, New Zealand, Spain, and Switzerland).[62] We use the industry employment observed in 1975 as weights to construct pre-determined local exposures,

$$\Delta IP_{ct}^{jp,oth} = \sum_{j \in J} \frac{L_{cj,1975}}{L_{c,1975}} \Delta IP_{jt}^{jp,oth} \tag{19}$$

where $\Delta IP_{jt}^{jp,oth}$ is the change in US imports from Japan (Asian Tigers, $\Delta IP_{jt}^{tg,oth}$) in industry j over a decade t (1980-1990, 1990-2000, and 2000-2010) adjusted by the absorption value. We use Equation (7) and an analogous construction for $\Delta IP_{jt}^{tg,oth}$ as our main measures of exposures to the Japan shock and Asian Tigers shock.

A.3.5 High-Skilled and Low-Skilled Immigration

We identify foreign-born (non-citizens at birth) working age (16 to 65) adults. As immigrants with and without college education supply different types of skills (Borjas, 2003;

[61] The level of industry aggregation for the CBP data in 1970 is broader than the subsequent periods. Thus, we use data for the closest alternative period with the 4-digit SIC codes.

[62] Similar to Batistich and Bond (2023), the instrument excludes Japan for obvious reasons and Germany for the reliability of trade data before its reunification.

Ottaviano and Peri, 2012), we further divide them into college (with some college or more) and non-college (high school degree or less) educated. We also define a range of 84 countries (and country groups) that span the world and are stable over the period of 1980 to 2010. Changes in immigrants, standardized by the initial population in working age in the CZ $Pop_{c,1980}$, are defined as follows:

$$\frac{\Delta H_{c,t}^{Foreign}}{Pop_{c,1980}} = \frac{H_{ct+10}^{Foreign} - H_{ct}^{foreign}}{Pop_{c,1980}}, \tag{20}$$

$$\frac{\Delta L_{c,t}^{Foreign}}{Pop_{c,1980}} = \frac{L_{ct+10}^{Foreign} - L_{ct}^{Foreign}}{Pop_{c,1980}}, \tag{21}$$

where $H_{ct}^{foreign}$ ($L_{ct}^{foreign}$) is the total labor supply of college educated (non-college educated) foreigners summed across all places of origin ($n = 1, ..., 84$) in CZ c and year t.

We use the pre-1980 immigration enclaves and the aggregate changes in immigrants post-1980 in shift-share variables as defined by (Goldsmith-Pinkham et al., 2020) to proxy the CZ-level variation of exposure to immigrants driven by the change in foreign worker supply. Hence, we calculate S_{nc}^{1970}, which is the share of all foreign born in working age (16 years and older) by country of origin n in each CZ c in 1970 relative to the total number of foreign-born working age in the country n in the US in 1970. Then, we calculate the following change for $t = 1980, 1990, 2000$, respectively:

$$\frac{\widehat{\Delta H_{c,t}^{Foreign}}}{Pop_{c,1980}} = \frac{\sum_{n=1}^{N} S_{nc}^{1970} \cdot H_{t+10}^{n} - \sum_{n=1}^{N} S_{nc}^{1970} \cdot H_{t}^{n}}{Pop_{c,1980}}, \tag{22}$$

$$\frac{\widehat{\Delta L_{c,t}^{Foreign}}}{Pop_{c,1980}} = \frac{\sum_{n=1}^{N} S_{nc}^{1970} \cdot L_{t+10}^{n} - \sum_{n=1}^{N} S_{nc}^{1970} \cdot L_{t}^{n}}{Pop_{c,1980}}, \tag{23}$$

where H_t^n (L_t^n) is the population in working age with college education (no college education) from country n residing in the whole US in year t. We use Equations (8) and (9) as our main measure of exposures to high-skilled and low-skilled immigrant inflows, respectively.

A.3.6 Population Aging

Inspired by Autor and Dorn (2009); DellaVigna and Pollet (2007) who analyze how aging can affect local labor markets, we capture variations in local age structures by constructing shares of the adult population for three age groups—young workers (18 to 45), old workers (46 to 65), and potential retirees (66 and over)—as predicted by the demographic structure in the CZ a decade earlier. This measure abstracts away from internal mobility responding to other changes during the decade.

We use the change in adult population share in each age group a (18 to 45, 46 to 65, and 66 and over) for CZ c between $t-10$ and t,

$$\Delta sh^a_{c,t} = \widehat{sh^a}_{c,t} - sh^a_{c,t-10} \tag{24}$$

where

$$sh^a_{c,t-10} = \frac{Pop^a_{t-10,c}}{Pop^{adult}_{t-10,c}} \quad \text{and} \quad \widehat{sh^a}_{c,t} = \frac{Pop^{a-10}_{t-10,c}(1-mort^{a-10}_{t-10})}{\sum_{a\in adult} Pop^{a-10}_{t-10,c}(1-mort^{a-10}_{t-10})} \tag{25}$$

The variable $Pop^a_{t-10,c}$ measures the population age-group a residing in CZ c in $t-10$. This population is also used to predict the population in t in the same CZ, adjusted for by the expected morality rate for that age group, namely, the term $(1-mort^{a-10}_{t-10})$. Equation (10) captures the predicted change in the age group a as the share of adult population, based only on the age structure of the CZ ten years earlier. We use Equation (10) constructed separately for each age group as our main measure of exposures to changes in age structure.

B Appendix: Tables and Figures

Table A.1: Example New Job Titles in "Health Technologists and Technicians"

Decade	Job Title	Closest Title (previous period)	RNWI
	first responder	first aid nurse	0.503
	retinal angiographer	ocular care technologist	0.488
2000s	head of cytogenetics	assistant research bacteriology	0.436
	international classification of diseases coder	medical records coder	0.429
	certified retinal angiographer	technician certified medical	0.422
	surgical orderly	hospital orderly	0.225
	inspector environmental protection	inspector safety	0.224
1990s	inspector safety analysis research	inspector safety	0.221
	environmental protection officer	plant protection officer	0.217
	technician radioisotope	isotope technician	0.211
	perfusionist	dialysis technician	0.414
	transplant coordinator	coordinator volunteer services	0.388
1980s	tumor registrar	registrar	0.359
	special procedures technologist magnetic resonance imaging	electroencephalographic technologist	0.349
	paramedic	ambulance driver	0.348

Notes: This table provides examples of new job titles within an occupation category of "Health Technologists and Technicians," the "closest" matched job title in the prior decade, and the Raw New Work Intensity ($RNWI$) scores for each decade.

Table A.2: Example New Job Titles in "Teachers, Except Post-secondary"

Decade	Job Title	Closest Title (previous period)	RNWI
	early interventionist	supervisor early childhood program	0.595
	classifications officer cc cm	inspector cylinder	0.585
2000s	behavior interventionist	teacher abnormal psychology	0.58
	habilitative interventionist	corrective manual arts therapist	0.561
	least restricted environment facilitator	key person	0.556
	teacher machine shorthand	teacher	0.358
	teacher key punch	teacher	0.353
1990s	teacher skilled trades	skilled laborer	0.349
	teacher television repair	technician television	0.338
	teacher business machines	computer operator factory machine	0.336
	teacher visually impaired	teacher blind	0.391
	teacher hearing impaired	teacher blind	0.383
1980s	four h club agent	youth agent	0.38
	teacher emotionally impaired	teacher mentally retarded	0.328
	teacher physically impaired	teacher mentally retarded	0.317

Notes: This table provides examples of new job titles within an occupation category of "Teachers, Except Post-secondary" the "closest" matched job title in the prior decade, and the Raw New Work Intensity ($RNWI$) scores for each decade.

Table A.3: Examples Job Titles: New by CBOW and Existing by Lin (2011)

(Cleaned) Job Title	Closest Match	RNWI	Lin	None	Min.	p5	p10	p25
steward stewardess second	steward stewardess third	0.0109	0	1	0	0	0	0
boiling tub operator	tetryl boiling tub operator	0.0162	0	1	1	0	0	0
mixer operator carbon paste	carbon paste mixer operator panelboard	0.0253	0	1	1	0	0	0
car repairer	car repairer pullman	0.0378	0	1	1	0	0	0
feed farm management adviser	feed farm management advisor	0.0414	0	1	1	0	0	0
dissolver operator	tetryl dissolver operator	0.0423	0	1	1	0	0	0
lathe operator contact lens	lathe operator contact lenses	0.0427	0	1	1	0	0	0
bricklayer firebrick refractory tile	bricklayer helper firebrick refractory tile	0.0460	0	1	1	0	0	0
screw machine set up operator single spindle	screw machine operator single spindle	0.0495	0	1	1	0	0	0
centrifugal operator	remelt centrifugal operator	0.0533	0	1	1	0	0	0
steel plate caulker	steel plate calker	0.0540	0	1	1	0	0	0
crossband layer	layer	0.0542	0	1	1	0	0	0
paper coating machine operator	coating machine operator	0.0544	0	1	1	0	0	0
chucking machine set up operator multiple spindle vertical	chucking machine setup operator multiple spindle vertical	0.0580	0	1	1	1	0	0
oral maxillofacial surgeon	oral surgeon	0.0580	0	1	1	1	0	0
glass unloading equipment tender	glass loading equipment tender	0.0594	0	1	1	1	0	0
pipe cleaning priming machine operator	pipe cleaning machine operator	0.0605	0	1	1	1	0	0
welder fitter	welder fitter apprentice	0.0608	0	1	1	1	0	0
teacher preschool	teacher kindergarten	0.0631	0	1	1	1	0	0
woodenware assembler	brazer assembler	0.0632	0	1	1	1	0	0
carpet weaver jacquard loom	jacquard loom weaver	0.0633	0	1	1	1	0	0
electrical appliance servicer	electrical appliance servicer supervisor	0.0641	0	1	1	1	0	0
classified ad clerk	classified advertising clerk	0.0679	0	1	1	1	1	0
sales agent business services	sales agent financial services	0.0705	0	1	1	1	1	0
beveling edging machine operator helper	beveling edging machine operator	0.0763	0	1	1	1	1	0
stone polisher hand	marble polisher hand	0.0850	0	1	1	1	1	0
bow maker custom	bow maker	0.0913	0	1	1	1	1	0
supervisor machining	machining assembly supervisor	0.0915	0	1	1	1	1	0
boring machine set up operator jig	boring machine setup operator jig	0.0927	0	1	1	1	1	0
cutting machine tender	slicing machine tender	0.0982	0	1	1	1	1	0
warp knitting machine operator	raschel knitting machine operator	0.0982	0	1	1	1	1	0
field assembly supervisor	supervisor assembly	0.0989	0	1	1	1	1	0
industrial engineer	industrial health engineer	0.1028	0	1	1	1	1	1
carpenter maintenance	cabinetmaker maintenance	0.1637	0	1	1	1	1	1
desizing machine operator head end	croze machine operator	0.1640	0	1	1	1	1	1
repairer welding brazing burning machines	repairer welding equipment	0.1641	0	1	1	1	1	1
advertising material distributor	supervisor advertising material distributors	0.1647	0	1	1	1	1	1
shipping receiving clerk	shipping order clerk	0.1647	0	1	1	1	1	1
sales representative bottles bottling equipment	sales representative bottles jars	0.1928	0	1	1	1	1	1
slaughterer religious ritual	director of religious activities	0.5506	0	1	1	1	1	1
equestrian	horse trainer	0.5686	0	1	1	1	1	1

Notes: The table includes examples of job titles that Lin (2011) classifies as existing, yet CBOW classifies as new, listed in the ascending order of NWI.

Table A.4: Correlations (CZ-level NWI: All Periods)

	(1)	(2)	(3)
(1) NWI (1990)	1.000		
(2) NWI (2000)	0.715***	1.000	
(3) NWI (2010)	0.658***	0.806***	1.000

Notes: This table reports the correlation coefficients examined using CZ-level "new work" intensity scores across decades (*** p<0.01, ** p<0.05, * p<0.1).

Table A.5: Example Labor Market Areas with High/Low New Work Intensity

Year	High	Low
	Las Vegas, NV-AZ	Memphis, TN-AR-MS
	Baltimore, MD-Washington, DC-MD-VA-WV	Charlotte-Gastonia-Rock Hill, NC-SC
1980s	Bryan-College Station, TX	Hazard-Jackson, KY
	Austin-San Marcos, TX	Florence-Myrtle Beach, SC
	Gainesville, FL	Blue Ridge, GA-Cleveland, TN
	Bryan-College Station, TX	Bowling Green, KY
	Decatur-Champaign-Urbana, IL	Mobile, AL
1990s	San Jose, CA	Louisville, KY-IN
	Baltimore, MD-Washington, DC-MD-VA-WV	Columbia, TN
	Provo-Orem, UT	Toledo, OH
	Tallahassee, FL	Russellville, AR
	Baltimore, MD-Washington, DC-MD-VA-WV	Olean, NY-St. Marys, PA
2000s	Gainesville, FL	Tuscaloosa, AL
	Barnstable-Yarmouth, MA	Yakima, WA
	Charlottesville, VA	Garden City, KS-Guymon, OK-Dumas-Perryton, TX

Notes: This table lists the top and bottom five non-duplicated labor market areas (LMA) among sorted lists of CZs by new work intensity for each decade. Given CZs are unnamed combinations of counties with shared commuting patterns, LMAs are preferable to list given they are named and generally more recognizable than a given county within a CZ. LMAs are comprised of one or more CZs (CZs are aggregated to the LMA level to minimally meet Census confidentiality thresholds), therefore duplicate LMAs within the top (bottom) CZs are listed once in this table per decade.

Table A.6: New Work Intensity on Patents Per Capita by Commuting Zone

	(1)	(2)	(3)	(4)
	Panel	1980-1990	1980-2000	1980-2010
Patents (pc, std.)	0.427***	0.289***	0.439***	0.498***
	(0.0616)	(0.0747)	(0.0657)	(0.0661)
Observations	2166	722	722	722

Notes: This table shows the OLS correlations between "new work" intensity (Threshold p25) now as the dependent variable and patents per capita across CZs. In our construction of the local index of patented innovation, patents are located in the CZ where an inventor filed the patent. Column (1) shows results for a panel regression across three decades (1980-2010) and includes decades fixed effects. Columns (2) to (4) show results for cross-sectional average differences across one to three decades respectively. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

Table A.7: New Work Intensity on Aggregated Shocks by Commuting Zone, No Controls

	(1)	(2)	(3)	(4)
	Panel	1980-1990	1980-2000	1980-2010
Technology	-0.00275	0.111***	0.000997	-0.0179
	(0.0346)	(0.0381)	(0.0417)	(0.0406)
Trade	-0.252***	-0.279***	-0.287***	-0.262***
	(0.0269)	(0.0269)	(0.0294)	(0.0286)
Immigration	0.105***	0.0164	0.100***	0.102***
	(0.0382)	(0.0283)	(0.0345)	(0.0373)
Aging	0.456***	0.204***	0.420***	0.540***
	(0.0334)	(0.0269)	(0.0333)	(0.0413)
Constant	21.10***	21.10***	17.85***	25.91***
	(0.0275)	(0.0257)	(0.0279)	(0.0295)
Year FEs	Yes	No	No	No
Observations	2166	722	722	722

Notes: This table shows the OLS correlations between "new work" intensity (Threshold p25) and the four aggregate proxies for the global shocks as explanatory variables: "Technology," "Trade," "Immigration," and "Aging" as defined in Sections 5. Column (1) shows results for a panel regression across three decades (1980 to 2010) and includes decades fixed effects. Columns (2) to (4) show results for cross-sectional average differences across one to three decades respectively. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

Table A.8: Employment Growth on New Work Intensity by IPUMS 1990 Occupation Code

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Thresh. Min	Thresh. p5	Thresh. p10	Thresh. p25	Thresh. p50	Thresh. p75	Thresh. p90	Thresh. p95	Benchmark
Panel A: Aggregate Employment									
NWI	0.635***	0.645***	0.640***	0.674***	0.833***	1.215***	1.061*	-9.970	0.512***
	(0.102)	(0.102)	(0.102)	(0.109)	(0.121)	(0.322)	(0.588)	(9.640)	(0.170)
Panel B: College Employment									
NWI	0.488***	0.495***	0.493***	0.519***	0.620***	0.787***	0.914*	-25.01***	0.280*
	(0.101)	(0.101)	(0.101)	(0.108)	(0.124)	(0.300)	(0.471)	(8.570)	(0.153)
Panel C: High School Employment									
NWI	0.442***	0.446***	0.431***	0.417***	0.562***	0.319	1.477**	-26.14	0.567***
	(0.132)	(0.133)	(0.133)	(0.141)	(0.174)	(0.467)	(0.699)	(16.52)	(0.217)
Observations	1031	1031	1031	1031	1031	1031	1031	1031	1022

Notes: This table shows the OLS correlations between the change of employment (as log changes) and "new work" intensity (all thresholds) as the explanatory variable across IPUMS 1990 occupation codes. The exact number of occupations observed varies between IPUMS samples. Panel A report estimates with overall employment growth as the dependent variable, and Panels B & C report employment growth specific to education groups split at "College" (i.e. any years of education beyond high school) and "High School" (i.e. any educational attainment up to and including a high school diploma). Column 1 shows results for a panel regression across three decades (1980 to 2010) and including decades fixed effects Parentheses contain robust standard errors clustered at the occupational level (*** p<0.01, ** p<0.05, * p<0.1).

Table A.9: Employment Growth on New Work Intensity by Commuting Zone

	(1) Thresh. Min	(2) Thresh. p5	(3) Thresh. p10	(4) Thresh. p25	(5) Thresh. p50	(6) Thresh. p75	(7) Thresh. p90	(8) Thresh. p95	(9) Benchmark
Panel A: Aggregate Employment									
NWI	1.152***	1.705***	1.956***	2.450***	2.941***	3.788***	-29.55***	-208.2**	4.709***
	(0.209)	(0.213)	(0.218)	(0.243)	(0.291)	(0.739)	(2.877)	(89.61)	(0.489)
Panel B: College Employment									
NWI	0.358	0.942***	1.179***	1.601***	1.820***	0.189	-38.79***	70.78	4.090***
	(0.238)	(0.240)	(0.245)	(0.273)	(0.327)	(0.854)	(2.851)	(104.1)	(0.544)
Panel C: High School Employment									
NWI	0.230	0.638**	0.818***	1.066***	1.242***	0.477	-24.05***	-380.0***	2.801***
	(0.251)	(0.258)	(0.263)	(0.289)	(0.343)	(0.826)	(2.992)	(104.8)	(0.543)
Observations	2166	2166	2166	2166	2166	2166	2166	2166	2166

Notes: This table shows the OLS correlations between the change of employment (as log changes) and "new work" intensity (all thresholds) as the explanatory variable across CZs. Panel A report estimates with overall employment growth as the dependent variable, and Panels B & C report employment growth specific to education groups split at "College" (i.e. any years of education beyond high school) and "High School" (i.e. any educational attainment up to and including a high school diploma). All columns show results for a panel regression across three decades (1980 to 2010) and including decades fixed effects. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

Table A.10: New Work Intensity on Patents Per Capita by Commuting Zone

	(1) Thresh. Min	(2) Thresh. p5	(3) Thresh. p10	(4) Thresh. p25	(5) Thresh. p50	(6) Thresh. p75	(7) Thresh. p90	(8) Thresh. p95	(9) Benchmark
Patents per Cap.	0.912***	0.935***	0.915***	0.854***	0.710***	0.240***	-0.00213	-0.000504***	0.558***
	(0.163)	(0.169)	(0.167)	(0.161)	(0.136)	(0.0470)	(0.00226)	(0.000110)	(0.0846)
Observations	2166	2166	2166	2166	2166	2166	2166	2166	2166

Notes: This table shows the OLS correlations between "new work" intensity (Threshold p5) now as the dependent variable and patents per capita (standardized) across CZs. In our construction of the local index of patented innovation, patents are located in the CZ where an inventor filed the patent. Column 1 shows results for a panel regression across three decades (1980 to 2010) and includes decades fixed effects. Columns (2) to (4) show results for cross-sectional average differences across one to three decades respectively. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

Table A.11: New Work Intensity (All Thresholds) on Aggregated Shocks and Agglomeration Factors by Commuting Zone

	(1) Thresh. Min	(2) Thresh. p5	(3) Thresh. p10	(4) Thresh. p25	(5) Thresh. p50	(6) Thresh. p75	(7) Thresh. p90	(8) Thresh. p95	(9) Benchmark
Technology	0.0246	-0.00997	-0.0262	-0.0358	-0.0153	0.0157**	0.0146***	-0.0000469	0.00474
	(0.0270)	(0.0260)	(0.0256)	(0.0239)	(0.0202)	(0.00744)	(0.00261)	(0.0000587)	(0.0134)
Trade	0.0356	0.0288	0.0269	0.0228	0.0468**	0.00888	0.000518	0.000203***	0.00533
	(0.0252)	(0.0255)	(0.0254)	(0.0244)	(0.0207)	(0.00670)	(0.00159)	(0.0000574)	(0.0129)
Immigration	-0.0142	0.00611	0.0180	0.0244	-0.00617	-0.00244	-0.00334	-0.0000378	-0.00853
	(0.0238)	(0.0220)	(0.0209)	(0.0190)	(0.0164)	(0.00766)	(0.00295)	(0.0000519)	(0.0129)
Aging	0.0884***	0.118***	0.130***	0.111***	0.0747***	0.00543	-0.0133***	-0.000140**	0.116***
	(0.0305)	(0.0296)	(0.0287)	(0.0257)	(0.0206)	(0.00753)	(0.00297)	(0.0000705)	(0.0158)
Log Pop. Density	0.501***	0.527***	0.522***	0.502***	0.398***	0.114***	-0.0146***	-0.0000383	0.260***
	(0.0313)	(0.0310)	(0.0306)	(0.0286)	(0.0240)	(0.00917)	(0.00310)	(0.0000730)	(0.0165)
College Share	0.592***	0.592***	0.575***	0.565***	0.532***	0.194***	0.00666***	-0.000103	0.268***
	(0.0367)	(0.0369)	(0.0366)	(0.0341)	(0.0286)	(0.00927)	(0.00257)	(0.0000674)	(0.0195)
Industry Diversity	-0.0299	-0.0112	-0.00325	0.00798	-0.0148	-0.00651	-0.00429*	-0.00000896	0.0358***
	(0.0251)	(0.0234)	(0.0228)	(0.0217)	(0.0192)	(0.00824)	(0.00244)	(0.0000553)	(0.0107)
Manufacturing Share	-0.440***	-0.393***	-0.373***	-0.308***	-0.262***	-0.103***	-0.0252***	-0.0000209	-0.136***
	(0.0381)	(0.0382)	(0.0379)	(0.0354)	(0.0292)	(0.00991)	(0.00276)	(0.0000835)	(0.0209)
Emp. Trend	-0.385**	-0.302**	-0.267*	-0.151	-0.171*	-0.0824**	-0.0359***	-0.000363	-0.0496
	(0.151)	(0.143)	(0.137)	(0.121)	(0.103)	(0.0327)	(0.00930)	(0.000265)	(0.0674)
Observations	2166	2166	2166	2166	2166	2166	2166	2166	2166

Notes: This table shows the OLS correlations between "new work" intensity (all thresholds) and the following explanatory variables: four aggregate proxies for the global shocks "Technology," "Trade," "Immigration," and "Aging" as defined in Sections 5; and the local agglomeration variables measured in 1980: the log of population density, the share of local population (age 16+) with any college education , the index of industrial diversity (the complement of the employment-based Herfindahl-Hirschman index of 3-digit), and the employment share in manufacturing (see Section 6.1 for further details on these variables). The specification also includes a trend of employment growth in the preceding decade (1970 to 1980) and decades fixed effects. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

Table A.12: New Work Intensity on (Dis)aggregate Global Shocks by Commuting Zone

	(1) Panel	(2) 1980-1990	(3) 1980-2000	(4) 1980-2010
Panel A: Technology Disaggregated				
Robots	0.0135	0	0.0392	0.0383
	(0.0196)	(.)	(0.0379)	(0.0318)
Computers	-0.0367	0.0161	-0.0407*	-0.0364
	(0.0254)	(0.0252)	(0.0242)	(0.0246)
Panel B: Trade Disaggregated				
China	0.00879	-0.0765	-0.0621**	0.0116
	(0.0222)	(0.0847)	(0.0241)	(0.0230)
Japan	-0.0515***	0.0587*	-0.0158	-0.0990***
	(0.0182)	(0.0311)	(0.0294)	(0.0338)
Tigers	0.0160	0.000522	0.114**	0.114**
	(0.0157)	(0.0911)	(0.0503)	(0.0458)
Panel C: Immigration Disaggregated				
Immigration (High Edu)	-0.0122	0.106**	0.0316	-0.000920
	(0.0537)	(0.0451)	(0.0520)	(0.0577)
Immigration (Low Edu)	0.0351	-0.136***	0.0185	0.0332
	(0.0437)	(0.0366)	(0.0426)	(0.0475)
Panel D: Aging Disaggregated				
Older Workers	0.0569**	-0.0562**	0.0196	0.00918
	(0.0226)	(0.0235)	(0.0272)	(0.0363)
Retirees	0.0975***	0.0446**	0.111***	0.175***
	(0.0219)	(0.0224)	(0.0254)	(0.0326)
Agglomeration Factors	Yes	Yes	Yes	Yes
Employment Trend	Yes	Yes	Yes	Yes
Year FEs	Yes	No	No	No
N	2166	722	722	722

Notes: This table shows the OLS correlations between "new work" intensity (Threshold p25) and dis-aggregate proxies for one set of the global shocks while controlling for: the aggregated proxies for the other shocks "Technology," "Trade," "Immigration," and "Aging" as defined in Sections 5; the local agglomeration variables measured in 1980 (see Section 6.1 for further details on these variables); and the trend of employment growth over a number of decades prior to 1980: three decades in Columns (1) and (4), two decades in Column (3), and one decade in Column (2). The individual components of are local exposures to: Technology (Panel A) splits into computers and robots; Trade (Panel B) splits into imports from China, Japan, and the Asian Tigers; Immigration (Panel C) splits into high and low educated (split by less than a 4-year college degree vs. a college degree or more) immigration; and, Aging (Panel D) splits into Old Workers (age 46 to 65) and Expected Retirees (ages 66+). Column (1) shows results for a panel regression across three decades (1980-2010) and includes decades fixed effects. Columns (2) to (4) show results for cross-sectional average differences across one to three decades respectively. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

Table A.13: Labor Market Areas containing High-Skilled Cities

Labor Market Area	LMA Rank				
	Pop. Size	Pop. Density	College Share	Industry Diversity	Manufacturing Share
Baltimore, MD-Washington, DC-MD-VA-WV	4	13	19	107	44
Austin-San Marcos, TX	72	156	7	147	79
Santa Barbara-Santa Maria-Lompoc, CA	106	154	2	86	93
San Francisco-Oakland, CA	9	6	3	6	103
Denver-Boulder-Longmont, CO	27	60	5	21	110
San Diego, CA	21	18	9	50	115
New York-Nassau-Suffolk, NY	2	1	74	16	133
San Jose, CA	23	36	4	109	308
Boston-Worcester-Lowell, MA-NH-Providence, RI	30	8	106	42	312

Notes: This table lists labor market areas (LMA) of the CZs with the highest predicted potential for "new work" along with the LMA's population rank as well as the ranking for the local factors: population density, college share, industry diversity, and manufacturing share. See Table A.5 for an explanation of Labor Market Areas.

Table A.14: New Work Intensity on Global Shocks and Local Factors Interacted with High-Skilled Cities Indicator by Commuting Zone

	(1) Panel	(2) 1980-1990	(3) 1980-2000	(4) 1980-2010
Technology	-0.0715***	-0.0171	-0.0741**	-0.0780**
	(0.0267)	(0.0274)	(0.0298)	(0.0330)
Technology X High-Skilled City	0.0702*	0.0523	0.0601	0.0862*
	(0.0424)	(0.0538)	(0.0502)	(0.0511)
Trade	-0.00336	-0.0434*	-0.0365	-0.000421
	(0.0231)	(0.0250)	(0.0240)	(0.0248)
Trade X High-Skilled City	0.370***	0.248***	0.391***	0.399***
	(0.0673)	(0.0681)	(0.0614)	(0.0762)
Immigration (High Edu)	0.214**	0.418***	0.269***	0.202**
	(0.0836)	(0.0811)	(0.0726)	(0.0921)
Immigration (High Edu) X High-Skilled City	-0.312***	-0.465***	-0.339***	-0.268**
	(0.0988)	(0.0925)	(0.0871)	(0.107)
Immigration (Low Edu)	-0.113*	-0.346***	-0.141**	-0.0967
	(0.0649)	(0.0585)	(0.0565)	(0.0726)
Immigration (Low Edu) X High-Skilled City	0.0761	0.282***	0.128	0.0357
	(0.0961)	(0.0778)	(0.0794)	(0.104)
Aging	0.0923***	-0.0520*	0.0824***	0.135***
	(0.0248)	(0.0279)	(0.0291)	(0.0372)
Aging X High-Skilled City	0.0305	0.0674	-0.00234	-0.0314
	(0.0581)	(0.0427)	(0.0581)	(0.0718)
High-Skilled City	0.295***	0.153**	0.306***	0.329***
	(0.0936)	(0.0748)	(0.0842)	(0.0976)
Log Pop. Density	0.473***	0.304***	0.421***	0.475***
	(0.0375)	(0.0310)	(0.0344)	(0.0402)
College Share	0.490***	0.365***	0.440***	0.495***
	(0.0420)	(0.0337)	(0.0407)	(0.0446)
Industry Diversity	0.00673	0.0651**	0.0306	0.0101
	(0.0208)	(0.0257)	(0.0211)	(0.0211)
Manufacturing Share	-0.293***	-0.249***	-0.292***	-0.300***
	(0.0346)	(0.0351)	(0.0352)	(0.0374)
Emp. Trend	-0.0343	0.0810	-0.0145	-0.109*
	(0.121)	(0.130)	(0.0915)	(0.0636)
Constant	21.08***	21.09***	17.84***	25.92***
	(0.0467)	(0.0458)	(0.0449)	(0.0414)
Year FEs	Yes	No	No	No
Observations	2166	722	722	722

Notes: This table shows the OLS correlations between "new work" intensity (Threshold p25) and interacts the four aggregate proxies for the global shocks "Technology," "Trade," "Immigration," and "Aging" as defined in Sections 5 by CZs with predicted "high-skilled" for generating "new work" as defined by being in the top quartile of predicted "NWI" based on 1980 agglomeration factors (see Section 7.1 for details). The regressions also control for the local agglomeration variables measured in 1980 (see Section 6.1 for further details on these variables) and the trend of employment growth over a number of decades prior to 1980: three decades in Columns (1) and (4), two decades in Column (3), and one decade in Column (2). Column (1) shows results for a panel regression across three decades (1980 to 2010) and includes decades fixed effects. Columns (2) to (4) show results for cross-sectional average differences across one to three decades respectively. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

Table A.15: Example Occupations by Task Content

Occupation Title	Task Intensity	NWI	Occupation Title	Task Intensity	NWI
NR Cognitive Analytical			**NR Manual Interactive**		
physicists and astronomers	2.16	0.17	vocational and educational counselors	2.49	0.11
actuaries	2.09	0	psychologists	2.41	0.18
economists, market researchers, and survey researchers	2	0.50	social workers	2.25	0.28
management analysts	1.94	0.10	clergy and religious workers	2.16	0.06
aerospace engineer	1.71	0.22	funeral directors	2.15	0
urban and regional planners	1.60	0.50	licensed practical nurses	1.88	0.33
psychologists	1.58	0.18	managers and specialists in marketing, advertising, and PR	1.88	0.33
atmospheric and space scientists	1.57	0	business and promotion agents	1.88	0.22
agricultural and food scientists	1.52	0.18	office supervisors	1.88	0.11
operations and systems researchers and analysts	1.51	0	sales engineers	1.88	0

Notes: This table shows the top 10 occupations by "non-routine cognitive analytical" and "non-routine manual interactive" task intensities. Task intensity is the z scores among the distribution of the given task intensity across occupations, which is reported immediately after the occupation title followed by the occupation's NWI. A occupation's task intensities are time-invariant measures.

Table A.16: New Work Intensity derived from High Cognitive Analytical Occupations on Global Shocks and Local Factors by Commuting Zone

	(1) Panel	(2) 1980-1990	(3) 1980-2000	(4) 1980-2010
Technology	0.177***	0.241***	0.144***	0.239***
	(0.0364)	(0.0358)	(0.0298)	(0.0443)
Trade	0.0172	0.0285	0.0380	0.0257
	(0.0269)	(0.0281)	(0.0244)	(0.0296)
Immigration	0.00324	-0.0769***	0.0274*	0.0187
	(0.0208)	(0.0166)	(0.0143)	(0.0228)
Aging	0.185***	-0.0971***	0.0557*	0.163***
	(0.0380)	(0.0325)	(0.0300)	(0.0533)
Log Pop. Density	0.381***	0.413***	0.423***	0.449***
	(0.0490)	(0.0356)	(0.0300)	(0.0552)
College Share	0.814***	0.776***	0.650***	0.850***
	(0.0458)	(0.0433)	(0.0353)	(0.0492)
Industry Diversity	-0.0757	-0.0680	-0.0465	-0.0839
	(0.0500)	(0.0486)	(0.0310)	(0.0531)
Manufacturing Share	-0.433***	-0.431***	-0.370***	-0.461***
	(0.0544)	(0.0481)	(0.0400)	(0.0576)
Emp. Trend	-0.814***	-0.728***	-0.692***	-0.478***
	(0.180)	(0.147)	(0.0986)	(0.101)
Constant	6.538***	6.515***	6.268***	9.728***
	(0.0558)	(0.0474)	(0.0404)	(0.0471)
Year FEs	Yes	No	No	No
Observations	2166	722	722	722

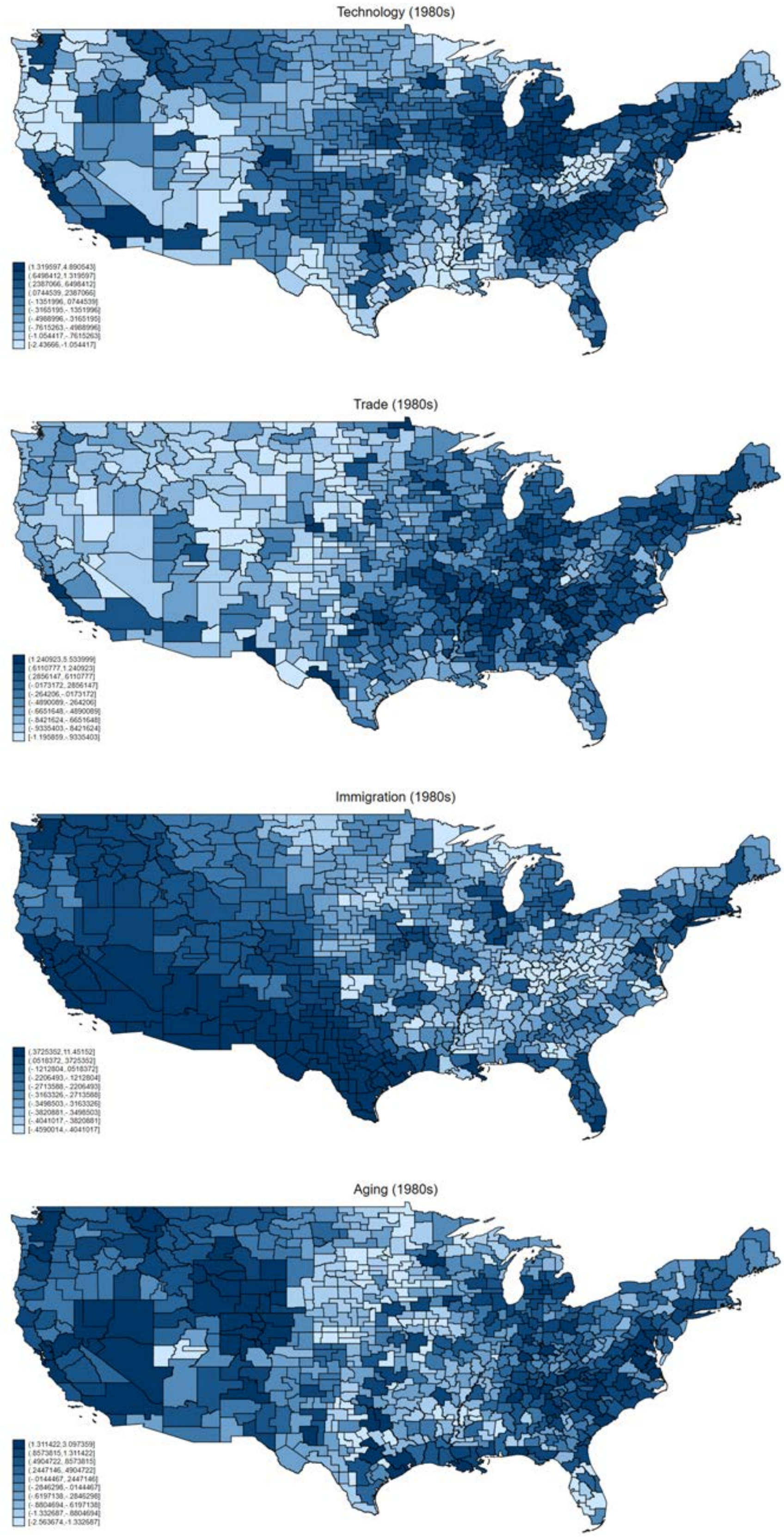
Notes: This table shows the OLS correlations between "new work" intensity (Threshold p25) specific to "Professional" and "Technician" occupations (see Section 7.2 for details) and the following explanatory variables: four aggregate proxies for the global shocks "Technology," "Trade," "Immigration," and "Aging" as defined in Sections 5; and the local agglomeration variables measured in 1980: the log of population density, the share of local population (age 16+) with any college education , the index of industrial diversity (the complement of the employment-based Herfindahl-Hirschman index of 3-digit), and the employment share in manufacturing (see Section 6.1 for further details on these variables); and the trend of employment growth over a number of decades prior to 1980: three decades in Columns (1) and (4), two decades in Column (3), and one decade in Column (2). Column (1) shows results for a panel regression across three decades (1980 to 2010) and includes decades fixed effects. Columns (2) to (4) show results for cross-sectional average differences across one to three decades, respectively. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

Table A.17: New Work Intensity derived from High Manual Interpersonal Occupations on Global Shocks and Local Factors by Commuting Zone

	(1) Panel	(2) 1980-1990	(3) 1980-2000	(4) 1980-2010
Technology	0.0748**	0.165***	0.0370	0.0685*
	(0.0320)	(0.0300)	(0.0250)	(0.0398)
Trade	-0.0390	-0.0667***	-0.0599***	-0.0322
	(0.0252)	(0.0251)	(0.0205)	(0.0278)
Immigration	-0.0316	-0.181***	-0.0253	-0.0130
	(0.0331)	(0.0315)	(0.0217)	(0.0315)
Aging	-0.0371	-0.324***	-0.142***	-0.0643
	(0.0316)	(0.0298)	(0.0263)	(0.0453)
Log Pop. Density	0.225***	0.138***	0.236***	0.290***
	(0.0472)	(0.0324)	(0.0252)	(0.0515)
College Share	0.394***	0.452***	0.368***	0.458***
	(0.0393)	(0.0399)	(0.0281)	(0.0438)
Industry Diversity	-0.0454	-0.0635*	-0.0422*	-0.0485
	(0.0410)	(0.0380)	(0.0222)	(0.0421)
Manufacturing Share	-0.484***	-0.458***	-0.364***	-0.476***
	(0.0460)	(0.0441)	(0.0341)	(0.0499)
Emp. Trend	-0.179	-0.220*	-0.284***	-0.332***
	(0.146)	(0.121)	(0.0847)	(0.0881)
Constant	7.685***	7.695***	8.072***	12.40***
	(0.0484)	(0.0388)	(0.0343)	(0.0414)
Year FEs	Yes	No	No	No
Observations	2166	722	722	722

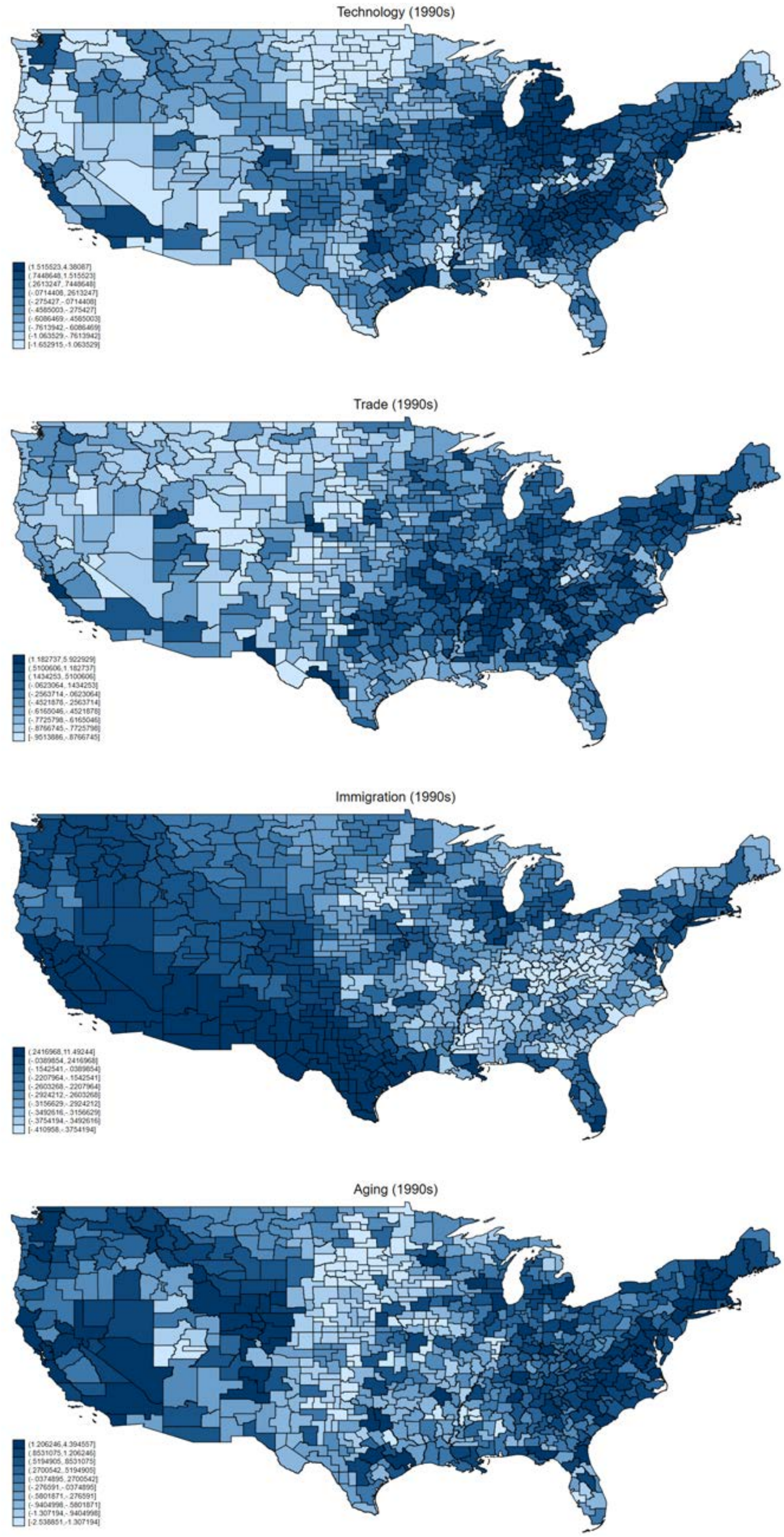
Notes: This table shows the OLS correlations between "new work" intensity (Threshold p25) specific to "Professional" and "Technician" occupations (see Section 7.2 for details) and the following explanatory variables: four aggregate proxies for the global shocks "Technology," "Trade," "Immigration," and "Aging" as defined in Sections 5; and the local agglomeration variables measured in 1980: the log of population density, the share of local population (age 16+) with any college education , the index of industrial diversity (the complement of the employment-based Herfindahl-Hirschman index of 3-digit), and the employment share in manufacturing (see Section 6.1 for further details on these variables); and the trend of employment growth over a number of decades prior to 1980: three decades in Columns (1) and (4), two decades in Column 3, and one decade in Column (2). Column (1) shows results for a panel regression across three decades (1980 to 2010) and includes decades fixed effects. Columns (2) to (4) show results for cross-sectional average differences across one to three decades, respectively. Parentheses contain robust standard errors clustered at the CZ level (*** p<0.01, ** p<0.05, * p<0.1).

Figure A.1: Aggregated Global Shocks across US Commuting Zones, 1980s



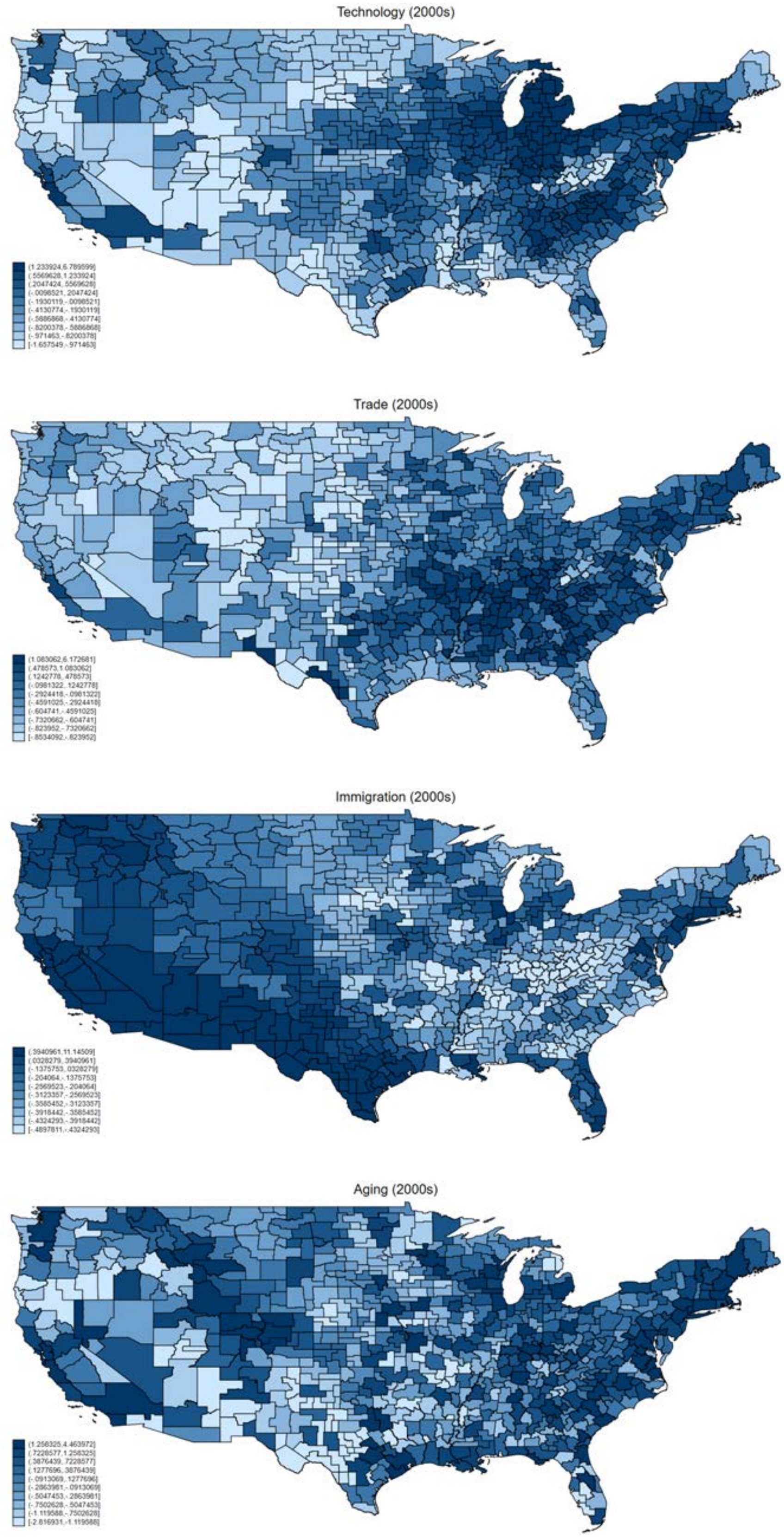
Notes: The figures show the geographic distribution of each of the global shocks—technology, trade, immigration, and population aging—in 1980. The construction of individual shocks are detailed in Section A.3 and the aggregation in Section 5.2.1.

Figure A.2: Aggregated Global Shocks across US Commuting Zones, 1990s



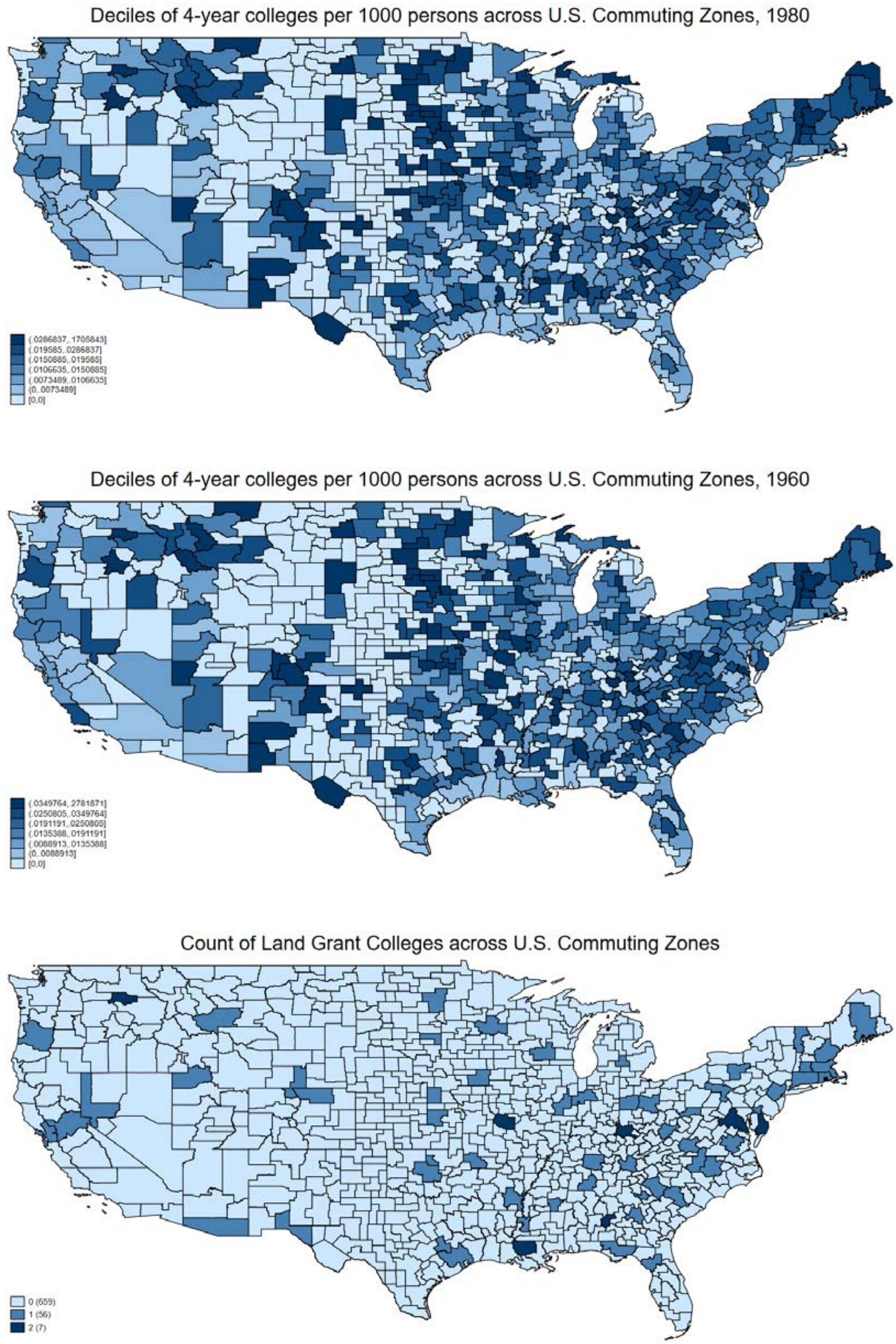
Notes: The figures show the geographic distribution of each of the global shocks—technology, trade, immigration, and population aging—in 1990. The construction of individual shocks are detailed in Section A.3 and the aggregation in Section 5.2.1.

Figure A.3: Aggregated Global Shocks across US Commuting Zones, 2000s



Notes: The figures show the geographic distribution of each of the global shocks—technology, trade, immigration, and population aging—in 2000. The construction of individual shocks are detailed in Section A.3 and the aggregation in Section 5.2.1.

Figure A.4: Human Capital Instruments across US Commuting Zones



Notes: The figures show the geographic distribution of each of human capital supply instrument: the density of 4-year colleges per capita (standardized) across CZs in 1980; the standardized density using 4-year institutions existing only by 1960; an indicator for the presence of an early-waves land-grant college established and designated before 1920.