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The Impact of Within-Occupation Technological Change on Spatial Sorting and Wage Inequality

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The Impact of Within-Occupation Technological Change on Spatial Sorting and Wage Inequality*

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Abstract

Both the demand for skilled labor and the skill wage premium have become increasingly dispersed across the United States. This paper examines how technological change within occupations drives these uneven local developments. Combining a novel measure of technological change—capturing shifts in task intensities within 430 detailed occupations—with patent data and microdata, I demonstrate that innovation reallocates labor toward cognitive-intensive tasks, especially in densely populated areas. Motivated by this, I show that greater exposure to technological change increases the relative employment of college-educated workers while causing within-occupation wage declines for less-educated workers, widening the college wage premium.

Keywords: technological change, task intensities, local labour markets, innovation diffusion, college wage premium.

JEL Codes: J23, J24, J31, O33, R12.

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Non-Technical Summary

Why does the wage gap between college-educated workers and less educated workers rise faster in densely populated areas in the United States? Why do workers holding only a high school degree or no degree fall behind in those regions—even within the same kinds of jobs? This study provides a new answer: it is not just the demand for different jobs that is changing, but what people do within those jobs—especially in places where technological change advances quickly.

This paper builds on the observation that as technology evolves, it subtly reshapes the tasks workers perform within occupations. For example, an administrative assistant today may spend less time filing papers and more time managing digital calendars or analyzing data. These task shifts tend to favor abilities and skills that are more concentrated among college-educated workers, such as problem-solving and reasoning. To measure this process, the study introduces a new way of tracking changes in the nature of work within detailed occupations by leveraging time-varying data on ability requirements from the Occupational Information Network (O*NET). Consistent with task-based theories and historical evidence, this new approach shows that jobs in the twenty-first century have become more cognitive-intensive.

Turning to local labor markets, the second part of this study shows that the uneven spread of innovation across regions—measured by the diffusion of patents through industries—drives the local differences in how work evolves. Urban areas, where new technologies and skilled workers are more concentrated, see a greater shift toward cognitive tasks within occupations. In numbers, every 10 percent increase in population density amplifies the positive effect of innovation on the growing importance of cognitive tasks by 8.3 percentage points. As a result, they attract more college-educated workers and widen the wage gap between college and non-college workers—even when those workers hold the same job title. This reveals an important channel through which technological change manifests unevenly across space, contributing to rising wage inequality.

The most alarming finding of this study is that the rise in wage inequality is mainly driven by falling wages among the least educated workers—namely, high school graduates and dropouts. While these workers are also increasingly squeezed into low-paying service occupations, deeper investigations show that around 80 percent of their wage losses in regions more exposed to technological change can be explained by declining wages within detailed occupations. The study applies advanced shift–share methodologies to ensure that these patterns are not simply driven by other regional differences in labor market characteristics—such as initial education levels, demographic composition, or pre-existing trends in population or wage growth. Although the sensitivity analysis identifies an important role for earlier population growth trends across local labor markets, the main findings remain robust and highly significant.

Overall, the study highlights the importance of considering fine-grained changes in the task content of occupations when analyzing how wage growth and inequality diverge across regions. Occupations are the natural units through which workers are reassigned to tasks, adjusting skill prices and reshaping the wage structure across groups. The local developments uncovered in this study—developments that disadvantage low-skilled workers most—provide critical information for policymakers. Reskilling initiatives that target low-skilled workers, especially in densely populated areas, could help mitigate the negative, skill-biased wage effects induced by the cognitive-biased nature of technological change within occupations.

1 Introduction

The college wage premium has not risen uniformly across space in the twenty-first century. Instead, relative skill prices have increased disproportionately in more populous regions. This pattern is illustrated in Figure 1, which shows a differential increase of approximately four percentage points in the college wage premium between regions with the lowest and highest population density in the United States. As the more rapid growth in wage inequality in dense cities alone accounts for one-quarter of the recent rise in national wage inequality (Baum-Snow and Pavan 2013), understanding the underlying forces shaping local labor markets is crucial for designing effective policies, improving job–worker matching, and reskilling displaced workers.

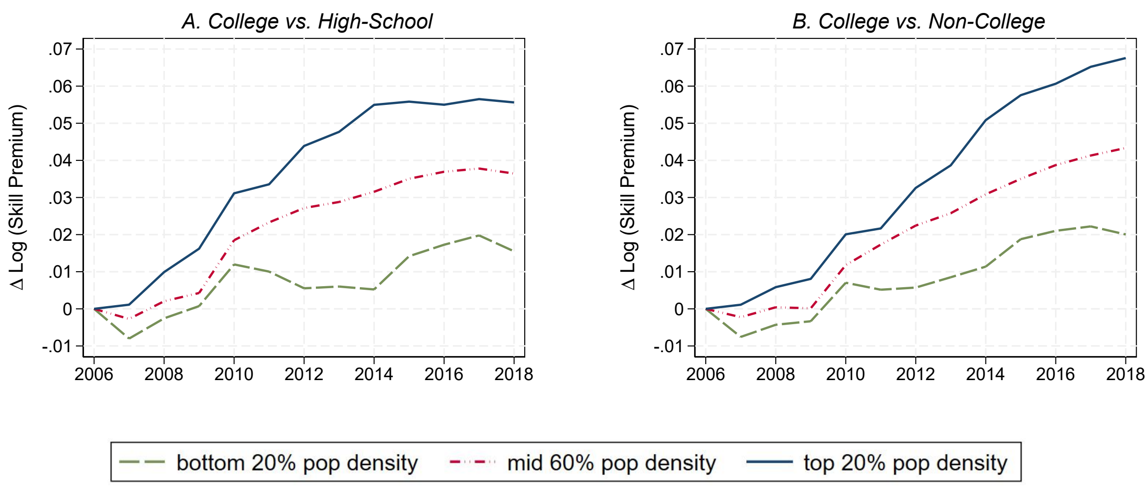

Figure 1: College Wage Premium Evolution for U.S. Regions with Different Population Densities

Notes: 1,078 consistent Public Use Microdata Areas (PUMAs) from IPUMS ACS data (Ruggles et al. 2023) are ranked by population density in 2005–07 and divided into three groups: bottom 20%, middle 60%, and top 20%. For each group, full-time, year-round workers (working more than 35 hours per week and more than 40 weeks per year) are pooled. Log college wage premiums are calculated for each year from 2006 to 2018 using a 3-year moving average. In Panel A, the college premium is defined as the average wage of college graduates (4-year bachelor's degree) relative to that of high school graduates and dropouts (excluding those with some college experience). In Panel B, the non-college group includes all workers without a 4-year bachelor's degree. ACS individual weights are multiplied by annual working hours to construct the weighted wage premium series.

There is broad consensus that technological change is a key driver of recent divergences in local employment and wage trends (e.g., Autor and Dorn 2013; Moretti 2013; Baum-Snow et al. 2018; Autor 2019). However, how it manifests across local labor markets remains relatively underexplored. While traditional studies often proxy technological change using parametric time trends (e.g., Tinbergen 1974; Katz and Murphy 1992), more recent empirical work usually focuses on the adoption of specific technologies (e.g., computers, robots, AI) or relies on static occupation descriptors from sources such as the Dictionary of Occupational Titles (DOT) or O*NET.

Although occupations are dynamic and serve as the natural units through which technological change reorganizes labor across tasks—affecting skill demand and relative wages—the within-occupation channel remains largely overlooked, particularly in the spatial economics literature. This paper addresses this gap by constructing a novel measure of within-occupation cognitive-biased technological change (WOCBTC, henceforth), linked to U.S. patent data and localized microdata. The analysis shows that stronger diffusion of innovation increases the local input of cognitive-intensive tasks predominantly in densely populated regions where labor is abundant. In turn, greater exposure to WOCBTC increases the employment of college-educated workers while depressing the wages of less-educated workers. As a result, local wage inequality between skill groups widens.

The theoretical task-based model of Acemoglu and Restrepo (2018; 2019) posits that changes in the task input mix depend on two factors: first, the automation of tasks; and second, the emergence of new tasks, which tend to be more cognitive-intensive compared to existing tasks. In the first part of this paper, I build on this intuition to conceptualize a novel approach to measuring within-occupation technological change. A key challenge for this approach is the consistent measurement of task changes (see, e.g., Autor 2013), which is essential to gauge the net impact of task automation and task creation. To overcome this hurdle, I rely on the revised ability rating procedure of the Occupational Information Network (O*NET), which dynamically evaluates occupations' ability requirements (e.g., mathematical reasoning or manual dexterity) by comparing their task content over time. To make systematic use of the high-dimensional ability data, I derive five broader task intensity dimensions using factor analysis. Combined with spatial differences in occupational composition, the computed task intensity changes are used to construct a measure of cognitive-biased technological change across local labor markets.

The second part of this paper investigates whether and how cognitive-biased task demand shifts within occupations relate to the localized diffusion of innovation. Answering this question is essential to ensure that the WOCBTC measure truly reflects occupations' adaptation to new technologies. To measure innovation across regions, I combine data on patent grants from the U.S. Patent and Trademark Office (USPTO) with a patent-to-industry crosswalk developed by Goldschlag et al. (2020). Exploiting differences in industrial specialization, I show that the diffusion of patents strongly predicts local labor markets' occupational task evolution. I confirm this relationship by using breakthrough patents from Kelly et al. (2021) to instrument the contemporary diffusion of patents with the time-lagged diffusion of patents that are novel and have a long-term impact. Importantly, the unveiled relationship between innovation and WOCBTC is not uniform across local labor markets but varies systematically with the initial population density: while a 10 percent increase in patent diffusion is associated with a 2.3 percent higher exposure to WOCBTC, each 10 percent rise in population density amplifies this relationship by an average of 8.1 percent. This finding reveals a so-far overlooked channel through which densely populated regions may evolve at a faster rate into cognitive-intensive hubs (see, e.g., Rossi-Hansberg et al. 2019).

Motivated by this new evidence, the third part of the study empirically tests whether cognitive task upgrading within occupations translates into faster local employment and wage growth. To establish causality, I use a Bartik-style shift–share design (Bartik 1991) to exploit exogenous variation in occupational task changes within industries. Recent advances in shift–share methodologies and inference (Adao et al. 2019; Borusyak et al. 2022) also enable me to address the spatial correlation of shocks across regions with similar industrial structures. Alongside computing standard errors using the industry-level inference method by Adao et al. (2019), I confirm the robustness of the main results through various shock-balance tests and an extensive sensitivity analysis as proposed by Borusyak et al. (2022). Despite the demonstration of notable group heterogeneity and an important role of preceding local population trends, the overall patterns remain robust across the different checks.

The empirical findings show that WOCBTC leads to a significant increase in overall employment, driven almost entirely by high-skilled workers: a 10 percent increase in regional exposure to WOCBTC corresponds to a 2.8 percent rise in full-time equivalent college employment. Despite the employment growth, the wages of college-educated workers remain relatively stable across labor markets. This finding aligns with Topel (1986) and Beaudry et al. (2010), who argue that workers anticipate localized changes in skill demand, leading to geographic mobility and wage equalization. By contrast, wage adjustments are not uniform for the least educated, who are typically also the least mobile group in the labor market (Topel 1986; Bound and Holzer 2000; Wozniak 2010; Notowidigdo 2020). Specifically, the wages of high school graduates and dropouts fall by a substantial 0.4 percent for every 10 percent increase in WOCBTC. Correcting the estimated effects for different compositional shifts reveals that the primary mechanism driving this pattern is that low-skilled workers in more exposed labor markets experience faster wage deterioration within detailed occupations. Systematic re-sorting into low-paying occupations plays a comparatively minor role. This economic result underpins the novel approach to measuring technological change in this study, which exploits exclusively variation within occupations.

This study contributes to three strands of literature. First, it adds to research emphasizing task and wage changes within occupations (Autor et al. 2003; Spitz-Oener 2006; Antonczyk et al. 2009; Firpo et al. 2011; Ross 2017; Hershbein and Kahn 2018; Atalay et al. 2020; Freeman et al. 2020; Cortes et al. 2021). Consistent with this literature, I show that demand for cognitive skills has continued to rise in the twenty-first century, challenging the popular "great reversal" hypothesis (Beaudry et al. 2016), which focuses on the slowdown in the growth of non-routine cognitive occupations but overlooks changes occurring within occupations. My study advances the within-occupation literature by highlighting the local dimension of task changes and related labor market dynamics. A closely related study is conducted by Hershbein and Kahn (2018), who examine regional shifts in skill demand during the Great Recession using localized job vacancy data. My analysis differs in that it investigates the long-run impact of within-occupation technological change and links it to persistent features of local labor markets—such as industrial structure and population density—rather than to a single, though important, economic event.

Second, this study contributes to the literature that highlights the role of technological change in driving spatial worker sorting and wage changes (Berry and Glaeser 2005; Beaudry et al. 2010; Autor and Dorn 2013; Baum-Snow and Pavan 2013; Moretti 2013; Giannone 2017; Baum-Snow et al. 2018; Autor 2019). Many of these studies show that shifts in the relative skill demand occur more rapidly in densely populated areas, disproportionately benefiting college-educated workers. In this context, Baum-Snow et al. (2018) show that the disproportionate increase in high- relative to low-skilled workers accounts for nearly all of the more rapid rise in skill prices in large cities. In another study, Autor (2019) provides descriptive evidence that the declining relative wages of non-college workers in denser cities have recently coincided with a trend of these workers being squeezed into low-paying occupations. While these insights are enlightening, they leave unresolved the question of what fundamentally drives these uneven local developments. This paper sheds new light on this issue by demonstrating the important role of task changes within occupations.

Lastly, this paper also contributes to a small body of research on the origins and spatial distribution of "new work" precipitated by technological change. Previous studies find that innovation primarily generates new work in larger cities (Lin 2011; Berger and Frey 2016), consistent with my finding that the impact of innovation on cognitive-biased task restructuring is more substantial in densely populated areas. Compared to a more recent study by Autor et al. (2024), my approach builds on the same theoretical framework developed by Acemoglu and Restrepo (2018; 2019), but differs in that it examines how the interplay between task automation and task creation reshapes work within narrowly defined occupations, rather than focusing on the emergence of new micro-titles within broader occupational categories. In line with a key finding of Autor et al. (2024), this study shows that new cognitive-intensive work within occupations penalizes low-skilled workers.

The remainder of this paper is organized as follows. Section 2 describes the construction of the within-occupation technological change measure and illustrates the systematic task changes within occupations in the twenty-first century. Section 3 investigates the relationship between localized task shifts within occupations and the diffusion of innovation, highlighting the role of population density. Section 4 presents the results of the main analysis, including effects on employment growth, skill composition, and the college wage premium across local labor markets. Section 5 concludes the study and discusses relevant implications.

2 Within-Occupation Cognitive-Biased Technological Change

It is a well-established economic fact that technological change over recent decades has increased the cognitive task input in the economy, benefiting high-skilled workers who have a comparative advantage in such tasks (e.g., Tinbergen 1974; Katz and Murphy 1992; Acemoglu 1998; Autor and Katz 1999; Autor et al. 2003; Acemoglu and Autor 2011).

The novel approach adopted in this study is to construct a measure that effectively isolates cognitive-biased task changes within detailed occupations. To do so, one would ideally compare all task changes directly. However, this presents a major challenge, as representative data sources typically do not collect consistent information on job tasks (Autor 2013). Rather than relying on static occupation-level measures—which are only indirectly related to potential technology exposure and overlook the fact that most task changes occur within rather than between occupations (Atalay et al. 2020; Freeman et al. 2020)—this study adopts a different strategy by drawing on the revised O*NET ability rating procedure (Fleisher and Tsacoumis 2012). Specifically, a newly implemented feature enables O*NET job analysts to incorporate fine-grained changes in over 19,000 tasks between consecutive rating cycles to evaluate occupations' ability requirements. As a result, the measured changes in ability requirements accurately reflect the evolving task composition of occupations—a fundamental improvement over the original rating procedure, in which analysts assessed information only at a single point in time. Further details on the revised rating procedure are provided in Section B.3 of the Appendix.

2.1 O*NET Occupation Data

The O*NET ability domain comprises 52 abilities (see Appendix Section B.2) that are updated in rating cycles. To identify long-distance changes in occupations' ability requirements, I use data from O*NET versions 16.0 (July 2011) and 25.0 (August 2020). Because only a portion of occupations is updated in each cycle, I follow Freeman et al. (2020) and center each database around the average year of the latest updates. As a result, the two datasets reflect occupations' ability requirements in 2008 and 2017, respectively.

Before linking the O*NET ability data with pooled microdata from the American Community Survey, obtained via IPUMS (Ruggles et al. 2023), I undertake two additional steps. First, I construct a post-2000 balanced panel of 430 occupations in the ACS. This step is essential to isolate task changes within consistently defined occupations. Although balanced occupation panels are available (e.g., Meyer and Osborne 2005; Dorn 2009), they are based on 1990 classifications. While these are preferable for analyses beginning in the twentieth century, my updated panel more accurately reflects the contemporary labor market, as it is based on the 2010 Standard Occupational Classification (SOC). In the second step, I match the finer O*NET occupations to the panel using an employment-weighted crosswalk. After assigning the ability scores to the occupation panel, nearly all occupations have undergone at least one update between the two focal years, while most occupations have been updated multiple times. Following Autor et al. (2003), I treat the 15 out of 430 occupations with no updates as having unchanged ability requirements.[1]

2.2 Factor Analysis

This section extracts broader task dimensions from the multidimensional ability data. There are two approaches to achieving this goal: (i) constructing composite task measures using a subset of preselected abilities in principal component analysis (PCA), and (ii) evaluating the variation in all abilities simultaneously using factor analysis (FA).[2] The first approach assumes that only a subset of abilities is relevant for explaining a particular task dimension. This requires prior knowledge of how abilities are assigned to tasks in the labor market, which is a limitation given the complexity of some ability measures. For example, memorization or time-sharing abilities may be crucial for a wide array of different tasks. Factor analysis offers a data-driven approach to uncover the underlying structure of abilities without presupposing which abilities map to which tasks. This

[1] Appendix Sections B.1 and F document the panel construction and the crosswalk implemented in the ACS. The matching process for O*NET occupations to the occupation panel is described in Section B.4 of the Appendix.

[2] The first approach is used by Autor et al. (2003), Yamaguchi (2012), Caines et al. (2017), Guvenen et al. (2020), and Aghion et al. (2023). The second approach is used, for example, by Ingram and Neumann (2006), Poletaev and Robinson (2008), and Robinson (2018).

is particularly useful in the context of complex ability measures, where prior assumptions about their mapping to task categories may not hold. Therefore, this paper draws on the more flexible second approach.

Let $\mathbf{x} = (x_1, x_2, \dots, x_p)'$ be a p-dimensional vector of observed ability measures. Factor analysis assumes that each observed ability is a linear function of a smaller number of unobserved common factors (task dimensions) plus an ability-specific error term. Formally, the model is specified as:

$$\mathbf{x} = \boldsymbol{\mu} + \boldsymbol{\Lambda}\mathbf{f} + \boldsymbol{\epsilon} \tag{1}$$

where $\boldsymbol{\mu}$ is a $p \times 1$ vector of means, $\boldsymbol{\Lambda}$ is a $p \times k$ matrix of factor loadings, $\mathbf{f}$ is a $k \times 1$ vector of latent common factors, and $\boldsymbol{\epsilon}$ is a $p \times 1$ vector of unique factors (errors)—the components of each ability that are not explained by the common factors. These errors are assumed to be uncorrelated with $\mathbf{f}$ and across observed abilities. To ensure that the factor scores accurately represent the occupational structure of the U.S. workforce, I weight occupations using employment shares from the 2008 ACS. Then, I assign both 2008 and 2017 ability scores to each individual in the sample while keeping the occupational distribution constant. This yields occupation-year-specific factor scores relative to the 2008 employment-weighted mean, enabling the computation of interpretable changes in factor scores within occupations, net of shifts in occupation shares.[3]

Table 1 summarizes the factor analysis output. By construction, the five derived factors are orthogonal, representing different task dimensions.[4] The factor with the highest explanatory power (27%) reflects the cognitive intensity of occupations, with problem-solving and reasoning abilities as the highest factor loadings. The second factor (26%) relates to physical abilities such as body strength and flexibility. The third factor (25%) is associated with sensory-perceptual abilities that are critical for coordination-intensive tasks. The two remaining factors account for 7% and 6% of the variation. These two factors appear to capture the manual and communication intensity of occupations, respectively. The task dimensions represented by the five factors are broadly in line with Ingram and Neumann (2006) and Robinson (2018). To confirm the plausibility of the self-selected factor definitions, I additionally check each factor's highest-ranked occupations. For example, physicists, architects, and engineers score highest in cognitive inten-

[3] Alternative factor analysis strategies have been explored, all yielding economically uninterpretable results. For example, conducting two separate factor analyses for 2008 and 2017 produces different factor loadings across years, making within-occupation comparisons infeasible.

[4] Orthogonality is achieved using the principal factor method with varimax factor rotation (Fabrigar et al. 1999; Costello and Osborne 2005). The five factors, which are selected based on the Kaiser rule that their eigenvalue is greater than one (Kaiser 1960), explain 90% of the total variation in the 52-dimensional ability data.

sity, while dancers, fitness workers, and construction workers rank highest in physical intensity. The highest-ranked occupations further indicate that the fifth factor is associated with routine communication tasks, such as making announcements via telephone or other electronic equipment and providing standardized explanations. It is important to note that this differs from the non-routine interpersonal task dimension conceptualized by Autor et al. (2003), which requires a high level of social skill (see, e.g., Deming 2017).

A picture of how the five task intensities (cognitive, manual, communication, physical, and coordination) are distributed across the employed U.S. workforce can be gathered from Figure 2. In addition to plotting the employment-weighted intensity distributions of 2008 and 2017, the figure also highlights a counterfactual distribution, representing the within-occupation margin. The aggregate task intensity decompositions are computed following Atalay et al. (2020):

$$\overline{TI}_{i,2017} = \overline{TI}_{i,2008} + \sum_{k=1}^{K} \theta_{k,2008} \times (\widetilde{TI}_{i,k,2017} - \widetilde{TI}_{i,k,2008}) + \sum_{k=1}^{K} (\theta_{k,2017} - \theta_{k,2008}) \times \widetilde{TI}_{i,k,2017} \tag{2}$$

where $\widetilde{TI}_{k,2008}$ and $\widetilde{TI}_{k,2017}$ denote the year-specific task intensities of occupation k, while $\theta_{k,2008}$ and $\theta_{k,2017}$ are the corresponding supply-adjusted employment shares. Based on equation 2, the weighted average intensity i in 2017 equals the average intensity in 2008 (*addend 1*), adjusted by within-occupation intensity changes (*addend 2*) and shifts in occupations' relative shares of total working hours between 2008 and 2017 (*addend 3*). It is evident from Figure 2 that the distributions of the intensive margin (*addend 1* + *addend 2*) closely mirror the 2017 task intensity distributions, implying that the observed shifts are primarily driven by within-occupation changes.

Panel A of Figure 2 shows a notable increase in cognitive intensity of 0.07 standard deviation units between 2008 and 2017.[5] The most pronounced shifts are observed in manual and communication intensities, each declining by 0.27 standard deviation units. In addition, the coordination intensity decreases by 0.08 standard deviation units, primarily visible in the upper tail. This suggests an intensity decline among occupations where coordination-intensive tasks are most relevant. Perhaps the most unexpected result is the rightward shift in physical intensity by 0.08 standard deviation units in Panel D, suggesting that physically demanding tasks have become more central in the labor market. While surprising at first glance, this observation aligns with Ingram and Neumann (2006), who document rising returns to physical tasks in the U.S.

[5] To aid interpretation, the measured changes in standardized task intensities (factors) can be evaluated, for example, relative to their 75/25 employment-weighted percentile values in 2008: cognitive [−0.84:0.82]; physical [−0.93:0.77]; manual [−0.56:0.84]; communication [−0.59:0.86]; coordination [−0.62:0.57].

Table 1: Highest Ability Factor Loadings and Highest Ranked Occupations by Factor

Highest Factor Loadings			*Factor Scores*	
*O*NET Ability*	*Loading*	*Highest Ranked Occupations in 2008*	*2008*	*2017*
Factor 1: Cognitive Intensity				
Deductive Reasoning	0.880	1. Astronomers and physicists	2.76	2.74
Problem Sensitivity	0.877	2. Architects (except naval)	2.65	2.46
Inductive Reasoning	0.859	3. Environmental engineers	2.26	1.57
Speed of Closure	0.845	4. Physical scientists, n.e.c.	2.02	2.06
Flexibility of Closure	0.840	5. Marine engineers and naval architects	2.00	1.96
Factor 2: Physical Intensity				
Stamina	0.898	1. Dancers and choreographers	4.30	4.39
Gross Body Coordination	0.880	2. Recreation and fitness workers	2.30	2.67
Trunk Strength	0.842	3. Structural iron and steel workers	2.22	2.30
Dynamic Strength	0.836	4. Masons and reinforcing ironworkers	2.16	2.06
Extent Flexibility	0.834	5. Massage therapists	2.09	2.19
Factor 3: Coordination Intensity				
Night Vision	0.942	1. Aircraft pilots and flight engineers	4.88	4.83
Peripheral Vision	0.939	2. Taxi drivers and chauffeurs	4.22	3.82
Glare Sensitivity	0.908	3. Bus drivers	4.17	3.89
Spatial Orientation	0.905	4. Ship and boat captains and operators	3.80	3.74
Sound Localisation	0.893	5. Motor vehicle operators, n.e.c.	3.70	3.37
Factor 4: Manual Intensity				
Finger Dexterity	0.686	1. Data entry keyers	4.28	2.60
Wrist-Finger Speed	0.547	2. Dentists	3.76	3.61
Perceptual Speed	0.513	3. Optometrists	3.17	2.87
Arm-Hand Steadiness	0.470	4. Medical and dental laboratory technicians	3.12	2.80
Control Precision	0.467	5. Aircraft pilots and flight engineers	2.91	2.72
Factor 5: Communication Intensity				
Speech Recognition	0.616	1. Announcers	3.32	3.12
Speech Clarity	0.591	2. Telephone operators	2.96	2.96
Time Sharing	0.587	3. Communication equipment operators, n.e.c.	2.78	3.01
Oral Expression	0.527	4. Switchboard operators	2.75	3.02
Oral Comprehension	0.510	5. Bailiffs, correctional officers and jailers	2.45	2.26

Notes: 52 standardized O*NET ability scores are assigned to 430 consistently defined occupations. Factor analysis is conducted on the employed population sample from the 2008 ACS. To hold the occupational distribution constant, each individual is duplicated and assigned both 2008 and 2017 ability scores. Principal factor extraction with varimax rotation is used to derive orthogonal factors; all factors with an eigenvalue greater than one are retained. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is 0.96. Factors are standardized such that factor scores represent standard deviations from the 2008 employment-weighted mean.

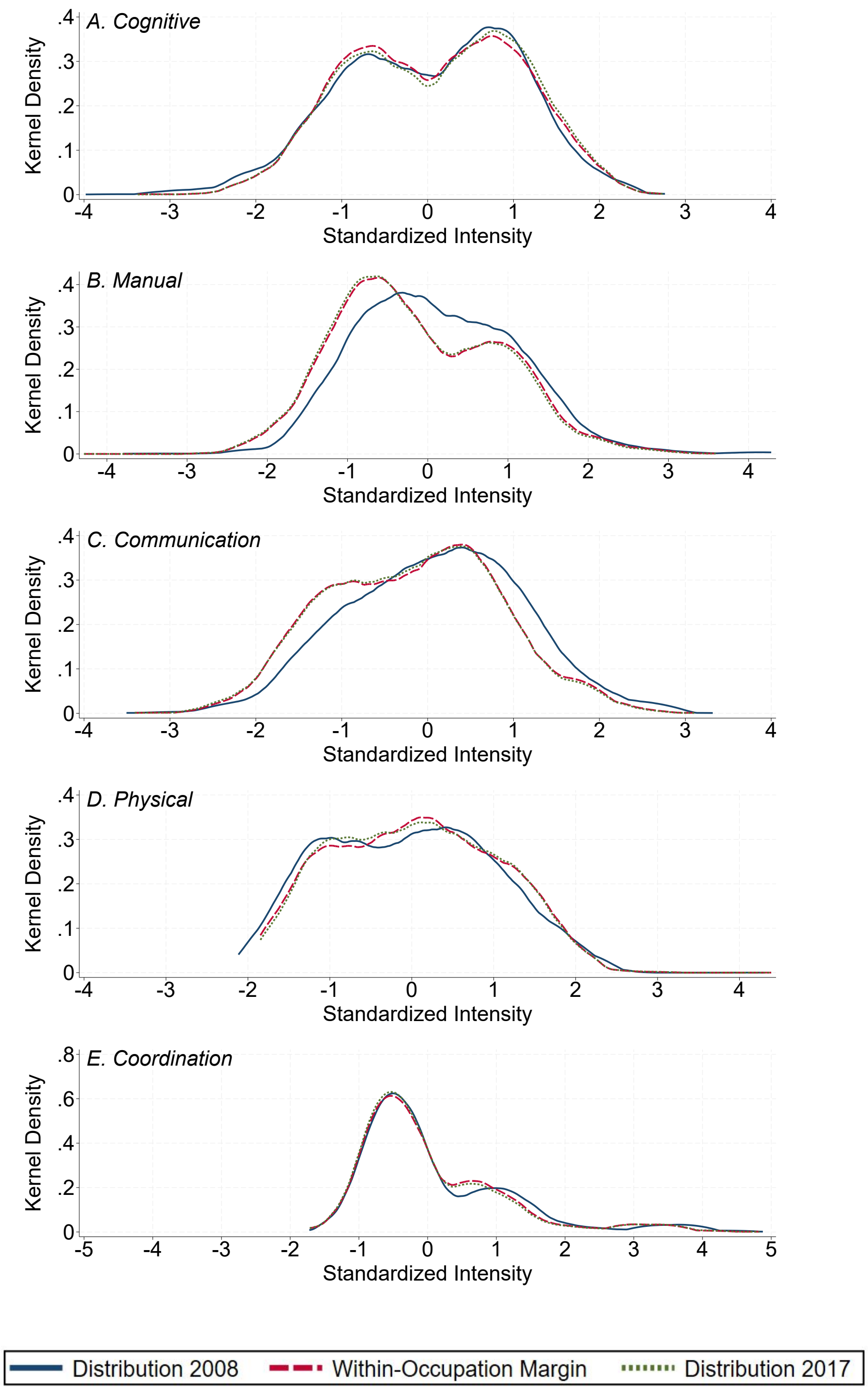

Figure 2: Task Intensity Distributions of the U.S. Workforce: 2008, Intensive Margin and 2017

Notes: The five kernel density distributions represent occupation-year-specific task intensity scores smoothed over the employed U.S. workforce in 2008 and 2017. The within-occupation margin holds the occupational employment distribution constant at 2008 and uses occupations' task intensities from 2017. For a representative illustration of the density distributions, ACS individual weights are multiplied by individuals' annual working hours. The bandwidth used for plotting the distributions is 0.3.

2.3 Occupation-Level Measure

Based on Acemoglu and Restrepo (2018; 2019), the aggregate task composition evolves over time due to two forces driven by technological progress: first, the replacement of tasks through automation; and second, the emergence of new tasks. Autor et al. (2024) shows that the aggregate model can naturally be extended to a multi-sector setting, where sectors correspond to occupations that differ in their task intensities. Building on this framework, I make use of an additional conjecture that is consistent with both the model and recent historical evidence: technological change expands the pool of cognitive-intensive tasks while narrowing the pool of other tasks. Put differently, technological change within occupations is cognitive-biased.

To put more structure on the observed task intensity changes within occupations, I define occupations as bundles of tasks (Acemoglu and Autor 2011). To measure the cognitive bias in task changes, it is sufficient to represent each occupation using two task bundles: cognitive-intensive and non-cognitive-intensive tasks. While the cognitive task intensity can be directly drawn from the factor analysis, the assumption of factor orthogonality allows me to classify the remaining four task intensities (manual, communication, physical, and coordination) as non-cognitive. Accordingly, the cognitive bias in task intensity changes for occupation k between 2008 and 2017 can be defined as follows:

$$\Delta WOCB_k = \underbrace{(\widetilde{CTI}_{k,2017} - \widetilde{CTI}_{k,2008})}_{\text{Direct Effect}} - \underbrace{\sum_{n=1}^{N}(\widetilde{NCTI}_{k,2017} - \widetilde{NCTI}_{k,2008}) \times \frac{1}{N}}_{\text{Replacement Effect}} \tag{3}$$

where $\Delta WOCB_k$ is the change in within-occupation cognitive bias, which can be decomposed into a direct effect and a replacement effect.[6] The direct effect is occupation $k's$ change in cognitive task intensity ($\Delta\widetilde{CTI}_k$). The replacement effect is $k's$ average change in non-cognitive task intensities ($\Delta\widetilde{NCTI}_k$) with $N = 4$. By construction, the bias is zero if both effects move in the same direction and with the same magnitude. However, if the increase in cognitive intensity is larger than the increase in non-cognitive intensity, or if the non-cognitive intensity decreases, task changes within occupation k are positively cognitive-biased.

Figure 3 summarizes the direct, replacement, and total effects by aggregating detailed occupations at the intermediate SOC level. The direct cognitive effect is most pronounced in construction and extraction occupations, while the replacement of non-cognitive-intensive tasks is strongest in transportation and material-moving occupations. Notably, the total change is positive across all

[6] Note that equivalent measures capturing the bias of any other task dimension could be constructed by rearranging the five factors.

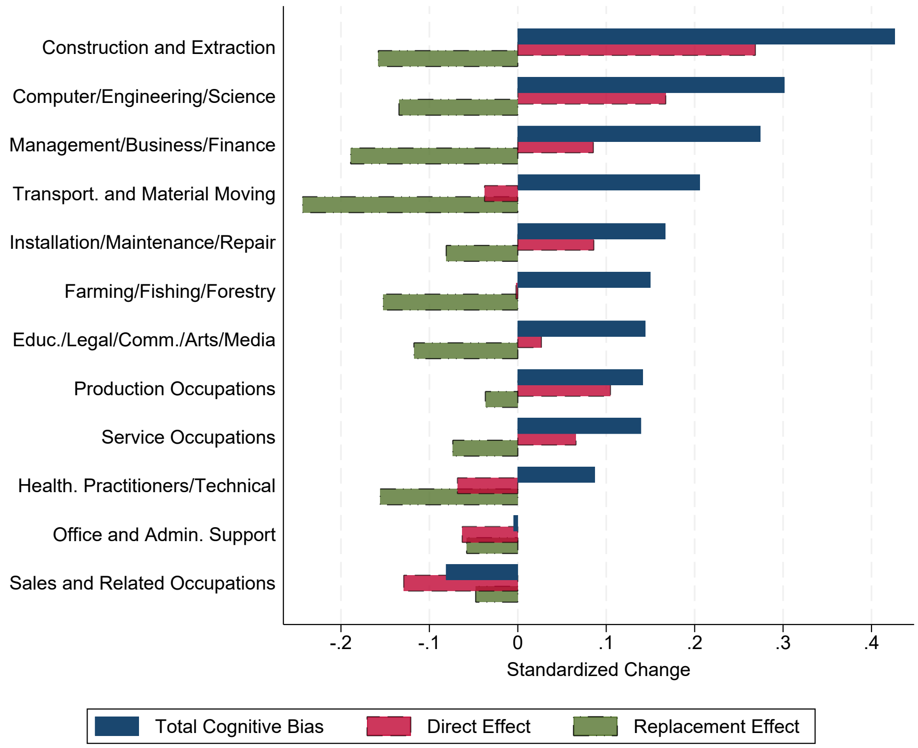

Figure 3: Cognitive and Non-Cognitive Task Intensity Changes Within Occupations

Notes: 430 detailed occupations are aggregated to the SOC intermediate occupation level using 2008 supply-adjusted employment shares as weights. An occupation's cognitive bias is calculated as the direct effect minus the replacement effect, as defined in equation 3. The average change in within-occupation cognitive bias across occupation groups is expressed in standard deviation units relative to the 2008 employment-weighted mean.

occupation groups except for office and sales occupations.[7] The declining relative importance of cognitive-intensive tasks in office and sales occupations may seem surprising at first, as it runs counter to the general direction of technological change. Moreover, it is not in line with the observation by Hershbein and Kahn (2018) that the demand for skill rose most noticeably in routine cognitive occupations after the Great Recession. However, as the authors note, their data reflect employers' stated skill requirements in job advertisements rather than realized changes in skill demand. Crucially, post-crisis shifts in stated skill requirements may have resulted from an oversupplied labor market, allowing employers to be pickier.

Complementing the summarized changes across occupational groups, Table B.1 in the Appendix documents the largest shifts among all 430 occupations. Two key takeaways emerge from Figure 3 and Table B.1. First, the cognitive-biased task intensity changes within occupations

[7]Note that the net effect of cognitive relative to non-cognitive task shifts also depends on how the measure is constructed. Based on equation 3, I assign equal weight to occupations' cognitive intensity change (direct effect) and the average change of the four non-cognitive intensities (replacement effect). I also experimented with alternative weighting schemes, including assigning equal weights to all task intensities. These adjustments do not alter the general patterns presented in Figure 3.

exhibit substantial variation, which can be exploited to construct a measure at the local level. Second, although there are apparent differences between broader occupational groups, the direction of change is not driven by one specific group alone. In fact, most of the variation arises from differences between detailed occupations within the same higher-level occupation categories.

2.4 Local Labor Markets' Exposure to WOCBTC

To define local labor markets, I draw on the widely used concept of commuting zones (CZs, hereafter), introduced by Tolbert and Sizer (1996). This concept provides a meaningful representation of local labor markets, as workers are highly likely to both live and work within the same CZ.[8] The 741 CZs used in this study span the entirety of the United States, including Alaska and Hawaii, while excluding Puerto Rico and other island areas with insufficient population counts.

Local labor markets are specialized in different industries, which in turn shapes the demand for workers across occupations (see, e.g., Autor and Dorn 2013). I exploit the spatial variation in occupational composition, combined with the computed within-occupation changes in cognitive task bias, to construct the following measure:

$$WOCBTC_{l,t} = \sum_{k=1}^{K} \mathbf{\Phi}_{l,k,t} \left[(\widetilde{CTI}_{k,t+1} - \widetilde{CTI}_{k,t}) - (\widetilde{NCTI}_{k,t+1} - \widetilde{NCTI}_{k,t}) \right] \tag{4}$$

where the local exposure to $WOCBTC_{l,t}$ depends on the shares of total working hours $\mathbf{\Phi}_{l,k,t}$ for occupations $k = 1, ..., K$ within CZ l, and the occupation-specific changes in cognitive task bias measured between t and $t+1$. As defined in the previous section, these changes are composed of the change in cognitive task intensity and the average change in non-cognitive task intensities between 2008 and 2017. Since the occupation shares of total working hours within each CZ are held constant at their initial levels, the constructed measure captures CZ l's exposure to cognitive-biased technological change coming solely from expected within-occupation task shifts.

Although the local exposure measure is grounded in systematic data transformations and theory-consistent assumptions, alternative specifications may also be plausible. Therefore, I test the robustness of the main results in Section 4 using various modifications of the WOCBTC measure. The robustness checks are documented in Section D.1 of the Appendix. They include estimating the direct and replacement effects separately, assigning equal weights to all task intensities, and using ability classifications directly from O*NET instead of deriving task intensities with the help of factor analysis. Overall, the effects remain robust to these modifications.

[8] The procedure used to map ACS microdata to commuting zones (CZs) follows Dorn (2009) and is described in Section A.2 of the Appendix.

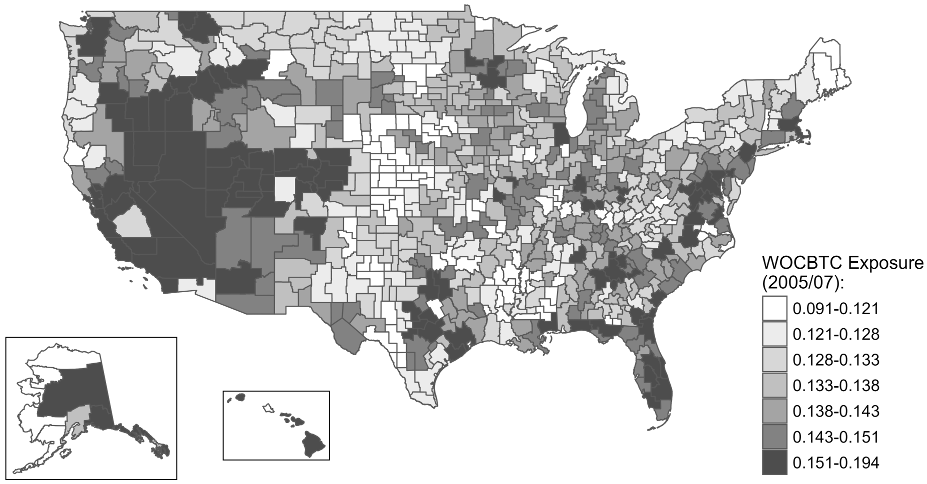

Figure 4: Local Labor Markets' Exposure to WOCBTC

Notes: The map displays 741 CZs based on the classification of Tolbert and Sizer (1996), covering the entire United States. Alaska and Hawaii are shown separately in the bottom left due to their geographic distance. The CZ-level WOCBTC measure is constructed as in equation 4. CZs are grouped into seven equally sized bins; darker shades indicate greater WOCBTC exposure. WOCBTC exposure is the average within-occupation change in standard deviation units relative to the 2008 employment-weighted mean.

Figure 4 visualizes the variation in exposure to cognitive-biased task shifts across the 741 CZs in the U.S., with darker colors indicating higher exposure to WOCBTC.[9] CZ-level exposure ranges from 0.091 in a rural area of Alaska to 0.194 in a metropolitan area of California. The local exposure scores are positive across all CZs, reflecting the overall shift toward cognitive-intensive tasks in the U.S. economy. The map also reveals regional clustering, with CZs in the western and eastern parts of the country exhibiting notably higher exposure. To account for this in the main analysis, I focus on between-CZ, within-state variation. In addition, I apply state-of-the-art shift–share inference methods that allow for potential error term correlation between regions with similar industrial structures (Adao et al. 2019; Borusyak et al. 2022), as explained in Section 4.1.

3 Innovation, WOCBTC and the Role of Population Density

The WOCBTC measure constructed in the previous section rests on the inherent assumption that cognitive-biased task intensity changes reflect the adaptation to new technologies. As this is a plausible but strong assumption, this section empirically tests whether the cognitive-biased task shifts are truly spurred by technological progress. To do so, I first construct a local measure of patent diffusion, following Lin (2011). Using the local diffusion of patents allows me to explore

[9] For comparison, Figure E.1 in the Appendix presents two separate maps showing CZs' exposure to changes in within-occupation cognitive intensity (direct effect) and non-cognitive intensity (replacement effect).

a potential link between innovation and task intensity changes, as patents often relate directly to complementing or automating work processes within occupations. In addition, this section examines the role of population density in shaping the adaptation to new technologies.

3.1 The Diffusion of Innovation into Local Labor Markets

The patent data are sourced from the United States Patent and Trademark Office (USPTO) and are described in detail in Appendix Section A.3. To link patents to CZs, I first construct an industry-level measure of patent diffusion, drawing on the observation that patents do not uniformly affect all industries (Goldschlag et al. 2020; Autor et al. 2024). For example, a patent related to the invention of a new excavation machine would most likely fall under the CPC subclass "soil working in agriculture or forestry." While the adoption of such a machine may impact industries reliant on soil work, it is unlikely to affect other industries.

To systematically assign patents to industries, I use the CPC-to-industry crosswalk provided by Goldschlag et al. (2020).[10] By combining fine-grained patent classifications with six-digit industry codes, the crosswalk yields a linkage matrix containing probabilities between zero and one, indicating the likelihood that patents within a given CPC subclass influence industry j.[11] This is denoted by the matrix $\mathbf{A}$. Next, I aggregate patents granted between 2005 and 2019 by CPC subclass, denoted by the one-column matrix $\boldsymbol{B}$. The CPC-level patent counts are then multiplied by the $J \times CPC$ linkage matrix $\mathbf{A}$ to construct a weighted measure of industry-level patent diffusion. Finally, I exploit differences in industrial composition across CZs to derive a local-level measure of patent diffusion, defined as:

$$Inn_{l,t} = \sum_{j=1}^{J} \mathbf{\Omega}_{l,j,t} \left[\mathbf{A}_{J,CPC} \otimes \mathbf{B}_{CPC,1} \right] \tag{5}$$

where $\mathbf{\Omega}_{l,j,t}$ denote industry employment shares, which are multiplied by the weighted industry-level patent diffusion and aggregated over all industries in CZ l.

Goldschlag et al. (2020) show that industries' exposure to innovation is highly persistent, suggesting that the local diffusion through industries over time is endogenous. To address this and gain a clearer view of local labor markets' exposure to long-term innovation, I construct a second measure using only "breakthrough innovations," as classified by Kelly et al. (2021).[12]

[10] CPC refers to the Cooperative Patent Classification. This crosswalk updates the earlier IPC-to-industry mapping by Lybbert and Zolas (2014), using probabilistic linkages derived from text mining of patent abstracts and industry classification descriptions.

[11] Since Goldschlag et al. (2020) use the NAICS industry classification system, I map the resulting patent diffusion probabilities to the broader but compatible IND1990 classification used in the IPUMS Census and ACS data.

[12] Kelly et al. (2021) classify U.S. patents by decade as breakthrough or non-breakthrough based on their novelty and long-run impact on future patents, using natural language processing tools.

Specifically, I use the top 10% of lagged breakthrough patents granted in the 1980s and 1990s, combined with lagged local industry compositions from the 2000 Census. While the diffusion of innovation appears more concentrated in the East and on the West Coast, it is worth noting that these regions are simultaneously the most populated in the U.S. This relationship, along with the link between innovation and WOCBTC, is analyzed in the next section.[13]

3.2 Empirical Results

Figure 5 illustrates the raw relationships between innovation diffusion, population density, and WOCBTC.[14] CZs are sorted into percentiles for each measure and weighted by their population shares relative to the total U.S. population in 2005–07. Panels A and B reveal a strong positive relationship between innovation diffusion and cognitive-biased task shifts within occupations. As expected, this relationship remains robust whether innovation is measured using all patents granted between 2005 and 2019 or the top 10% of lagged breakthrough patents, reflecting the persistence of innovation over time. Panel C shows a strong positive correlation between CZs' population density and WOCBTC exposure, while the relationship between population density and the diffusion of innovation in Panel D is somewhat weaker but still clearly positive. Although purely descriptive, the figure suggests that population agglomeration may play a crucial role in the local adoption of new technologies within occupations. To better disentangle the effect of CZs' initial population density from that of innovation, I estimate models of the form:

$$WOCBTC_{l,s,t} = \alpha_t + \beta_1 \, Inn_{l,s,t} + \beta_2 \, Den_{l,s,t_0} + \gamma \, X_{l,s,t_0} + \delta_s + e_{l,s,t} \tag{6}$$

where the dependent variable is the normalized $WOCBTC_{l,s,t}$ exposure in CZ l in state s. $Inn_{l,s,t}$ is the log innovation diffusion based on patents granted between 2005 and 2019, and Den_{l,s,t_0} is l's log population density in 2005–07. The control vector X_{l,s,t_0} captures CZs' initial college worker share, the share of offshorable occupations, manufacturing share, routine task intensity, and employment shares of the five major occupation groups.[15] In addition, the model includes a vector of state dummies, δ_s, to account for state-dependent institutional factors such as unionization,

[13] Figures E.2 and E.3 in the Appendix visualize the diffusion of patents across industries, as well as the geographical contemporary and long-term patent diffusion across CZs.

[14] See Section A.2 of the Appendix for details on how the CZ-level population density is calculated. For the construction of the worker sample using ACS data, see Appendix Section A.1.

[15] The selection of the covariates is based on the literature on routine-biased technological change and trade competition in the U.S. (see, e.g., Autor and Dorn 2013; Autor et al. 2013; Autor et al. 2015), as well as task offshorability (see, e.g., Blinder et al. 2009; Grossman and Rossi-Hansberg 2008; Firpo et al. 2011). Including these labor market controls mitigates bias by reducing variation in the error term correlated with WOCBTC and the explanatory variables of interest. For brevity, the control variable coefficients are omitted from the presented tables.

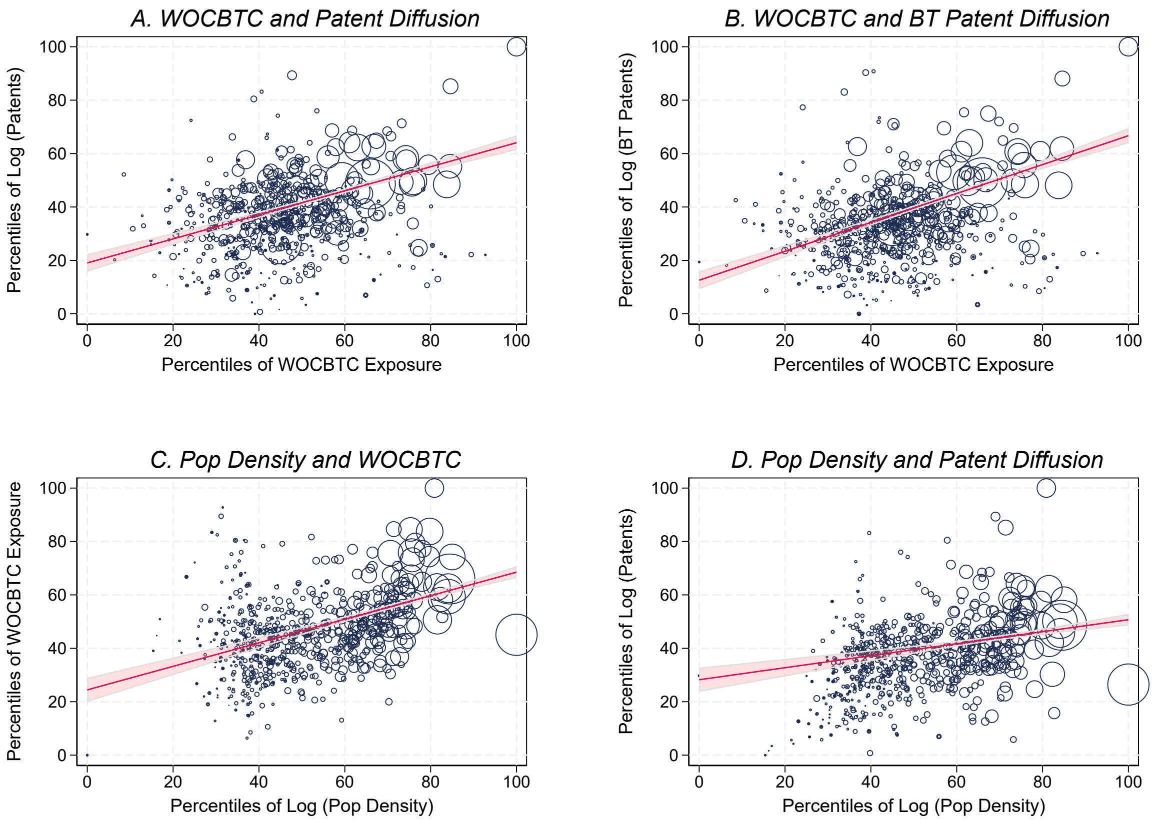

Figure 5: Relationships between Patent Diffusion, Exposure to WOCBTC and Population Density across Local Labor Markets

Notes: The figure presents relationships across 741 CZs. Panel A plots WOCBTC exposure against the log diffusion of patents (2005–2019). Panel B plots WOCBTC exposure against the lagged log diffusion of the top 10% breakthrough patents (1981–2000) from Kelly et al. (2021). Panel C displays the relationship between log population density and WOCBTC exposure, while Panel D plots log population density against the log diffusion of patents. WOCBTC is constructed as in equation 4. Local patent diffusion is measured via industry-level flows, using the crosswalk by Goldschlag et al. (2020) and CZs' industrial composition, following equation 5. CZs are grouped into percentiles, weighted by their population shares in 2005–07.

minimum wages, and labor laws. Standard errors are clustered at the state level.

I begin with a baseline OLS model that includes only a constant and patent diffusion as independent variables. For ease of interpretation, all variables are normalized to range between zero and one. The coefficient in column (1) of Table 2 suggests that a 10% increase in log patent diffusion is associated, on average, with a 5.29% higher exposure to WOCBTC. Notably, spatial differences in patent diffusion account for approximately one-quarter of the total variation in within-occupation cognitive-biased task intensity shifts across CZs, as reflected by an R^2 of 0.24. The strong predictive power reassures that the novel measure of WOCBTC is genuinely linked to technological progress.

Including population density as an explanatory variable (column (2)) reveals that a 10%

increase in log population density is associated with a 3.43% higher exposure to WOCBTC. However, when the full set of controls is introduced (column (4)), this relationship becomes both statistically and economically insignificant. This likely reflects omitted variable bias in columns (1)–(3), stemming from the fact that metropolitan areas differ from less-dense suburban and rural areas across several dimensions, including skill endowment and occupational structure. Controlling for initial labor market characteristics is therefore important to capture the underlying relationship between local population density and WOCBTC. In contrast, the association between innovation and WOCBTC remains positive and statistically significant—albeit slightly attenuated—when population density and additional controls are included. Furthermore, including control variables improves the precision of the point estimate related to innovation, reinforcing the robustness of the observed positive relationship with WOCBTC.

The final column extends equation 6 by additionally including an interaction term between innovation diffusion and population density ($Inn_{l,s,t} \times Den_{l,s,t_0}$), allowing the effect of innovation on WOCBTC to vary with the degree of agglomeration across CZs.[16] The results indicate that population agglomeration has no direct effect on WOCBTC but significantly amplifies the impact of innovation. Taken at face value, a 10% increase in innovation diffusion is associated with a 2.46% rise in WOCBTC exposure. This effect is amplified by 6.21 times the centered value of a CZ's population density. For example, at the 90$^{\text{th}}$ percentile, where the centered population density of a CZ is 0.22, the total effect of innovation reaches 3.83% (2.46% + 0.22 $\times$ 6.21%). These findings complement earlier work by Beaudry et al. (2010) and Berger and Frey (2016), who highlight the importance of relative skill concentration (i.e., the amount of high- relative to low-skilled workers) in the adoption of computer capital. In contrast, my results underscore the broader influence of population density (i.e., the abundance of skills) on technology adoption.

To address the previously mentioned endogeneity of patent flows, I follow Autor et al. (2024) and instrument the contemporary patent diffusion with the diffusion of the top 10% breakthrough patents from the two preceding decades.[17] The intuition behind this strategy is that breakthrough patents stimulate downstream innovation within the same patent class, whereas contemporary patent flows do not trigger immediate breakthrough developments (Kelly et al. 2021; Autor et al.

[16] To improve interpretability, all covariates are mean-centered. This means that the coefficients on innovation and population density represent average partial associations (i.e., when the interacting variable is at its mean). As noted by Wooldridge (2016), mean-centering also helps reduce multicollinearity between interaction and main effects without affecting the interaction term itself. To maintain consistency with this terminology, the description of the OLS results in this paragraph intentionally uses "effect language," which here refers to associational effects rather than causal effects.

[17] Autor et al. (2024) implement this identification strategy at the broad occupation and industry level. I extend their approach to the local labor market level. The 2SLS results reported in this section remain highly robust when varying the breakthrough threshold (e.g., 5% or 20%) and/or the time lags.

Table 2: The Impact of Innovation Diffusion and Population Density on WOCBTC

(Dependent Variable: Local Labor Markets' Exposure to WOCBTC)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Panel A. OLS Estimates					
Innovation	0.529***	0.437***	0.481***	0.371***	0.246***
	(0.117)	(0.111)	(0.100)	(0.073)	(0.064)
Pop Density		0.343***	0.315***	-0.061	-0.035
		(0.094)	(0.049)	(0.074)	(0.071)
Innovation×Pop Density					0.621***
					(0.214)
R^2	0.24	0.35	0.70	0.81	0.81
Panel B. 2SLS Estimates					
Innovation	0.666***	0.510***	0.534***	0.401***	0.226**
	(0.123)	(0.111)	(0.111)	(0.099)	(0.097)
Pop Density		0.326***	0.301***	-0.058	-0.025
		(0.078)	(0.053)	(0.070)	(0.066)
Innovation×Pop Density					0.813***
					(0.261)
F-stat. (Innovation)	842.48	662.27	639.97	402.03	214.76
F-stat. (Innovation×Pop Density)					431.31
Census state dummies	X	X	√	√	√
Labor market controls	X	X	X	√	√

Notes: The dependent variable is CZs' exposure to WOCBTC, based on the local occupational structure in 2005–07. In Panel A, innovation diffusion is the log diffusion of patents through industries into CZs between 2005 and 2019, using CZs' industrial composition in 2005–07. In Panel B, patent diffusion is instrumented by the log diffusion of the top 10% of breakthrough patents (1981–2000) from Kelly et al. (2021), based on CZs' industrial structure in 2000. Other covariates include log population density, college share, exposure to offshoring, manufacturing share, routine intensity, and the employment shares of the five major occupation groups, all measured at 2005–07 levels. All variables are normalized to range between 0 and 1. All models include Census state dummies and a constant. Models are weighted by the population shares of CZs in 2005–07. Robust standard errors clustered at the state level are shown in parentheses. ***/**/* represent the 1%, 5%, and 10% significance levels.

2024). Constructed at the CZ level based on predetermined industrial structures, the resulting spatial variation captures plausibly exogenous differences in long-term innovation exposure.

The 2SLS estimates in Panel B of Table 2 closely mirror the OLS results. This is not surprising, given the high persistence of patent flows through industries and the simultaneous stability of local industrial composition over time—reflected by F-statistics well above 100 in the first-stage regressions. The only notable difference is a larger interaction effect compared to the OLS results, indicating that every 10% increase in population density amplifies the long-term impact of innovation on cognitive-biased task intensity changes by a substantial 8.13%.

The significant interaction term in Table 2 indicates that the local adaptation to new technologies varies systematically across CZs with different population densities. To further unpack this relationship, I divide CZs into metropolitan and non-metropolitan labor markets, classifying a CZ as metropolitan if at least one household resides in a Census-defined metropolitan area.[18] Estimating equation 6 for metropolitan and non-metropolitan labor markets separately also helps to isolate the effect of innovation on WOCBTC from unobserved location differences not captured by population density. In addition, Table 3 presents the estimated effects of innovation on the five task intensity changes individually to provide better insight into the channels through which innovation shapes the cognitive-biased local task evolution. All estimations follow the specification in column (4) of Table 2, including state fixed effects and the labor market control vector.

Across all labor markets, innovation increases the relative cognitive intensity within occupations, with both the direct and replacement effects contributing substantially to this technology-driven task evolution. With the exception of coordination intensity, all estimated effects reported in Table 2 are highly significant and closely align with the broader task intensity trends in the U.S. economy illustrated in Figure 2, confirming the strong link between innovation and within-occupation task shifts. Quantitatively, a 10% increase in innovation diffusion raises the localised cognitive intensity by 3.83%, while manual and communication intensities decline by 3.53% and 4.09%, respectively. Interestingly, even the unexpected overall increase in physical intensity identified in the previous section appears to be significantly associated with innovation (2.87%)—a promising avenue for future research, though beyond the scope of this study.

When estimating the effect of innovation on WOCBTC separately for metropolitan and non-metropolitan labor markets, it becomes evident that metropolitan areas drive the overall significant and positive relationship. In areas without a metropolitan core, the effect becomes both statistically and economically insignificant when using the lagged diffusion of breakthrough patents for identification. Moreover, the task intensity effects differ substantially between the OLS and 2SLS estimates, with the effect on communication intensity even reversing from negative to positive. Overall, the findings clearly suggest a weaker relationship between innovation diffusion and WOCBTC in non-metropolitan areas.[19]

The key takeaway from this section is that the uneven diffusion of innovation disproportionately increases within-occupation cognitive task input in densely populated labor markets. Intuitively, this pattern may help to explain recent local divergences in skill premiums shown in Figure 1. To substantiate this link, it is necessary to demonstrate that WOCBTC influences both the supply of skills and local wage setting. The next section investigates this hypothesis.

[18]The results are robust under alternative classifications—for example, requiring all households to live in a metropolitan area or setting the threshold at a 50% metropolitan share.

[19]When interpreting the results in columns (5) and (6), it is important to consider that the occupational and industrial composition in non-metropolitan CZs, by construction, contains greater measurement error compared to CZs encompassing a large share of Census-defined metropolitan areas. As discussed in Appendix Section A.2, this stems from the incongruities between ACS PUMA and CZ boundaries in less populated areas.

Table 3: The Impact of Innovation Diffusion on WOCBTC for Different Local Labor Markets
(Dependent Variables: Expected Change in Local Labor Markets' Cognitive Task Bias & Task Intensities)

	All LLMs		***Metropolitan***		***Non-Metropolitan***	
	OLS	*2SLS*	*OLS*	*2SLS*	*OLS*	*2SLS*
A: WOCBTC	0.371***	0.401***	0.400***	0.439***	0.220*	0.028
(Total Effect)	(0.073)	(0.099)	(0.084)	(0.105)	(0.130)	(0.207)
R^2 / F-stat.	0.81	402.03	0.84	262.96	0.51	141.96
B: Δ Cognitive	0.370***	0.383***	0.423***	0.436***	0.313**	0.250
(Direct Effect)	(0.092)	(0.110)	(0.108)	(0.118)	(0.147)	(0.316)
R^2 / F-stat.	0.72	402.03	0.77	262.96	0.54	141.96
C: Δ Non-Cognitive	-0.167***	-0.207***	-0.144***	-0.202**	0.041	0.319
(Replacement Effect)	(0.039)	(0.071)	(0.052)	(0.083)	(0.128)	(0.205)
R^2 / F-stat.	0.72	402.03	0.78	262.96	0.42	141.96
D: Δ Manual	-0.225***	-0.353***	-0.235**	-0.363**	0.172	0.079
	(0.073)	(0.135)	(0.094)	(0.154)	(0.161)	(0.280)
R^2 / F-stat.	0.76	402.03	0.80	262.96	0.51	141.96
E: Δ Communication	-0.323***	-0.409***	-0.334***	-0.451***	-0.166	0.207
	(0.069)	(0.096)	(0.085)	(0.107)	(0.178)	(0.185)
R^2 / F-stat.	0.68	402.03	0.76	262.96	0.47	141.96
F: Δ Physical	0.208***	0.287**	0.268***	0.365***	0.169	0.009
	(0.073)	(0.112)	(0.082)	(0.111)	(0.146)	(0.242)
R^2 / F-stat.	0.70	402.03	0.76	262.96	0.55	141.96
G: Δ Coordination	0.028	0.081	0.047	0.083	-0.016	0.341
	(0.048)	(0.068)	(0.060)	(0.081)	(0.142)	(0.265)
R^2 / F-stat.	0.50	402.03	0.62	262.96	0.45	141.96
Census state dummies	✓	✓	✓	✓	✓	✓
Labor market controls	✓	✓	✓	✓	✓	✓
Broad occ emp. shares	✓	✓	✓	✓	✓	✓
Observations	741	741	378	378	363	363

Notes: CZs are classified as metropolitan if at least one household in the designated CZ resides in a Census-defined metropolitan area, and as non-metropolitan otherwise. The dependent variables are WOCBTC exposure (Panel A) and predicted task intensity changes (Panels B–G), based on the local occupational composition in 2005–07. In the OLS regressions, innovation diffusion is the log diffusion of patents through industries into CZs between 2005 and 2019, using CZs' industrial composition in 2005–07. In the 2SLS regressions, patent diffusion is instrumented by the log diffusion of the top 10% of breakthrough patents (1981–2000) from Kelly et al. (2021), based on CZs' industrial structure in 2000. Other covariates include log population density, college share, exposure to offshoring, manufacturing share, routine intensity, and the employment shares of the five major occupation groups, all measured at 2005–07 levels. All variables are normalized to range between 0 and 1. All models include Census state dummies and a constant. Models are weighted by the population shares of CZs in 2005–07. Robust standard errors clustered at the state level are shown in parentheses. ***/**/* represent the 1%, 5%, and 10% significance levels.

4 Labor Market Analysis

4.1 Shift–Share IV

The main challenge in identifying the long-term impact of WOCBTC on differential employment and wage developments lies in the endogenous nature of technological change. Recall that the WOCBTC exposure measure constructed in Section 2.4 is based on two components: first, task-intensity changes within occupations, and second, CZs' initial occupational composition. The occupational structure observed in 2005–07 is likely influenced by contemporaneous economic disturbances, introducing measurement error and potential bias in either direction. To isolate more exogenous variation that is correlated with WOCBTC but uncorrelated with contemporary confounders, I adopt the identification strategy used by Autor and Dorn (2013). Specifically, I construct a Bartik-style shift–share instrument (Bartik 1991) by interacting local industrial specialization with predetermined national occupation shares within industries:

$$\widehat{WOCBTC}_{l,t} = \sum_{j=1}^{J} \mathbf{\Omega}_{j,l,2000} \times \mathbb{E}\left[WOCBTC_{j,-l,2000}\right] \tag{7}$$

where the employment share $\mathbf{\Omega}_{j,l}$ of each industry j in CZ l is calculated using the lagged industrial composition from the 5% sample of the 2000 Census.[20] The second factor in equation 7 captures each industry's expected change in cognitive task bias, constructed by multiplying national occupation shares within industries by the associated within-occupation cognitive-biased task intensity changes derived in Section 2. Following Autor and Duggan (2003), I exclude the state containing CZ l when computing the industry-specific WOCBTC exposure to avoid mechanical correlation between the instrument and the original exposure measure. This leave-one-out correction is denoted by the subscript $-l$. Aggregating the product of local industry shares and expected WOCBTC across industries yields a predicted measure of CZ l's exposure to WOCBTC.

The identifying assumption is that industries employing occupations with larger technology-induced cognitive-biased task intensity changes are not differentially affected by other labor market shocks. This follows Adao et al. (2019) and Borusyak et al. (2022), who propose a framework that leverages exogenous variation in shocks while allowing exposure shares to be endogenous ("shock exogeneity"). In a different approach, Goldsmith-Pinkham et al. (2020) assumes exogenous exposure shares but endogenous shocks ("share exogeneity"). Although I strengthen the identification using predetermined local industry shares, these may not be fully exogenous be-

[20] Workers are assigned to 224 detailed industries using the consistent industry classification IND1990 available in IPUMS Census data.

cause other unobserved shocks could potentially influence CZ-level outcomes through the same mixture of persistent industries. Shock exogeneity seems more plausible, especially given the prior section's finding that cognitive-biased task shifts within occupations are closely linked to breakthrough innovations from earlier decades.

To assess whether the cognitive-biased demand shocks are quasi-randomly assigned to CZs, I conduct shock-balance tests (see, e.g., Dauth et al. 2021; Borusyak et al. 2022) by regressing potential confounders on the shift–share instrument and a constant. The results are reported in Table 4. For comparability, all shock-balance variables are standardized to have a mean of zero and a standard deviation of one. Panel A presents estimates corresponding to initial local labor market characteristics in 2005–07, which are identical to the control variables used in the fully specified model presented in the following section. Overall, only two out of eight variables exhibit a significant relationship with the shift–share IV. However, the significant associations with the share of foreign-born workers and workers near retirement age suggest that these groups may experience different labor supply dynamics. In numbers, a 10% higher predicted exposure to WOCBTC is associated with a 0.55 standard deviation higher share of foreign-born workers and a 0.22 standard deviation lower share of individuals aged over 55. Besides controlling for these characteristics in the model, I further examine their role by splitting the sample by age, gender, and country of birth in a robustness check in Appendix Section D.2. Despite noticeable heterogeneity—particularly across age groups—the overall employment and wage patterns presented in the following sections remain clear and consistent.

Panel B of Table 4 assesses the role of various pre-trends, capturing changes from 1990 to 2000 in skill intensification (college share), worker agglomeration (working-age population), exposure to trade shocks (manufacturing share), and worker productivity (average wages). An obvious threat to the identifying assumption is that a faster preceding increase in relative skill supply in some regions may have induced technological progress to become more skill-complementary (Acemoglu 1998). If such a supply-driven technology effect were sufficiently strong, it could influence the long-run relative wage evolution of differently skilled workers. However, the economically and statistically insignificant coefficient for the change in the share of college-educated workers provides no empirical evidence for this concern. Put differently, historical variation in relative skill supply across CZs does not predict their subsequent exposure to cognitive-biased task intensity changes. Likewise, the shift–share IV shows no significant relationship with lagged changes in local manufacturing employment or average wages, although these estimates are somewhat larger than those for lagged relative skill supply changes.

Table 4: Shock-Balance Tests at the Commuting Zone Level
(Dependent Variables: Standardised CZ Characteristics)

Regional Balance Variable	Estimate	SE
Panel A. Initial labor market characteristics in 2005–07		
% of college-educated	2.353	[2.775]
% of employment among women	-0.309	[0.741]
% of foreign-born	5.485	[3.208]
% of working-age population ≥ 55	-2.197	[1.040]
% of manufacturing employment	-2.169	[1.466]
Occupation offshoribility	2.799	[2.594]
Routine task intensity	-2.319	[1.558]
Log population density	1.391	[2.349]
Panel B. Pre-trends: 1990-2000		
Δ share college-educated	0.153	[0.626]
Δ share manufacturing employment	0.786	[0.511]
Δ log working-age population	5.057	[2.199]
Δ log average wages	1.786	[1.114]

Notes: $N = 741$ CZs. The table reports shock-balance estimates from bivariate 2SLS regressions of CZ-level characteristics on the shift–share IV. The instrumented WOCBTC measure is normalized to range between 0 and 1. All dependent variables are standardized to have zero mean and unit standard deviation. Panel A presents estimates for initial labor market characteristics. The occupation offshorability index follows Firpo et al. (2011), and the routine task intensity measure is an updated version of the manual routine index by Autor and Dorn (2013). Both indices are originally defined at the occupation level. CZ-level exposure is then calculated using occupation shares from the ACS 2005–07 sample. Panel B shows estimates for pre-trends, constructed from changes in CZ-level averages between 1990 and 2000 using Census 5% samples. All models include a constant and are weighted by the population shares of CZs in 2005–07. Exposure-robust standard errors are clustered at the broad industry level, using the approach of Adao et al. (2019).

The only pre-trend that stands out as a significant predictor of CZs' exposure to cognitive-biased task intensity changes in the twenty-first century is the preceding growth in the working-age population. This pre-trend is strongly correlated with the shift–share IV at the 1% level and economically substantial: a 10% greater predicted exposure to WOCBTC is associated with a 0.51 standard deviation higher population growth rate between 1990 and 2000. Although the sensitivity analysis in Appendix Section D.3 shows that accounting for agglomeration pre-trends dampens the estimated effects of WOCBTC on relative employment and wage growth, this finding supports the prior suggestion that agglomeration effects and technological change positively influence each other rather than undermining the study's overall conclusions. However, due to the lack of historically time-varying occupation-level data, I cannot directly determine whether uneven population growth between 1990 and 2000 caused the divergent cognitive task intensity developments across CZs a decade later, or whether the persistence of technological progress independently shaped long-term spatial agglomeration. While this study assumes the latter to uphold the identifying assumption, it also highlights the possibility that local labor markets have been caught in a self-reinforcing cycle of cognitive-biased technological change and population growth over recent decades.

Another key challenge in using a shift–share IV lies in statistical inference, as CZs with similar industrial structures are prone to correlated error terms (Adao et al. 2019; Borusyak et al. 2022). This correlation risks understating conventional standard errors. Recent methodological advances in shift–share IV inference address this issue. In particular, Adao et al. (2019) propose computing exposure-robust standard errors by first estimating IV regressions at the industry level (i.e., shock level) and then applying the resulting standard errors at the local level. I adopt this approach in the following empirical analysis. Throughout the remainder of the paper, I report both conventional state-clustered and exposure-robust industry-clustered standard errors for comparison.[21]

4.2 Employment Effects

I classify workers into three skill groups based on their educational attainment. Low-skilled workers comprise high school dropouts and high school graduates without college experience. Middle-skilled workers have some college education but no bachelor's degree, while high-skilled workers hold at least a four-year bachelor's degree.[22] In this section, I begin by examining the effects on employment growth. The estimated model, which is applied interchangeably to relative skill supply and wage growth outcomes, takes the following form:

$$100 \times \Delta\, Emp_{l,s,t} \;=\; \alpha_t \;+\; \beta\, WOCBTC_{l,s,t} \;+\; \gamma\, X_{l,s,t_0} \;+\; \delta_s \;+\; e_{l,s,t} \tag{8}$$

where the dependent variable is the decennial change in log worker counts or log full-time equivalent (FTE) employment[23] in CZ l in state s. The key explanatory variable, $WOCBTC_{j,s,t}$, measures within-occupation cognitive-biased technological change. In the 2SLS model, this measure

[21]The exposure-robust standard errors based on Adao et al. (2019) are conceptually similar to those in Borusyak et al. (2022). In theory, Adao et al. (2019) standard errors are slightly more conservative, as their construction relies on one additional assumption.

[22]The three-group skill classification is motivated by the well-established economic insight that technological change in recent decades has primarily crowded out middle-skilled jobs, which have been more susceptible to automation (e.g., Autor et al. 2003; Goos et al. 2009; Autor and Dorn 2013). Categorizing workers into three skill groups—instead of distinguishing only between high- and low-skilled workers—allows for the identification of potential polarization effects.

[23]Following Autor et al. (2024), I calculate FTE employment by summing annual working hours of individuals in a CZ and dividing them by the product of 35 working hours and 50 weeks.

is instrumented using the shift–share IV. The coefficient of interest is β. Census state dummies, δ_s, are included to isolate variation between CZs within states. Additionally, I control for initial local labor market characteristics, summarized by X_{j,s,t_0}. This set of controls corresponds to the same variables examined in Panel A of Table 4. To account for differences in labor market size, all models are weighted by CZs' initial population shares in 2005–07.

Table 5 reports the OLS and 2SLS estimates, with coefficients multiplied by 100 to approximate percentage changes. Beginning with naïve OLS estimation without controls, the results in columns (1) and (4) suggest that a 10% increase in WOCBTC exposure is associated with a 3.14% differential rise in worker counts and a 2.79% increase in FTE employment. Noteworthy is the high explanatory power, as WOCBTC exposure alone accounts for 36% and 30% of the cross-CZ variation in employment growth. To reassure that the observed positive relationship is not driven by a particular type of local labor market, Figure E.4 in the Appendix splits the CZ sample by initial size and skill endowment, showing that neither of these characteristics systematically biases the relationship between WOCBTC exposure and employment growth.

Notably, the point estimates drop after controlling for initial labor market characteristics in columns (3) and (6). Simultaneously, including the full set of controls reveals substantial heterogeneity across skill groups. The results clearly indicate that the estimated employment gains are concentrated among higher-skilled workers with at least some college education. This is consistent with the nature of technological progress in the twenty-first century, which increases the importance of cognitive-intensive tasks—tasks in which higher-skilled workers tend to have a comparative advantage. By contrast, the effect on employment growth among the least educated is weaker and, at most, statistically significant at the 10% level.

The 2SLS estimates qualitatively mirror the OLS results but are larger in magnitude. This upward adjustment likely reflects the correction of attenuation bias arising from contemporaneous local labor market confounders. A similar pattern is observed in the closely related study by Autor and Dorn (2013), which employs the same identification strategy. In the fully specified 2SLS model, a 10% higher exposure to WOCBTC leads to a 1.54% differential increase in total FTE employment, with corresponding skill-specific growth rates of 2.81%, 1.64%, and 0.93% for high-, middle-, and low-skilled workers, respectively. When accounting for potential correlation in the error term across CZs with similar industrial structures, the use of exposure-robust standard errors (shown in square brackets) renders the low-skill employment effect statistically insignificant. By contrast, the effects on total and high-skill employment remain highly significant under the exposure-robust inference approach of Adao et al. (2019).

Table 5: Effect of WOCBTC on Employment Growth across Local Labor Markets

(Dependent Variable: Decennial Change in Log Worker Counts & Log FTE Employment)

	Δ *Raw Worker Counts*			Δ *FTE Employment*		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Panel A. All Workers						
OLS	31.42***	28.39***	10.85***	27.90***	26.94***	8.88***
	(3.70)	(3.53)	(2.99)	(3.76)	(3.57)	(3.28)
R^2	0.37	0.65	0.80	0.30	0.63	0.78
Shift–Share IV	36.77***	28.16***	17.84***	33.11***	26.53***	15.43***
	(5.13)	(3.24)	(3.82)	(5.51)	(2.76)	(3.48)
	[6.00]	[8.46]	[7.14]	[5.58]	[8.35]	[6.92]
Panel B. High-Skill Workers (College+)						
OLS	29.10***	30.82***	19.80***	25.95***	29.25***	18.25***
	(4.30)	(3.55)	(4.49)	(4.39)	(3.24)	(4.78)
R^2	0.23	0.51	0.58	0.19	0.48	0.53
Shift–Share IV	34.67***	31.86***	29.31***	31.58***	30.77***	28.11***
	(6.24)	(4.33)	(5.62)	(6.25)	(4.09)	(5.89)
	[8.07]	[6.79]	[9.39]	[8.13]	[6.20]	[9.70]
Panel C. Medium-Skill Workers (Some College)						
OLS	15.09***	7.90	12.37***	9.94	6.52	9.60**
	(5.61)	(4.91)	(4.31)	(5.99)	(4.49)	(3.99)
R^2	0.08	0.64	0.72	0.04	0.64	0.72
Shift–Share IV	28.96***	11.56	21.61***	23.51***	9.22	16.42***
	(8.12)	(7.25)	(5.42)	(8.34)	(6.20)	(4.89)
	[16.97]	[9.80]	[9.01]	[16.85]	[9.01]	[9.12]
Panel D. Low-Skill Workers (High School and Dropouts)						
OLS	28.88***	18.93***	5.54*	25.40***	15.70***	3.92
	(3.64)	(3.79)	(3.25)	(3.74)	(3.99)	(3.39)
R^2	0.26	0.62	0.74	0.20	0.62	0.72
Shift–Share IV	36.00***	18.33***	10.55*	33.52***	15.25***	9.32*
	(5.17)	(3.91)	(5.53)	(5.72)	(3.78)	(5.33)
	[7.63]	[7.18]	[7.73]	[8.03]	[6.53]	[7.23]
F-stat.	86.46	77.47	160.60	86.46	77.47	160.60
Census state dummies	X	√	√	X	√	√
Labor market controls	X	X	√	X	X	√

Notes: $N = 741$ CZs. The table reports OLS and 2SLS estimation results. The WOCBTC measure is normalized to range between 0 and 1. In the 2SLS estimations, WOCBTC is instrumented using the shift–share IV defined in equation 7. The dependent variables are the log changes in raw worker counts (Panel A) and FTE employment (Panel B) between 2005–07 and 2015–19. The three skill groups are college+ (H), some college experience but no bachelor's degree (M), and high school graduates and dropouts (L). Outcome variables are multiplied by 100/1.1 to represent decennial percentage changes. Control variables include initial labor market characteristics (college share, foreign population share, female employment share, exposure to occupation offshorability, routine task intensity, manufacturing share, and population density), and 50 Census state dummies. All models include a constant and are weighted by CZs' population shares in 2005–07. Standard errors clustered at the state level are shown in parentheses. ***/**/* represent significance at the 1%, 5%, and 10% levels for the state-level cluster approach. Adao et al. (2019) exposure-robust standard errors clustered at the broad industry level are shown in square brackets.

Table 6: Effect of WOCBTC on Changes in Relative Skill Shares across Local Labor Markets
(2SLS. Dependent Variable: Decennial Change in Log Relative FTE Skill Shares)

	Δ *Rel. Worker Counts*			Δ *Rel. FTE Employment*		
	ln(H/M)	*ln(H/L)*	*ln(M/L)*	*ln(H/M)*	*ln(H/L)*	*ln(M/L)*
Panel A: Aggregate Changes						
	7.70*	18.75**	11.05	11.69***	18.79**	7.09
	(4.66)	(7.35)	(7.43)	(4.47)	(8.07)	(7.41)
	[7.08]	[6.85]	[5.57]	[6.78]	[8.30]	[6.87]
Panel B: Changes Within Broad Occupations						
B.1 Management/Business/ Science/Arts	10.36	21.56***	11.20	12.77*	16.64**	3.87
	(6.92)	(6.07)	(8.70)	(6.81)	(6.55)	(8.67)
	[7.92]	[10.37]	[6.02]	[8.09]	[11.47]	[8.10]
B.2 Service	-7.12	3.37	10.49	-2.99	-1.12	1.86
	(12.63)	(12.26)	(8.61)	(15.53)	(14.83)	(9.26)
	[8.06]	[10.44]	[10.62]	[8.98]	[11.07]	[9.98]
B.3 Sales and Office Admin.	13.84*	16.91*	3.08	22.63**	25.57**	2.94
	(7.18)	(9.34)	(7.10)	(8.84)	(9.95)	(7.08)
	[6.37]	[4.96]	[7.70]	[7.04]	[5.12]	[8.01]
B.4 Resources/Construction/ Maintenance	-27.56	1.30	28.86*	-36.37	-8.30	28.08
	(23.46)	(15.58)	(17.16)	(26.43)	(18.03)	(17.78)
	[18.13]	[17.64]	[11.23]	[21.74]	[19.76]	[13.85]
B.5 Production and Transport.	-0.77	16.02	16.79	6.91	17.00	10.08
	(17.89)	(20.45)	(17.61)	(16.30)	(19.69)	(16.09)
	[15.41]	[13.72]	[11.20]	[13.43]	[16.53]	[10.95]

Notes: $N = 741$ CZs. The table reports 2SLS estimation results. The normalized WOCBTC measure (ranging from 0 to 1) is instrumented using the shift–share IV defined in equation 7. The dependent variables are the log change in relative raw worker counts (columns (1)–(3)) and relative FTE employment (columns (4)–(6)) between 2005–07 and 2015–19. The three skill groups are college+ (H), some college (M), and high school graduates and dropouts (L). The five occupation groups in Panel B correspond to the SOC 2010 major occupation groups. Outcome variables are multiplied by 100/1.1 to represent decennial percentage changes. Control variables include initial labor market characteristics (college share, foreign population share, female employment share, exposure to occupation offshorability, routine task intensity, manufacturing share, and population density), and 50 Census state dummies. All models include a constant and are weighted by CZs' population shares in 2005–07. The first-stage F-statistic is 160.60. Standard errors clustered at the state level are reported in parentheses. ***/**/* represent significance at the 1%, 5%, and, 10% levels for the state-level cluster approach. Adao et al. (2019) exposure-robust standard errors clustered at the broad industry level are shown in square brackets.

Table 6 addresses two further questions arising from the employment growth effects reported in Table 5. First, are the differential effects strong enough to result in a systematic crowding out of lower-skilled workers in more exposed CZs? Second, if so, in which major occupation groups do these shifts occur? To shed light on these questions, I apply the 2SLS model to occupation-group-specific relative log changes in worker counts and full-time equivalent (FTE) employment as outcome variables. Panel A of Table 6 shows that a 10% increase in local WOCBTC exposure raises the relative share of high- to low-skilled workers by 1.88%. The effect is consistent across both raw worker counts and FTE employment. By contrast, middle-skilled workers with some college education experience greater displacement by high-skilled workers in FTE terms, with a 0.77% relative decline in worker counts and an additional 0.40% (1.17% – 0.77%) drop when accounting for relative changes in work hours.

In Panel B of Table 6, the skill composition effect is estimated for the five major occupation groups. Consistent with traditional skill-sorting models based on comparative advantage (e.g., Roy 1951), high-skilled workers predominantly crowd out lower-skilled workers in cognitive-intensive occupations. This includes both non-routine cognitive (management, business, science, and arts) and routine cognitive occupations (sales and office administration). Notably, the exposure-robust standard errors are smaller than the state-clustered standard errors for the crowding-out effect within routine cognitive occupations.

Furthermore, the results in Panel B show that middle-skilled workers increasingly displace low-skilled workers in resources and construction occupations, with similarly lower exposure-robust standard errors. From an economic perspective, this rising relative share of middle- to low-skilled workers is unsurprising, as construction and extraction occupations show the largest increase in cognitive task intensity among all occupation groups, as demonstrated in Figure 3. Consequently, firms in the construction sector may become more cautious when hiring workers without college experience.

4.3 Wage Effects and Skill Premiums

This section examines the differential impact of WOCBTC on local wage growth and changes in the skill premium. Because observed wage changes may be confounded by concurrent compositional shifts across CZs, I follow the literature in constructing composition-adjusted wages (e.g., Autor et al. 1998; Beaudry et al. 2010; Autor et al. 2024). Specifically, Appendix Table D.2 shows that higher WOCBTC exposure attracts a disproportionately larger share of experienced workers (aged 50–64). As experience typically entails a positive wage premium, ignoring this would overstate wage increases and understate wage declines in more exposed CZs. Moreover, the increase in high-skill employment reported in Tables 5 and 6 likely extends to finer educational subgroups, further obscuring the impact of WOCBTC on skill-specific wage growth. The construction of composition-adjusted wages is described in Section C of the Appendix. Briefly, I first estimate Mincer wage regressions to predict skill-specific wages conditional on selected worker characteristics (gender, six finer education groups, age, foreign-born status, and race). Second, the predicted wages are collapsed to the CZ level. Finally, CZ-level predicted wage changes are used to net out compositional shifts from the observed wage changes.

Table 7: Effect of WOCBTC on Wage & Skill Premium Changes across Local Labor Markets
(Dependent Variables: Decennial Change in Log Wages & Log Skill Premiums)

	Δ *Wages*				Δ *Skill Premiums*		
	$ln(w_{all})$	$ln(w_h)$	$ln(w_m)$	$ln(w_l)$	$ln(w_h/w_m)$	$ln(w_h/w_l)$	$ln(w_m/w_l)$
Panel A. State fixed effects included							
OLS	-0.92	1.39*	-2.54***	-3.88***	3.93***	5.27***	1.34**
	(1.11)	(0.71)	(0.68)	(1.07)	(0.38)	(0.56)	(0.60)
R^2	0.58	0.45	0.59	0.61	0.40	0.46	0.24
Shift–Share IV	-0.77	1.52	-2.43***	-3.86***	3.95***	5.39***	1.43**
	(1.36)	(0.97)	(0.89)	(1.18)	(0.44)	(0.57)	(0.59)
	[0.71]	[0.92]	[0.98]	[1.22]	[1.51]	[1.70]	[0.58]
Panel B. All controls included							
OLS	-1.61**	-0.34	-1.54***	-2.72***	1.20**	2.39***	1.18**
	(0.61)	(0.51)	(0.56)	(0.81)	(0.51)	(0.78)	(0.58)
R^2	0.67	0.56	0.66	0.66	0.47	0.54	0.27
Shift–Share IV	-2.54***	-0.96	-2.60***	-4.13***	1.64**	3.17***	1.53**
	(0.80)	(0.79)	(0.91)	(0.93)	(0.75)	(0.93)	(0.72)
	[0.88]	[0.70]	[0.82]	[1.27]	[1.06]	[1.43]	[0.70]

Notes: $N = 741$ CZs. The table reports OLS and 2SLS estimation results. In the 2SLS specifications, the normalized WOCBTC measure (ranging from 0 to 1) is instrumented using the shift–share IV defined in equation 7. The dependent variables are the log change in average wages (columns (1)–(3)) and skill premiums (columns (4)–(6)) between 2005–07 and 2015–19. The three skill groups are college+ (H), some college (M), and high school graduates and dropouts (L). Wages are adjusted for differential compositional changes across CZs by gender, six education groups, a quadratic in age, foreign-born status, and race (White/Black/Other). Outcome variables are multiplied by 100/1.1 to represent decennial percentage changes. Control variables include initial labor market characteristics (college share, foreign population share, female employment share, exposure to occupation offshorability, routine task intensity, manufacturing share, and population density), and 50 Census state dummies. All models include a constant and are weighted by CZs' population shares in 2005–07. The first-stage F-statistics are 77.47 (Panel A) and 160.60 (Panel B). Standard errors clustered at the state level are reported in parentheses. ***/**/* represent significance at the 1%, 5%, and 10% levels for the state-level cluster approach. Adao et al. (2019) exposure-robust standard errors clustered at the broad industry level are shown in square brackets.

The estimated effects of WOCBTC on composition-adjusted log hourly wage and skill premium changes in Table 7 pertain to full-time, year-round workers (i.e., those working more than 35 hours per week and over 40 weeks per year).[24] Skill premium changes are measured as decennial log changes in wage ratios between skill groups. Column (1) of Table 7 indicates that WOCBTC exposure is associated with a negative average wage effect. Including the full set of controls lowers the point estimates further and increases their precision. Using the shift–share IV to account for endogeneity strengthens this negative effect. Taking the 2SLS estimates at face value, a 10% increase in WOCBTC leads to a statistically significant 0.25% local wage decline.

As with the employment results in Table 5, the wage effects vary substantially by skill group. Low-skilled workers experience the largest differential decline (–0.41%), followed by middle-skilled

[24]Due to the additional sample restriction (see Section A.1 of the Appendix), only a subset of the worker sample from the previous section is retained for the wage analysis. The results remain robust when relaxing this restriction.

workers (–0.26%), while the impact on high-skilled workers is smaller and statistically insignificant (–0.10%). Notably, the baseline OLS regression result in Panel A suggests an opposite trend for high-skilled workers, with a 0.14% wage gain. However, this effect becomes statistically insignificant when using the shift–share identification strategy.

The skill-specific wage changes in columns (2)–(4) translate directly into the differential skill premium changes shown in columns (5)–(8). According to the fully specified 2SLS model, a 10% increase in WOCBTC exposure raises the log skill premium of college graduates relative to high school graduates and dropouts by 0.32%. Significant relative wage shifts are also observed between high- and middle-skilled workers (0.16%) as well as between middle- and low-skilled workers (0.15%).

While the employment effects discussed in Section 4.2 are intuitive and align with the cognitive-biased nature of technological change, the wage effects warrant deeper economic reflection. As noted by Topel (1986), and subsequently by Bound and Holzer (2000) and Notowidigdo (2020), local wages tend to be most flexible among the least mobile groups, whereas mobility increases with educational attainment. The initially rising returns to cognitive skills in CZs more exposed to WOCBTC likely equalized in the medium run due to proportional supply adjustments among college-educated workers (see, e.g., Topel 1986; Beaudry et al. 2010). By contrast, the geographically inelastic supply of high school graduates and dropouts may have led to an oversupply of low-skilled labor in CZs where the task input shifted disproportionately toward cognitive-intensive tasks. In conjunction with the declining relative demand for low-skilled workers within occupations, this likely exerted additional downward pressure on their wages—contributing to the widening college wage premium.

The persistence of these local imbalances raises the question of why low-skilled workers remain in (or relocate to) CZs that increasingly specialize in cognitive-intensive tasks and simultaneously pay comparatively lower wages. The next section sheds light on this puzzle by comparing two potential mechanisms through which low-skilled workers' wages may systematically decline in more exposed CZs.

4.4 Wage Changes within Occupations vis-à-vis Occupational Deskilling

The most intuitive mechanism for explaining the decline in low-skilled workers' wages is that the returns to non-cognitive skills within occupations deteriorate more rapidly in CZs that are more exposed to WOCBTC. This, in turn, may lead to slower wage growth within occupations for low-skilled workers, who are typically specialized in non-cognitive skills. A second potential mechanism may stem from supply-side adjustments across occupations. In particular, the faster inflow of high-skilled workers into CZs that are more exposed to WOCBTC may generate consumption spillovers due to rising demand for low-skilled services (Mazzolari and Ragusa 2013; Cerina et al. 2023). In addition, it may foster so-called "extreme-skill complementarities" in production (Eeckhout et al. 2014). A squeezing of low-skilled workers into lower-wage service and production occupations would exert further downward pressure on their wages. Related to this hypothesis, Autor (2019) provides evidence that such occupational deskilling among non-college workers has been most pronounced in dense urban areas in recent decades.[25] Given the strong positive association between CZs' exposure to WOCBTC and population density (see Section 3), this potential mechanism requires closer examination.

To obtain initial insights into the two mechanisms, I isolate the pool of low-skilled workers (high school graduates and dropouts without college experience) and run two sets of 2SLS regressions using the shift–share identification strategy outlined in Section 4.1. In the first set of regressions (Panel A of Table 8), the outcome variable is the log wage change for low-skilled workers within the five SOC major occupation groups. These groups provide a broad occupational classification based on their task content. The results are strikingly clear, revealing substantial negative wage effects across all occupation groups. Moreover, the point estimates are statistically significant at the 1% level for routine manual occupations (columns (5) and (6)) and at the 5% level for non-routine cognitive occupations (column (2)). For most estimated wage effects, standard errors are slightly larger when applying the Adao et al. (2019) inference method—which accounts for correlated shocks across CZs with similar industrial structures. For routine cognitive occupations (column (4)), however, exposure-robust standard errors are slightly smaller.

The second set of regressions (Panel B of Table 8) examines occupational supply responses. Here, the outcome variable is the log change in low-skill FTE employment in occupation group k relative to total FTE employment of low-skilled workers in a given CZ.[26] The point estimate shown in column (3) implies that every 10% increase in WOCBTC exposure raises the FTE share of low-skilled workers employed in service occupations by 1.87%. This systematic sorting into service occupations—the lowest-paying occupation group in the labor market—is consistent with the consumption spillover hypothesis and also aligns with Autor (2019). In addition, there is evidence of positive sorting of low-skilled workers into production and transportation occupations

[25] The term "deskilling" is adopted from Autor (2019), referring to the observation that the set of jobs in which non-college workers perform specialized work commanding higher pay has increasingly narrowed over time.

[26] Note that this is conceptually different from Table 6, which reports estimates related to changes in relative employment shares between skill groups. By contrast, the results in Table 8 refer to relative changes in occupational employment among low-skilled workers. This provides a clearer picture of their supply adjustments, unconditional on overall employment changes in CZs and relative employment shifts between skill groups.

Table 8: Low-Skilled Workers' Wage Changes within and Resorting between Occupation Groups
(2SLS. Dependent Variables: Decennial Change in Log Wages & Log Occupation Shares)

	All	*Man./Bus./ Sc./Arts.*	*Service*	*Sales and Office*	*Res./Cons./ Maint.*	*Prod. and Transp.*
Panel A. Wage changes within occupation groups						
$\Delta\ ln(w_l)$	-4.13***	-3.97**	-2.37	-1.69	-4.74***	-4.41***
	(0.93)	(1.71)	(1.87)	(1.20)	(1.70)	(1.20)
	[1.27]	[2.19]	[2.41]	[0.80]	[1.80]	[1.29]
Panel B. Changes in relative FTE supply between occupation groups						
$\Delta\ ln(L_k/L)$		-10.16	18.74***	-4.90	-13.52	10.74
		(9.71)	(6.58)	(6.66)	(9.95)	(9.18)
		[6.04]	[9.60]	[5.46]	[5.89]	[3.97]

Notes: $N = 741$ CZs. The table reports 2SLS estimation results. The normalized WOCBTC measure (ranging from 0 to 1) is instrumented using the shift–share IV defined in equation 7. The dependent variable in Panel A is the composition-adjusted log change in average wages of all low-skilled workers (column (1)) and within SOC major occupation groups (columns (2)–(6)). In Panel B, the dependent variable is the log change in low-skill FTE employment across major occupation groups relative to total FTE employment. Wages are adjusted for differential compositional changes across CZs (gender, detailed education, age, foreign-born status, and race). Outcome variables are multiplied by 100/1.1 to represent decennial percentage changes. Control variables include initial labor market characteristics (college share, foreign population share, female employment share, exposure to occupation offshorability, routine task intensity, manufacturing share, and population density), and 50 Census state dummies. All models include a constant and are weighted by CZs' population shares in 2005–07. The first-stage F-statistic is 160.60. Standard errors are clustered at the state level and shown in parentheses. ***/**/* represent significance at the 1%, 5%, and 10% levels for the state-level cluster approach. Adao et al. (2019) exposure-robust standard errors clustered at the broad industry level are shown in square brackets.

in more exposed CZs. The estimated positive effect of 1.07% is statistically significant under the exposure-robust inference strategy proposed by Adao et al. (2019). The low-skill labor supply in all other occupation groups declines. Although these declines are economically notable, they are statistically insignificant—likely due, at least in part, to the comparatively small sample sizes when further disaggregating localized skill-specific employment changes by occupation group.

While Table 8 suggests that both mechanisms may contribute to the decline in low-skilled workers' wages, it remains silent on their relative importance. Ideally, one would compare wage dynamics across CZs with and without occupational supply adjustments. However, counterfactual wage evolutions in the absence of occupational re-sorting are unobserved. To address this challenge, I extend the strategy used in the previous section and construct composition-adjusted wages by predicting wages conditional on occupation, in addition to adjusting for demographic shifts. Specifically, I adjust for occupational re-sorting at two levels. First, I include five dummies to account for employment shifts across the five major occupation groups. Second, I incorporate a richer set of dummies capturing all 430 detailed occupations. This finer occupation adjustment additionally conditions on low-skilled workers' task specialization within major occupation

Table 9: Adjusted Effect of WOCBTC on Low-Skilled Workers' Wages and the College Premium
(2SLS. Dependent Variables: Decennial Change in Log Wages & Log College Premium)

		Adjusted for demographic comp.		*+ Adjusted for broad occ comp.*		*+ Adjusted for 430 occupations*	
	unadjusted	*predicted*	*adjusted*	*predicted*	*adjusted*	*predicted*	*adjusted*
$\Delta\ ln(w_L)$	-3.26***	0.87	-4.13***	0.49	-3.75***	-0.01	-3.25***
	(0.84)	(0.62)	(0.93)	(0.54)	(0.85)	(0.45)	(0.75)
	[0.98]	[0.73]	[1.27]	[0.62]	[1.14]	[0.46]	[0.98]
$\Delta\ ln(w_h/w_l)$	2.90***	-0.26	3.17***	0.22	2.69***	0.14	2.76***
	(0.89)	(0.71)	(0.93)	(0.62)	(0.90)	(0.54)	(0.76)
	[1.34]	[0.49]	[1.43]	[0.46]	[1.18]	[0.59]	[1.05]

Notes: $N = 741$ CZs. The table reports 2SLS estimation results. The normalized WOCBTC measure (ranging from 0 to 1) is instrumented using the shift–share IV defined in equation 7. The dependent variables are the unadjusted, predicted, and composition-adjusted changes in wages and the college wage premium. The college premium change is defined as the log change in the ratio of average hourly wages between high-skilled (college+) and low-skilled (high school graduates and dropouts) workers. Columns (2) and (3) present wage changes adjusted for demographic compositional shifts (gender, detailed education, age, foreign-born status, and race). Columns (4) and (5) additionally adjust for relative changes in employment shares across the five SOC 2010 major occupation groups. Columns (6) and (7) adjust for changes across all 430 detailed occupations. Outcome variables are multiplied by 100/1.1 to represent decennial percentage changes. Control variables include initial local labor market characteristics (college share, foreign population share, female employment share, exposure to occupation offshorability, routine task intensity, manufacturing share, and population density), and 50 Census state dummies. All models include a constant and are weighted by CZs' population shares in 2005–07. The first-stage F-statistic is 160.60. Standard errors are clustered at the state level and shown in parentheses. ***/**/* represent significance at the 1%, 5%, and 10% levels for the state-level cluster approach. Adao et al. (2019) exposure-robust standard errors clustered at the broad industry level are shown in square brackets.

groups.[27] The precise procedure is documented in Appendix Section C.

Table 9 summarizes the adjusted low-skill wage and college premium effects, which are the outcomes of the fully specified 2SLS regression model. Column (1) reports the baseline estimates using unadjusted local average wages. The point estimates in column (3) are reproduced from Table 7 in the previous section, adjusting only for demographic compositional shifts (gender, six finer education categories, age, foreign-born status, and race). The wage and college premium effects shown in columns (5) and (7) additionally adjust for occupational re-sorting at the broad and detailed occupation levels, respectively. Alongside the unadjusted and composition-adjusted effects, Table 9 also presents the predicted effects. These reflect the differential compositional changes across CZs, holding wages within demographic and occupational cells constant. By construction, the sum of the predicted and composition-adjusted effects equals the unadjusted effect.

Compared to the point estimates shown in column (3), adjusting wages for differential re-sorting between the five occupation groups changes the negative wage estimate from −4.13 to

[27] For illustration, Figure E.5 in the Appendix plots low-skilled workers' average task intensity evolutions (cognitive, manual, communication, physical, and coordination) for differently exposed CZs, holding task intensities within occupations constant.

–3.75. Adjusting instead for differential re-sorting across all 430 detailed occupations further attenuates the estimate to –3.25. In economic terms, the occupational deskilling of low-skilled workers across broad occupation groups accounts for 9.2 percent $\left(\frac{-4.13+3.75}{-4.13}\right)$ of the effect shown in column (3), while differential re-sorting across all 430 occupations explains 21.3 percent $\left(\frac{-4.13+3.25}{-4.13}\right)$, thus adding 12.1 percentage points of explanatory value. Although this is a noticeable proportion, the major share of 78.7 percent must be attributed to wage declines within detailed occupations.

Similarly, the contributory role of differential occupational adjustments in explaining the increase in the college wage premium in more exposed CZs is comparatively modest, accounting for 15.1 percent $\left(\frac{3.17-2.69}{3.17}\right)$ or 12.9 percent $\left(\frac{3.17-2.76}{3.17}\right)$, depending on the level of occupational adjustment. These findings underscore that the primary driver of the low-skill wage decline and the rising college premium induced by WOCBTC is within-occupation wage deterioration. They suggest that structural changes in the returns to task-related skills within occupations play a central role in the uneven local wage evolutions of the U.S. labor market.

5 Conclusion

In the twenty-first century, skill premiums have diverged sharply across local labor markets. While the spatial economics literature attributes this primarily to increasing skill agglomeration in larger cities, it pays less attention to how technological change manifests differently across space—driving these parallel trends. Building on the theoretical task-based framework of Acemoglu and Restrepo (2018; 2019) and complementing the empirical work of Autor et al. (2024), this study evaluates the role of task changes within occupations in shaping local skill demand and wage divergence. Although occupations are the natural unit where task evolution occurs, empirical research has largely neglected the within-occupation dimension due to measurement challenges. This study addresses this gap by using a key feature of the revised O*NET ability rating procedure to construct a novel measure of cognitive-biased technological change, reflecting the direction of task intensity changes within 430 detailed occupations.

Implementing the new measure at the local level and combining it with patent data and microdata, I demonstrate that the local diffusion of innovation systematically increases the relative importance of cognitive-intensive tasks within occupations. Leveraging the diffusion of lagged breakthrough patents from earlier decades, I establish that this relationship can be considered causal. An important factor in how rapidly innovation shifts the local task composition toward cognitive-intensive tasks is the population density of local labor markets. While occupational adaptation to new technologies is cumbersome in rural and suburban areas—where (skilled) labor is scarce—every 10 percent increase in population density amplifies the positive impact of innovation on cognitive-biased occupational task input by 8.13 percent.

Using a Bartik-style shift–share approach to exploit exogenous variation in cognitive-biased demand shocks, the final part of this study reveals that differential exposure to WOCBTC strongly predicts local divergences in skill-specific employment and wage developments. While overall labor demand increases, the employment gains from WOCBTC diminish notably at lower education levels. At the same time, workers without a college degree experience relative wage losses, pushing up the local college wage premium by 0.32 percent for every 10 percent increase in WOCBTC exposure. Comparing two potential mechanisms shows that the bulk of the low-skill wage decline can be attributed to deteriorating wages within detailed occupations, while deskilling through systematic re-sorting to lower-paying occupations accounts for only one-fifth of the total negative wage effect.

The findings of this paper provide empirical evidence that changes in skill demand within occupations are crucial to understanding regional employment and wage dynamics. The extent to which inflexible supply responses of low-skilled workers to cognitive-biased demand shifts amplify these unequal wage effects remains an important area for further research. Given that metropolitan areas are substantially more exposed to WOCBTC, better local amenities in larger cities could plausibly contribute to keeping low-skilled workers stuck and generating an oversupply that further depresses their wages. Although a full understanding of supply dynamics across skill groups requires further study, this paper lays the groundwork for such analysis at the detailed occupational level. Especially, focusing on real wage changes—accounting for local differences in rent and housing prices, as highlighted in the work of Moretti (2013) and Diamond (2016)—could provide a valuable additional perspective on the findings of this study.

Overall, the relative decline in low-skilled workers' wages within occupations spurred by technological change is worrisome, as it places the most disadvantaged group in the labor market at even greater risk. In addition, this trend likely contributes to the erosion of the non-college urban wage premium over recent decades, as highlighted by Autor (2019), thereby fueling rising inequality in large cities. Effective tools to address the decline in low-skilled workers' wages and the widening wage gap between skill groups could include occupational reskilling initiatives and tailored local interventions—particularly in densely populated regions where technological change manifests at a more rapid rate within occupations.

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Appendices

A Microdata and Patent Data

A.1 American Community Survey (ACS) Data

Addressing the research questions at hand requires the construction of localized information on employment and wage growth by skill level. As a large sample size is crucial for this purpose, I use 3-year and 5-year pooled ACS data from 2005–2007 and 2015–2019, drawn from IPUMS (Ruggles et al. 2023). These periods align with the two focal years of the task intensity measures derived from O*NET data in Section 2. The pooled samples comprise the U.S. population aged 18–64, excluding individuals residing in institutional group quarters (mental institutions and prisons), those categorized as unpaid family workers, and those employed in military occupations.[28] Individuals' labor supply is measured by multiplying the number of weeks worked during the last twelve months by their reported usual weekly hours. To construct labor supply weights, I take the product of the ACS individual sampling weights and the labor supply units.

For the computation of wages and skill premiums, I restrict the sample to full-time, year-round workers, excluding all self-employed and those who worked less than 35 hours a week or less than 40 weeks during the last twelve months.[29] The annual pre-tax salary incomes used to construct the wage series are top-coded based on state-specific mean salaries and adjusted to constant 2010 U.S. dollars. Hourly wages are calculated by dividing the annual income by total hours worked (usual weekly hours multiplied by weeks worked). To mitigate outlier effects, I winsorize hourly wages at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles of the year-specific national wage distribution, following Autor and Dorn (2013).

A.2 Commuting Zones

In this study, local labor markets are defined as commuting zones (CZs) following Tolbert and Sizer (1996). To assign microdata to CZs, I use Public Use Microdata Areas (PUMAs)—the smallest identifiable geographic units in Census and ACS data—to probabilistically allocate workers to CZs based on the share of workers falling within the boundaries of a given CZ. In this approach, the same individuals are potentially assigned to multiple CZs. In such cases, their weights are

[28] Workers employed in military occupations are excluded due to missing O*NET data for this occupation group.

[29] The ACS reports the number of weeks worked in the previous calendar year in intervals. I center these intervals at their midpoint for the calculation of hourly wages. The main reason for excluding individuals who worked less than 40 weeks is the coarsening of reported intervals in the ACS below this threshold. Those working less than 35 hours per week are excluded to ensure the wage estimates are not confounded by systematic differences in supply dynamics between full-time and part-time workers.

adjusted so that the sum of their weights equals the original ACS sampling weight. This strategy follows Dorn (2009) and has been implemented in various studies (e.g., Autor and Dorn 2013; Autor et al. 2013).[30]

Although less than 20 percent of PUMAs overlap with multiple CZs, I note that most PUMA–CZ overlaps occur in rural areas. As a result, the noise in the data falls disproportionately on sparsely populated CZs. While this must be considered when interpreting the results in Sections 3 and 4, using the concept of CZs remains advantageous, as it allows for the specification of local labor markets based on a sound economic definition. This is crucial for analyzing their skill-specific employment and wage evolution.

One of the key questions in this study is whether technological change manifests at a different pace across rural, suburban, and metropolitan areas through cognitive-biased task changes. To investigate this, I use a variable from the IPUMS ACS data that captures the population-weighted average density of PUMAs.[31] Using the described mapping of PUMAs to CZs, I compute the logarithmic population density for each CZ under scrutiny. While CZs are roughly comparable in geographic size due to their construction, their log population densities vary markedly, ranging from 0.61 for a CZ in Alaska to 10.61 for a CZ in a metropolitan area of New York.

A.3 USPTO Patent Data

The United States Patent and Trademark Office (USPTO) has recorded all patent applications and grants since 1976. To align with the start and end years of the pooled ACS data used for the labor market analysis, I restrict the data to patents granted between 2005 and 2019 for constructing the baseline patent diffusion measure in Section 3.1.[32] To remain consistent with the related literature (Lin 2011; Goldschlag et al. 2020; Kelly et al. 2021; Autor et al. 2024), I focus exclusively on utility patents, which represent the largest share of all patents.

Each patent is classified according to the Cooperative Patent Classification (CPC) system into nine sections, which are further divided into hundreds of more detailed classes and subclasses. I

[30] In an earlier version of this paper, I used PUMAs rather than CZs as geographical units. While the results remain relatively robust across the two geographical designations, the estimates are notably more precise when using CZs. This likely stems from the fact that over 50 percent of individuals' residence PUMA does not match their work PUMA (based on my own explorations), which creates substantial measurement error.

[31] Population-weighted density differs from unadjusted density by accounting for the local context within PUMAs. For instance, in a southern Florida PUMA, most residents live in dense coastal areas, while much of the interior consists of uninhabitable wetlands. Ignoring this leads to a substantially lower overall density estimate for the PUMA, despite its urban areas being among the densest in the U.S.. To correct for this, the measure weights each resident's local density equally. This variable is directly obtained from IPUMS.

[32] Note that I do not include a lag between the patent data and the microdata or occupation-level data, as I rely on the patent grant date rather than the application date. Given an expected delay of around two years between application and grant, it is plausible to assume that innovations are at least partially implemented around the time of the patent grant.

exclude patents without abstracts, as these cannot be efficiently classified using the CPC structure. The USPTO further distinguishes between "inventional" and "additional" patents. I include only inventional patents, as these are assigned to CPC classes based on disclosed information, whereas additional patents are often added later solely for search purposes. Each patent can potentially be assigned to over 600 CPC subclasses, depending on the invention's general utility. This key feature of the patent data is exploited in Section 3.1 to construct the weighted measure of local innovation diffusion. Finally, I drop all patents that have been withdrawn for any reason, resulting in 5.3 million patents granted between 2005 and 2019.

B Occupations

B.1 A Contemporary Occupation Panel: *occ2010fr*

It is crucial to work with a balanced occupation panel in this study, which investigates the local impact of task intensity changes within occupations over time. While a balanced panel was carefully constructed by Dorn (2009), the associated occupation crosswalk ends in 2005. A widely used strategy among researchers is to extend this panel to accommodate more recent Census or ACS microdata (e.g., Deming 2017; Cortes et al. 2021). This, however, is not an optimal solution for this study, as the analysis begins after 2000—a period that marks an important break in the Census-based occupation classification structure. In particular, the number of tractable occupations increased substantially to better reflect new job types in the post-millennium knowledge-based economy. For example, more recent classifications distinguish between computer scientists, computer programmers, software developers, database administrators, and network and computer systems specialists, whereas earlier classifications grouped them into a single occupation category (computer software developers).

To capture the increased occupational granularity of the 2000s, I develop a new occupation panel, *occ2010fr*. This panel includes 430 occupations in total—approximately 30 percent more occupations compared to the panel constructed by Dorn (2009). It is important to note that this new panel is designed for use with Census and ACS data from 2000 onward and is not suitable for backward application to earlier decades. Thus, it complements rather than replaces the Dorn (2009) occupation panel, which remains preferable for studies relying on occupation-level data before the year 2000. In contrast, the new occupation panel is more suitable for future labor market research focusing on more recent developments, such as the impact of AI or industrial robots.[33]

To align the *occ2010fr* occupation panel across subsequent classification changes in the 2000s, I draw on various resources, such as Census and IPUMS crosswalks and conversion rates (see, e.g., Beckhusen 2020).[34] I address three types of changes: (1) the splitting of occupations into multiple occupations; (2) the merging of multiple occupations into a broader group; and (3) the emergence of new occupations. To deal with occupation splits, I group the finer occupations

[33] The balanced occupation panel constructed by Dorn (2009) is based on the 1990 Census occupation classification and spans several decades, building on the occupation system developed by Meyer and Osborne (2005). The new occupation panel constructed for this study is based on the SOC 2010 occupation classification.

[34] Census occupation conversion rates refer to the weighted distribution of workers transitioning from one occupational code in an earlier classification system to occupational codes in a subsequent system. These rates are based on dual-coded survey responses in Census or ACS microdata and can be used to harmonize occupation categories over time.

under a single category that retains the original broader occupation title and code. For mergers and the emergence of new occupations, I use official Census and ACS conversion rates to align occupations across classification revisions.

In cases where single occupations are split and mapped into two or more different occupation categories, I assign occupations based on the highest employment-weighted conversion rate, provided it accounts for at least 80% of the original occupation's workforce. If no single match reaches the 80% threshold, I construct a broader occupation category to maintain a consistent classification. Using the same rules, I apply conversion rates to assign newly emerging occupations to existing occupations or broader occupation categories. In fact, conversion rates exceed 80% in the vast majority of occupation mergers, allowing for a clear one-to-one mapping across the evolving Census-based classification system. The applied crosswalk strategy is therefore intended to minimize potential measurement error arising from ambiguous occupation classification changes while simultaneously retaining as much occupational granularity as possible.

Beyond the three types of classification changes, special treatment is required for residual occupations that are "not elsewhere classified (n.e.c.)." In some cases, I extend these Census-based occupation categories by including occupations within the same 2-digit or 3-digit occupation code when they cannot consistently be assigned to more detailed 6-digit occupations due to a structural break. The complete ACS crosswalk is documented in Section F, while a more detailed crosswalk version, which illustrates the applied methodology to construct the *occ2010fr* panel, is available on my website.[35]

B.2 O*NET Abilities

O*NET Ability	**Ability Description**
A. O*NET Cognitive Abilities	
Selective Attention	Concentrate on a task over a period of time without being distracted.
Time Sharing	Shift back and forth between two or more activities or sources of information (such as speech, sounds, touch, or other sources).
Category Flexibility	Generate or use different sets of rules for combining or grouping things in different ways.
Deductive Reasoning	Apply general rules to specific problems to produce answers that make sense.
Fluency of Ideas	Come up with a number of ideas about a topic (the number of ideas is important,

[35]In addition to its compatibility with IPUMS ACS data, the new occupation panel can also be used with IPUMS Current Population Survey (CPS) data from 2003 onward. Researchers who use the occupation panel in their work are kindly requested to cite this paper and refer to the panel by its name, *occ2010fr*. A detailed crosswalk file is available at this link.

O*NET Ability	Ability Description
	not their quality, correctness, or creativity).
Inductive Reasoning	Combine pieces of information to form general rules or conclusions (includes finding a relationship among seemingly unrelated events).
Information Ordering	Arrange things or actions in a certain order or pattern according to a specific rule or set of rules (e.g. patterns of numbers, letters, words, pictures, mathematical operations).
Originality	Come up with unusual or clever ideas about a given topic or situation, or to develop creative ways to solve a problem.
Problem Sensitivity	Tell when something is wrong or is likely to go wrong. It does not involve solving the problem, only recognizing that there is a problem.
Memorization	Remember information such as words, numbers, pictures, and procedures.
Flexibility of Closure	Identify or detect a known pattern (a figure, object, word, or sound) that is hidden in other distracting material.
Perceptual Speed	Quickly and accurately compare similarities and differences among sets of letters, numbers, objects, pictures, or patterns. The things to be compared may be presented at the same time or one after the other. This ability also includes comparing a presented object with a remembered object.
Speed of Closure	Quickly make sense of, combine, and organize information into meaningful patterns.
Mathematical Reasoning	Choose the right mathematical methods or formulas to solve a problem.
Number Facility	Add, subtract, multiply, or divide quickly and correctly.
Spatial Orientation	Know your location in relation to the environment or to know where other objects are in relation to you.
Visualization	Imagine how something will look after it is moved around or when its parts are moved or rearranged.
Oral Comprehension	Listen to and understand information and ideas presented through spoken words and sentences.
Oral Expression	Communicate information and ideas in speaking so others will understand.
Written Comprehension	Read and understand information and ideas presented in writing.
Written Expression	Communicate information and ideas in writing so others will understand.

B. O*NET Physical Abilities

Stamina	Exert yourself physically over long periods of time without getting winded or out of breath.
Dynamic Flexibility	Quickly and repeatedly bend, stretch, twist, or reach out with your body, arms and/or legs.
Extent Flexibility	Bend, stretch, twist, or reach with your body, arms, and/or legs.
Gross Body Coordination	Coordinate the movement of your arms, legs, and torso together when the whole body is in motion.
Gross Body Equilibrium	Keep or regain your body balance or stay upright when in an unstable position.
Dynamic Strength	Exert muscle force repeatedly or continuously over time. This involves muscular endurance and resistance to muscle fatigue.

O*NET Ability	Ability Description
Explosive Strength	Use short bursts of muscle force to propel oneself (as in jumping or sprinting), or to throw an object.
Static Strength	Exert maximum muscle force to lift, push, pull, or carry objects.
Trunk Strength	Use your abdominal and lower back muscles to support part of the body repeatedly or continuously over time without ”giving out” or fatiguing.
C. O*NET Psychomotor Abilities	
Control Precision	Quickly and repeatedly adjust the controls of a machine or a vehicle to exact positions.
Multilimb Coordination	Coordinate two or more limbs (for example, two arms, two legs, or one leg and one arm) while sitting, standing, or lying down. It does not involve performing the activities while the whole body is in motion.
Rate Control	Time your movements or the movement of a piece of equipment in anticipation of changes in the speed and/or direction of a moving object or scene.
Response Orientation	Choose quickly between two or more movements in response to two or more different signals (lights, sounds, pictures). It includes the speed with which the correct response is started with the hand, foot, or other body part.
Arm-Hand Steadiness	Keep your hand and arm steady while moving your arm or while holding your arm and hand in one position.
Finger Dexterity	Make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects.
Manual Dexterity	Quickly move your hand, your hand together with your arm, or your two hands to grasp, manipulate, or assemble objects.
Reaction Time	Quickly respond (with the hand, finger, or foot) to a signal (sound, light, picture) when it appears.
Speed of Limb Movement	Quickly move the arms and legs.
Wrist-Finger Speed	Make fast, simple, repeated movements of the fingers, hands, and wrists.
D. O*NET Visual Abilities	
Depth Perception	Judge which of several objects is closer or farther away from you, or to judge the distance between you and an object.
Far Vision	See details at a distance.
Glare Sensitivity	See objects in the presence of a glare or bright lighting.
Near Vision	See details at close range (within a few feet of the observer).
Night Vision	See under low-light conditions.
Peripheral Vision	See objects or movement of objects to one’s side when the eyes are looking ahead.
Visual Color Discrimination	Match or detect differences between colors, including shades of color and brightness.

B.3 O*NET Ability Rating Procedure

The Occupational Information Network (O*NET) replaced the Dictionary of Occupational Titles (DOT) in June 2003 with the release of the final analyst database (O*NET 4.0). For the creation of the analyst database, multiple job attributes were sourced from the DOT and reorganized according to a new content model (Hilton and Tippins 2010). Since then, new job items have been added and existing ones updated through a "multiple-method data collection program" (U.S. Department of Labor 2018). As a result, occupation ratings derived from job incumbents are frequently intermingled with ratings from job analysts. In addition, the rating procedure may change between two consecutive cycles, even for the same occupation. These measurement inconsistencies make it challenging for researchers to use time-varying O*NET data. The revised ability rating procedure, implemented after the eleventh rating cycle in 2011, addresses, to a large extent, the inconsistencies described and offers useful features that researchers can exploit for longitudinal studies.

Due to the complexity of certain ability items (e.g., inductive reasoning), ratings are made exclusively by specialized job analysts selected for their education and occupation-specific experience. Following cycle 11, when the vast majority of occupations had been updated at least once by job analysts, the original procedure underwent an essential revision (Fleisher and Tsacoumis 2012).[36] The key improvement is that job analysts receive information on changes in the task content and other relevant characteristics of occupations since the last rating, facilitating a dynamic and consistent re-evaluation of the 52 O*NET abilities.

Specifically, sixteen preselected and trained job analysts are provided with so-called "stimulus material" to rate occupations' ability requirements. This includes up-to-date information on various occupation-specific characteristics:

- Occupation title, definition, and vocational preparation (O*NET Job Zone).
- Mean importance of tasks for the targeted occupation, whereas tasks are classified into three categories based on survey answers of at least 15 job incumbents on their relevance and importance:[37]
  - *Core Tasks* with a relevance rating $\geq 67\%$ and a mean importance rating ≥ 3.

[36] During rating cycles 1–11, occupations were only partly rated by job analysts while some occupations were still equipped with outdated legacy data from the DOT. As discussed above, this hampers the comparison of ability data across occupations in earlier O*NET versions.

[37] The importance scale of task measures and other occupation characteristics is equivalent to the importance scale of abilities, ranging between 1 and 5. The relevance ratings range between 0% and 100%.

– *Supplementary Tasks* with a relevance rating > 67% but mean importance rating < 3, or, tasks rated on relevance between 10% and 66% regardless of the mean importance rating.

– *Non-Relevant Tasks* rated on relevance < 10%.

- Mean importance of Generalized Work Activities (GWAs) that (1) have a mean importance for the occupation ≥ 3.0, and (2) require the targeted ability to be performed.
- Mean rating of Work Context (WC) statements that (1) have a mean rating for the targeted occupation ≥ 3.0, and (2) require the targeted ability to work in that context.
- Mean importance of the 10 most important Knowledge domains associated with the occupation with a mean importance rating of ≥ 3.0.

In addition to up-to-date job information, if a task or another important job characteristic no longer meets the relevance threshold (e.g., due to automation), it is shown with a strikethrough in the stimulus material. Conversely, if a task has increased in importance or relevance since the previous rating, or if a new task has emerged, it is highlighted in bold and marked with an asterisk. For example, a task of electrical engineers might be presented as follows:

~~Operate computer-assisted engineering or design software or equipment to perform engineering tasks.~~

Operate computer-assisted engineering or design software or equipment to perform engineering tasks.*

Only after considering all current information and relevant job changes do the selected analysts submit their final ability rating on a scale from 1 (not important) to 5 (extremely important).[38] The process of the multi-step ability importance rating, along with the principles it is based on to ensure consistent evaluation, is described in more detail by Fleisher and Tsacoumis (2012).

B.4 Assigning Abilities to the Occupation Panel

In the next step, I map occupations' ability importance ratings from the 16.0 and 25.0 O*NET databases onto the *occ2010fr* occupation panel. As the main objective of the data preparation

[38]In addition to the importance ratings, abilities are also rated along a level scale. The importance rating appears more suitable for comparisons between occupations than the level rating, as the latter often relies on arbitrary examples from specific occupations rather than uniform anchors. However, level and importance ratings are highly correlated, with an average correlation of 0.92 (Handel 2016). Therefore, the results in this study are not sensitive to whether the level or importance rating is used to compute occupations' ability scores.

steps is to isolate changes within consistently defined occupations, I restrict the O*NET occupation sample to occupations available in both databases. This yields 862 O*NET occupations that can be mapped to my panel of 430 occupations.

Although the 8-digit O*NET occupation codes are more granular than the 6-digit codes in the ACS, both classification systems are nested within the Standard Occupational Classification (SOC), which can be used as an intermediate layer for assigning the ability data to my balanced occupation panel. When two or more O*NET occupations are mapped to a single occupation in the *occ2010fr* panel, I compute the weighted average of the ability scores of the finer O*NET occupations using employment count data from the Occupational Employment and Wage Statistics (OES).[39] If employment data are not available at a sufficiently detailed level, I use the unweighted average of the assigned O*NET occupations.

To equip residual occupation categories with data, I impute their ability scores using the (weighted) average of O*NET occupations of the same 2-digit occupation category. Importantly, whenever employment shares are used as weights to construct the 2008 and 2017 occupation-specific ability scores, I hold employment shares constant between the two years. This is crucial to avoid conflating changes in ability requirements within *occ2010fr* occupations with changes driven by relative shifts in employment shares between more detailed O*NET occupations.[40]

[39]The Occupational Employment and Wage Statistics (OES) program of the Bureau of Labor Statistics (BLS) conducts a survey every six months to produce estimates of employment and wages for detailed occupations based on the SOC system.

[40]To achieve this goal, I use 2008 employment shares to construct ability scores for both 2008 and 2017. In cases where 2008 employment data are unavailable, I use 2017 employment shares instead. If employment data are missing for both years, I compute ability scores as the unweighted average of the assigned O*NET occupations.

B.5 Occupations' Largest Cognitive Task Bias Changes

Table B.1: Occupations with the Largest Increase and Decrease in Within-Occupation Cognitive Bias, Direct Effect and Replacement Effect between 2008 and 2017

Largest Increases		*Largest Decreases*	
Occupation	*Change*	*Occupation*	*Change*
A. Total Cognitive Bias			
Construction laborers	1.579	Library assistants, clerical	-0.825
Graders and sorters, agricultural products	1.156	Office machine operators, exc. computer	-0.700
Maids and housekeeping cleaners	1.139	Ushers/lobby attendants/ticket takers	-0.668
Cabinetmakers and bench carpenters	1.020	Industrial and refractory machinery mechanics	-0.644
Embalmers and funeral attendants	0.904	Lodging managers	-0.633
Public relations and fundraising managers	0.867	Personal appearance workers, nec	-0.583
Computer and information systems managers	0.866	Medical and health services managers	-0.567
B. Direct Effect			
Graders and sorters, agricultural products	1.356	Parking attendants	-0.955
Maids and housekeeping cleaners	1.272	Office machine operators, exc. computer	-0.854
Construction laborers	1.219	Automotive glass installers and repairers	-0.728
Embalmers and funeral attendants	1.151	Environmental engineers	-0.694
Photographic process workers	0.831	Industrial/refractory machinery mechanics	-0.676
Massage therapists	0.707	Lodging managers	-0.656
Optometrists	0.653	Financial examiners	-0.619
C. Replacement Effect			
Technical writers	0.459	Public relations and fundraising managers	-0.672
Atmospheric and space scientists	0.426	Cabinetmakers and bench carpenters	-0.656
Security and fire alarm systems installers	0.412	Computer and information systems managers	-0.617
Door-to-door sales, news and street vendors	0.397	Environmental engineers	-0.610
Advertising sales agents	0.377	Coin/vending/amusement machine repairers	-0.572
Proofreaders and copy markers	0.368	Marketing and sales managers	-0.556
Administrative services managers	0.306	Data entry keyers	-0.550

Notes: The total change in occupation-specific cognitive bias is calculated as the direct effect minus the replacement effect (see equation 3 in Section 2.3). All task intensity changes used to calculate the total cognitive bias change, the direct effect, and the replacement effect are measured in standard deviation units relative to the 2008 employment-weighted mean. For 15 out of the 430 occupations in the occupation panel, no change in total cognitive bias is expected, as the O*NET ability data for these occupations were not updated between the two O*NET versions (16.0 and 25.0) used for the calculations.

C Composition-Adjusted Wages

As shown in Section 4.2, within-occupation technological change directly affects the skill composition of local labor markets. If the only compositional shifts occurring differentially across CZs were between broader skill groups (low-, middle-, and high-skill), no further adjustments would be required to precisely estimate the local (relative) wage effects. However, the impact of technological change on workers' geographic mobility and employment growth likely also differs across finer demographic subgroups within each skill group. This may confound the estimated (relative) wage effects, which should ideally reflect changes in skill prices.

To adjust for uneven local compositional shifts, I first estimate cross-sectional skill-specific log hourly wage regressions for the start period (2005–07) and the end period (2015–19), using supply-weighted ACS microdata (see Section A.1). These Mincer wage regressions take the form:

$$w_{igt} = \alpha_{igt} + \beta_{1gt} X_{igt} + e_{igt} \tag{9}$$

where w_{igt} is the log hourly wage of worker i of skill group g at time t. Worker characteristics are summarized by X_{igt}, including a polynomial in age; six education dummies to split each of the three skill groups into two finer education levels ((1.1) high school dropouts, (1.2) high school graduates, (2.1) college experience without degree, (2.2) college experience with associate degree, (3.1) four-year bachelor's degree, and (3.2) master's degree or doctorate; a dummy for gender; a foreign-born dummy; and three race dummies (White/Black/Other)). The predicted wages from these regressions hold skill prices within each demographic cell constant.

Next, I let the observed and predicted wages collapse to the commuting zone (CZ) level to compute local mean wages for each broad skill group. Composition-adjusted wages are then constructed by taking the log difference between the observed and predicted mean wages.[41]

To unpack the role of occupational re-sorting in Section 4.4, which might cloud the effect on differential skill-specific wage growth, I repeat the same procedure but extend the Mincer wage regressions by including occupation dummies:

$$w_{igt} = \alpha_{igt} + \beta_{1gt} X_{igt} + \beta_{2gt} Occ_{igt} + e_{igt} \tag{10}$$

In the first extension, I include dummies for the five SOC major occupation groups. Second, I include the full set of 430 occupation dummies to control for differential occupational re-sorting

[41] This approach is used, for example, by Autor et al. (2024) to construct composition-adjusted wage bills.

across CZs at the most detailed level. Following the same procedure as before, I collapse the predicted and observed wages to the CZ level to compute mean wages adjusted for both demographic and occupational shifts.

Using the log difference between CZs' composition-adjusted wages in 2005–07 and 2015–19 as the outcome variable yields differential percentage wage growth effects that correspond to the relative changes in within-occupation skill prices shown in Table 9 in Section 4.4.

D Sensitivity Analysis

The following sensitivity analysis addresses three potential threats to the robustness of the results presented in Sections 4.2 and 4.3: (1) the construction of the WOCBTC measure; (2) the possibility that the results are driven by a specific subgroup of the working-age population; and (3) the omission of relevant economic factors and pre-trends in the regression model. While Tables D.1–D.5 provide valuable additional insights, the overall pattern—that WOCBTC increases the (relative) employment of high-skilled workers and decreases the (relative) wages of low-skilled workers—remains robust.

The OLS estimates in Table D.1 show that both the direct effect (column (2)) and the replacement effect (column (3)) yield qualitatively similar results when used independently to estimate differential local employment and wage outcomes. However, the direct effect appears more pronounced for wages, whereas the replacement effect has a more substantial impact on employment. Moreover, assigning equal weights to all task intensities (column (4)) does not alter the direction or magnitude of the estimated effects, nor does the use of alternative weighting strategies (e.g., using factor shares as weights), which are not reported here.

The method used to derive task intensities from the multidimensional ability data appears to be more decisive. The measure used in column (5)—constructed by taking the difference between the average of all cognitive abilities and the average of all other abilities based on predetermined O*NET categorizations—suggests a much weaker effect on overall employment compared to the baseline measure in column (1). In addition, the wage effect is more pronounced among workers with some college experience, while the overall negative wage effect remains fairly robust. These quantitative differences, combined with the lower precision of the point estimates, underscore the value of using systematic tools, such as factor analysis, rather than manually selecting and combining O*NET job characteristics.

Motivated by the results of the shock balance tests in Section 4.1, I further disaggregate CZs by age, gender, and country of birth to check the robustness of the employment and wage effects across subgroups. While the overall patterns shown in Tables D.2–D.3 are consistent across all subgroups, the most noticeable quantitative differences appear in the employment growth effects between workers of different age cohorts. Specifically, the employment-increasing effects are substantially larger for more experienced workers, including those in the lowest skill tier (high school graduates and dropouts). A 10% increase in WOCBTC leads to a 1.76% decline in FTE employment among the least-skilled younger workers (18–34), while it increases FTE employment by 2.41% and 3.50% for prime-age workers (35–49) and the most experienced workers (50–64) within the same education group, respectively. These results support the intuition that cognitive skills are partially accumulated throughout the life cycle and are not fully captured by workers' educational level, which is used as the skill proxy in this study.

Tables D.4–D.5 present the main estimates from the fully specified model, sequentially adding omitted but potentially economically important control variables. In column (2), I control for CZs' initial employment shares across the five SOC major occupation groups. This robustness check is warranted based on Figure 3 in Section 2.3, which shows differences in cognitive task bias changes between higher-level occupation categories. However, confirming the assumption that the localized demand shocks are driven by technology-induced cognitive-biased task changes within detailed occupations, controlling for employment shares of broader occupations leaves the results virtually unchanged.

Another concern relates to the timing of the study, which overlaps with the impact of the financial crisis. Although most disruptive effects of the crisis likely dissipated over the course of a decade, it is possible that local labor markets more severely affected by the crisis experienced systematically different wage and employment trajectories in the aftermath. This intuition is supported by a related study conducted by Hershbein and Kahn (2018). However, controlling for local differences in crisis-related unemployment shocks (measured between 2005–07 and 2009–11) in Column (3) does not alter the main results.

The only omitted control that noticeably dampens the estimated employment and wage effects is the preceding local population growth between 1990 and 2000 (column (6)). As indicated in Table 4 in Section 4.1, omitting population growth pre-trends likely generates slightly upward-biased employment estimates and downward-biased wage estimates, inflating the overall impact of WOCBTC. Nonetheless, the results remain statistically significant and economically strong across all alternative model specifications explored in this section, including those controlling for preceding working-age population growth.

D.1 Alternative Measure Constructions

Table D.1: Different WOCBTC Measures and the Effect on Employment and Wage Growth

(OLS. Dependent Variables: Decennial Change in Log FTE Employment & Log Wages)

	WOCBTC	*Direct Effect*	*Replacement Effect*	*Equal TI Weights*	*O*NET Ability Categorization*
Panel A. Effect on FTE Employment					
$ln(L_{all}^{fte})$	8.88***	4.34	11.92***	13.91***	1.60
	(3.28)	(2.95)	(3.26)	(3.77)	(4.94)
$ln(L_{h}^{fte})$	18.25***	10.62**	20.29***	25.56***	4.86
	(4.78)	(4.37)	(5.20)	(5.62)	(5.80)
$ln(L_{m}^{fte})$	9.60**	7.65**	5.60	9.82*	-1.16
	(3.99)	(2.97)	(4.40)	(5.26)	(4.21)
$ln(L_{l}^{fte})$	3.92	-0.14	10.28**	9.73**	0.36
	(3.39)	(2.68)	(4.25)	(4.76)	(6.86)
Panel B. Effect on Wages					
$ln(w_{all})$	-1.61***	-1.49***	-0.44	-1.29	-1.79**
	(0.61)	(0.51)	(0.71)	(0.84)	(0.87)
$ln(w_{h})$	-0.34	-0.57	0.53	0.17	-1.14
	(0.51)	(0.42)	(0.67)	(0.73)	(0.75)
$ln(w_{m})$	-1.54***	-1.20**	-0.98*	-1.63**	-2.73***
	(0.56)	(0.51)	(0.54)	(0.65)	(0.87)
$ln(w_{l})$	-2.72***	-2.11***	-1.74*	-2.89***	-1.60
	(0.81)	(0.77)	(0.94)	(1.06)	(1.05)
Census state dummies	√	√	√	√	√
Labour market controls	√	√	√	√	√

Notes: N = 741 CZs. The table reports OLS estimation results. The original WOCBTC measure and all alternative task-based measures are normalized (ranging from 0 to 1). The replacement effect measure is reversed from negative to positive for better comparison. The dependent variables are the log changes in FTE employment and wages between 2005–07 and 2015–19. Outcome variables are multiplied by 100/1.1 to represent decennial percentage changes. Column (1) replicates the fully specified model using the baseline WOCBTC measure. Column (2) reports the direct effect based on the predicted change in cognitive task intensity, while column (3) shows the replacement effect based on the predicted change in non-cognitive task intensity. Column (4) uses an alternative weighting approach that gives equal weight to all five task categories ($WOCBTC_{equal} = \Delta Cognitive - \Delta Manual - \Delta Physical - \Delta Communication - \Delta Coordination$). The measure in column (5) is constructed as the difference between the average of all cognitive and the average of all non-cognitive ability scores using predetermined O*NET classifications. Control variables include initial local labor market characteristics (college share, foreign population share, female employment share, exposure to occupation offshorability, routine task intensity, manufacturing share, and population density), and 50 Census state dummies. All models include a constant and are weighted by CZs' population shares in 2005–07. Standard errors are clustered at the state level and shown in parentheses. ***/**/* represent the 1%, 5%, and 10% significance levels.

D.2 Group Heterogeneity

Table D.2: Heterogeneity in the Effect of WOCBTC on Employment Growth
(Dependent Variable: Decennial Change in Log FTE Employment)

		Different Age Groups			*Gender-Specific*		*Country of Birth*	
	All	***18-34***	***35-49***	***50-64***	***Men***	***Women***	***U.S.***	***Foreign***
Panel A. OLS Estimation								
$ln(L_{all}^{fte})$	8.88***	-0.18	8.19**	21.28***	7.19**	11.75***	6.76	12.33*
	(3.28)	(4.39)	(3.89)	(4.09)	(3.42)	(3.57)	(4.40)	(6.37)
$ln(L_{h}^{fte})$	18.25***	13.25**	14.41**	27.41***	16.88***	20.88***	15.26***	15.52
	(4.78)	(5.71)	(4.55)	(4.73)	(5.55)	(4.46)	(5.63)	(10.85)
$ln(L_{m}^{fte})$	9.60**	12.55**	4.39	11.76**	8.74**	10.42**	5.13	35.03***
	(3.99)	(5.34)	(4.82)	(4.86)	(4.12)	(4.74)	(4.14)	(12.74)
$ln(L_{l}^{fte})$	3.92	-13.66**	11.93**	23.51***	0.65	8.92**	5.73	-6.13
	(3.39)	(6.57)	(4.97)	(3.97)	(3.39)	(4.41)	(4.68)	(9.62)
Panel B. SSIV Estimation								
$ln(L_{all}^{fte})$	15.43***	-1.53	15.72***	35.86***	15.22***	16.76***	10.66*	11.88
	(3.48)	(4.12)	(6.02)	(5.38)	(3.59)	(3.96)	(6.07)	(9.08)
	[6.92]	[11.40]	[11.37]	[9.09]	[7.55]	[7.22]	[6.81]	[14.97]
$ln(L_{h}^{fte})$	28.11***	17.86*	22.06**	45.33***	26.66***	31.09***	21.78***	23.63*
	(5.89)	(10.00)	(10.52)	(8.59)	(6.21)	(6.63)	(8.28)	(12.43)
	[9.70]	[11.58]	[16.31]	[13.71]	[10.31]	[9.63]	[11.28]	[23.94]
$ln(L_{m}^{fte})$	16.42***	12.36	11.78*	28.34***	19.33***	13.49**	10.57*	22.46
	(4.89)	(7.50)	(6.12)	(8.05)	(6.54)	(5.26)	(6.13)	(14.43)
	[9.12]	[13.94]	[10.48]	[8.36]	[11.18]	[7.98]	[7.86]	[20.26]
$ln(L_{l}^{fte})$	9.32*	-17.60*	24.08***	34.49***	5.30	15.46**	7.59	-11.31
	(5.33)	(9.02)	(8.46)	(5.28)	(5.05)	(6.69)	(5.22)	(14.06)
	[7.23]	[12.52]	[12.95]	[9.78]	[7.77]	[8.27]	[6.22]	[12.93]

Notes: $N = 741$ CZs. The table reports OLS and 2SLS estimation results. The WOCBTC measure is normalized (ranging from 0 to 1). In the 2SLS specifications, WOCBTC is instrumented using the shift-share IV defined in equation 7 in Section 4.1. The dependent variables are the group-specific log changes in FTE employment between 2005–07 and 2015–19. Outcome variables are multiplied by 100/1.1 to represent decennial percentage changes. Column (1) replicates the fully specified model for the entire labor force. Columns (2)–(4) report estimates for three age groups (18–34, 35–49, and 50–64). Columns (5) and (6) show results separately for male and female workers, while columns (7) and (8) report estimates for U.S.-born and foreign-born workers. Control variables include initial labor market characteristics (college share, foreign population share, female employment share, exposure to occupation offshorability, routine task intensity, manufacturing share, and population density), and 50 Census state dummies. All models include a constant and are weighted by CZs' population shares in 2005–07. Standard errors clustered at the state level are shown in parentheses. ***/**/* represent the 1%, 5%, and 10% significance levels. Adao et al. (2019) exposure-robust standard errors clustered at the broad industry level are shown in square brackets.

Table D.3: Heterogeneity in the Effect of WOCBTC on Wage Growth
(Dependent Variable: Decennial Change in Log Wages)

		Different Age Groups			*Gender-Specific*		*Country of Birth*	
	All	***18-34***	***35-49***	***50-64***	***Men***	***Women***	***U.S.***	***Foreign***
Panel A. OLS Estimation								
$ln(w_{all})$	-1.61**	-2.12***	-1.82**	-0.65	-1.92**	-1.18**	-1.48***	-0.64
	(0.61)	(0.68)	(0.72)	(0.65)	(0.83)	(0.57)	(0.49)	(1.32)
$ln(w_h)$	-0.34	-0.56	-0.18	-0.32	-0.70	0.27	-0.13	-2.34
	(0.51)	(0.97)	(0.63)	(0.91)	(0.69)	(0.79)	(0.47)	(1.56)
$ln(w_m)$	-1.54***	-3.08***	-1.48**	0.36	-1.29*	-1.83***	-1.57***	1.68
	(0.56)	(1.00)	(0.65)	(0.57)	(0.68)	(0.65)	(0.58)	(2.26)
$ln(w_l)$	-2.72***	-2.76***	-3.41**	-2.21**	-3.03***	-2.29***	-2.48***	-0.41
	(0.81)	(1.04)	(1.33)	(1.05)	(0.96)	(0.81)	(0.62)	(2.43)
Panel B. SSIV Estimation								
$ln(w_{all})$	-2.54***	-2.76***	-2.92***	-1.61*	-2.72***	-2.22***	-2.21***	-2.79
	(0.80)	(1.04)	(0.89)	(0.98)	(0.93)	(0.83)	(0.74)	(1.94)
	[0.88]	[1.47]	[1.02]	[0.87]	[1.00]	[0.83]	[0.80]	[1.16]
$ln(w_h)$	-0.96	-0.49	-1.42	-1.08	-0.85	-0.81	-0.79	-0.08
	(0.79)	(1.48)	(1.07)	(1.24)	(0.91)	(1.06)	(0.79)	(2.76)
	[0.70]	[1.40]	[1.32]	[1.32]	[0.94]	[0.62]	[0.67]	[3.08]
$ln(w_m)$	-2.60***	-4.51***	-2.37*	-0.32	-2.43**	-2.63**	-2.25**	-5.94*
	(0.91)	(1.29)	(1.22)	(1.16)	(1.08)	(1.06)	(0.98)	(3.21)
	[0.82]	[1.82]	[0.96]	[0.62]	[1.02]	[0.89]	[0.87]	[2.06]
$ln(w_l)$	-4.13***	-3.41***	-4.64***	-4.31***	-4.37***	-3.99***	-3.49***	-5.15*
	(0.93)	(0.99)	(1.33)	(1.21)	(1.06)	(1.10)	(0.80)	(2.97)
	[1.27]	[1.90]	[1.63]	[1.09]	[1.41]	[1.27]	[0.98]	[2.60]

Notes: $N = 741$ CZs. The table reports OLS and 2SLS estimation results. The WOCBTC measure is normalized (ranging from 0 to 1). In the 2SLS specifications, WOCBTC is instrumented using the shift-share IV defined in equation 7 in Section 4.1. The dependent variables are the group-specific log changes in wages between 2005–07 and 2015–19. Outcome variables are multiplied by 100/1.1 to represent decennial percentage changes. Column (1) replicates the fully specified model for the entire labor force. Columns (2)–(4) report estimates for three age groups (18–34, 35–49, and 50–64). Columns (5) and (6) show results separately for male and female workers, while columns (7) and (8) report estimates for U.S.-born and foreign-born workers. Control variables include initial labor market characteristics (college share, foreign population share, female employment share, exposure to occupation offshorability, routine task intensity, manufacturing share, and population density), and 50 Census state dummies. All models include a constant and are weighted by CZs' population shares in 2005–07. Standard errors clustered at the state level are shown in parentheses. ***/**/* represent the 1%, 5%, and 10% significance levels. Adao et al. (2019) exposure-robust standard errors clustered at the broad industry level are shown in square brackets.

D.3 Different Model Specifications

Table D.4: Sensitivity Analysis for the Effect of WOCBTC on Employment Growth

(Dependent Variable: Decennial Change in Log FTE Employment)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Panel A. OLS Estimation							
$ln(L_{all}^{fte})$	8.88***	6.01	8.88***	8.62***	9.19***	5.28	7.84**
	(3.28)	(3.93)	(3.22)	(3.20)	(3.13)	(3.19)	(3.27)
$ln(L_{h}^{fte})$	18.25***	15.24***	17.93***	17.67***	18.34***	14.31***	16.90***
	(4.78)	(5.71)	(4.55)	(4.73)	(4.60)	(4.52)	(4.90)
$ln(L_{m}^{fte})$	9.60**	7.50**	9.00**	9.27**	9.97**	8.20**	8.75**
	(3.99)	(3.49)	(3.92)	(3.86)	(3.96)	(3.83)	(3.88)
$ln(L_{l}^{fte})$	3.92	1.32	4.17	3.95	4.27	0.01	3.88
	(3.39)	(3.59)	(3.54)	(3.41)	(3.40)	(3.48)	(3.41)
Panel B. SSIV Estimation							
$ln(L_{all}^{fte})$	15.43***	13.62***	15.81***	14.95***	15.05***	8.00**	13.97***
	(3.48)	(5.28)	(3.52)	(3.58)	(3.53)	(3.92)	(3.89)
	[6.92]	[8.83]	[7.26]	[6.39]	[6.63]	[7.13]	[6.39]
$ln(L_{h}^{fte})$	28.11***	27.73***	27.95***	27.02***	27.94***	21.05***	26.19***
	(5.89)	(7.67)	(5.54)	(6.24)	(5.87)	(6.36)	(6.55)
	[9.70]	[11.82]	[10.41]	[8.35]	[9.42]	[8.99]	[9.89]
$ln(L_{m}^{fte})$	16.42***	15.10***	15.44***	15.79***	15.97***	13.03**	15.17***
	(4.89)	(4.63)	(5.04)	(4.96)	(5.08)	(5.32)	5.11)
	[9.12]	[10.22]	[9.50]	[8.62]	[8.82]	[9.05]	[9.41]
$ln(L_{l}^{fte})$	9.32*	7.53	10.23*	9.40*	8.89*	1.88	9.43*
	(5.33)	(5.86)	(5.86)	(5.34)	(4.99)	(6.23)	(5.34)
	[7.23]	[8.72]	[7.06]	[7.36]	[6.86]	[8.92]	[6.57]
Census state dummies	√	√	√	√	√	√	√
Labour market controls	√	√	√	√	√	√	√
Broad occupation shares		√					
GFC unemployment shock			√				
Δ Skill intensity (1990-2000)				√			
Δ Manufact share (1990-2000)					√		
Δ Population (1990-2000)						√	
Δ Wages (1990-2000)							√

Notes: N = 741 CZs. The table reports OLS and 2SLS estimation results. The WOCBTC measure is normalized (ranging from 0 to 1). In the 2SLS specifications, WOCBTC is instrumented using the shift-share IV defined in equation 7 in Section 4.1. The dependent variables are the skill-specific log changes in FTE employment between 2005–07 and 2015–19. Outcome variables are multiplied by 100/1.1 to represent decennial percentage changes. Column (1) replicates the fully specified model, including 50 state dummies and selected labor market controls (college share, foreign population share, female employment share, exposure to occupation offshorability, routine task intensity, manufacturing share, and population density). Column (2) additionally controls for five initial SOC major occupation shares in 2005–07. Column (3) includes a shock measure of the global financial crisis, defined as the increase in CZs' unemployment rate relative to their labor force between 2005–07 and 2009–11. Columns (4)–(7) account for pre-trends between 1990 and 2000 by including, respectively, the change in the college share, the change in the manufacturing share, the log change in skill-specific population counts, and the growth rate in average skill-specific log wages. All models include a constant and are weighted by CZs' population shares in 2005–07. Standard errors clustered at the state level are shown in parentheses. ***/**/* represent the 1%, 5%, and 10% significance levels for the state-level cluster approach. Adao et al. (2019) exposure-robust standard errors clustered at the broad industry level are shown in square brackets.

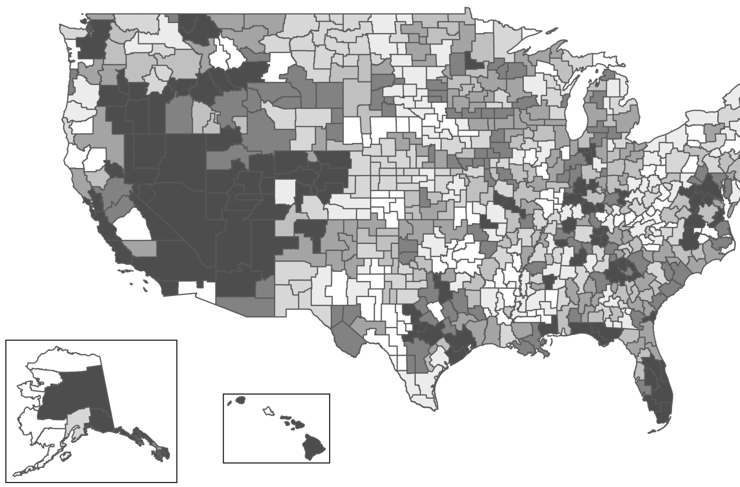
Table D.5: Sensitivity Analysis for the Effect of WOCBTC on Wage Growth

(Dependent Variable: Decennial Change in Log Wages)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Panel A. OLS Estimation							
$ln(w_{all})$	-1.61**	-1.63**	-1.35**	-1.63***	-1.56**	-1.14**	-1.69***
	(0.61)	(0.72)	(0.65)	(0.59)	(0.59)	(0.56)	(0.57)
$ln(w_h)$	-0.34	-0.63	-0.30	-0.36	-0.35	-0.29	-0.38
	(0.51)	(0.64)	(0.50)	(0.52)	(0.51)	(0.48)	(0.50)
$ln(w_m)$	-1.54***	-1.61**	-1.24**	-1.53**	-1.46***	-1.44**	-1.54***
	(0.56)	(0.68)	(0.61)	(0.58)	(0.53)	(0.56)	(0.54)
$ln(w_l)$	-2.72***	-2.52***	-2.38***	-2.75***	-2.67***	-2.10***	-2.73***
	(0.81)	(0.88)	(0.85)	(0.79)	(0.78)	(0.71)	(0.77)
Panel B. SSIV Estimation							
$ln(w_{all})$	-2.54***	-2.05**	-2.00***	-2.58***	-2.59***	-1.59*	-2.67***
	(0.80)	(0.84)	(0.76)	(0.79)	(0.78)	(0.83)	(0.78)
	[0.88]	[0.92]	[0.87]	[0.85]	[0.88]	[1.00]	[0.81]
$ln(w_h)$	-0.96	-0.93	-0.91	-1.01	-0.95	-0.93	-1.05
	(0.79)	(0.96)	(0.79)	(0.80)	(0.78)	(0.86)	(0.80)
	[0.70]	[0.94]	[0.72]	[0.64]	[0.68]	[0.66]	[0.70]
$ln(w_m)$	-2.60***	-2.50**	-1.97**	-2.58***	-2.69***	-2.39**	-2.62***
	(0.91)	(1.04)	(0.86)	(0.91)	(0.89)	(0.95)	(0.94)
	[0.82]	[0.90]	[0.76]	[0.82]	[0.82]	[0.94]	[0.88]
$ln(w_l)$	-4.13***	-3.41***	-3.42***	-4.18***	-4.18***	-3.05***	-4.11***
	(0.93)	(1.00)	(0.87)	(0.92)	(0.91)	(1.00)	(0.90)
	[1.27]	[1.24]	[1.17]	[1.24]	[1.27]	[1.37]	[1.22]
Census state dummies	√	√	√	√	√	√	√
Labour market controls	√	√	√	√	√	√	√
Broad occupation shares		√					
GFC unemployment shock			√				
Δ Skill intensity (1990-2000)				√			
Δ Manufact share (1990-2000)					√		
Δ Population (1990-2000)						√	
Δ Wages (1990-2000)							√

Notes: $N = 741$ CZs. The table reports OLS and 2SLS estimation results. The WOCBTC measure is normalized (ranging from 0 to 1). In the 2SLS specifications, WOCBTC is instrumented using the shift-share IV defined in equation 7 in Section 4.1. The dependent variables are the skill-specific log wage changes between 2005–07 and 2015–19. Outcome variables are multiplied by 100/1.1 to represent decennial percentage changes. Column (1) replicates the fully specified model, including 50 state dummies and selected labor market controls (college share, foreign population share, female employment share, exposure to occupation offshorability, routine task intensity, manufacturing share, and population density). Column (2) additionally controls for five initial SOC major occupation shares in 2005–07. Column (3) includes a shock measure of the global financial crisis, defined as the increase in CZs' unemployment rate relative to their labor force between 2005–07 and 2009–11. Columns (4)–(7) account for pre-trends between 1990 and 2000 by including, respectively, the change in the college share, the change in the manufacturing share, the log change in skill-specific population counts, and the growth rate in average skill-specific log wages. All models include a constant and are weighted by CZs' population shares in 2005–07. Standard errors clustered at the state level are shown in parentheses. ***/**/* represent the 1%, 5%, and 10% significance levels for the state-level cluster approach. Adao et al. (2019) exposure-robust standard errors clustered at the broad industry level are shown in square brackets.

E Appendix Figures



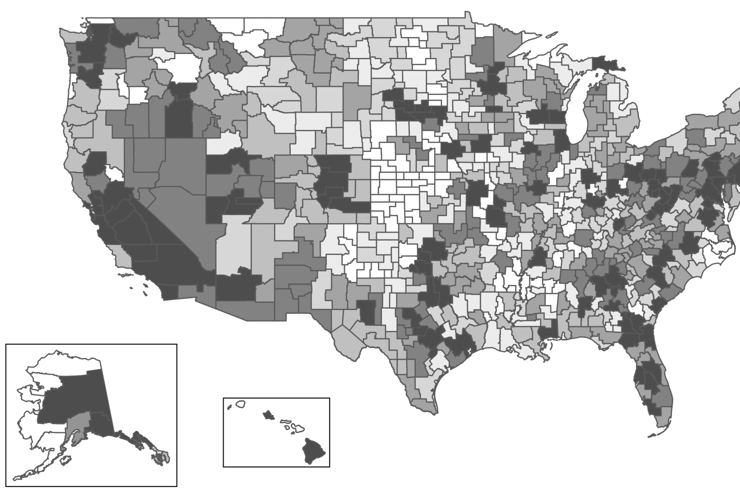


Figure E.1: Local Labour Markets' Exposure to Cognitive and Non-Cognitive Task Shifts

Notes: The map displays 741 CZs based on the classification of Tolbert and Sizer (1996), covering the entire United States. Alaska and Hawaii are shown separately in the bottom left due to their geographic distance. The CZ-level measures of predicted cognitive and non-cognitive task intensity changes correspond to the occupation-weighted direct and replacement effects (see equations 3 and 4 in Section 2). The non-cognitive change measure reflects the average change in manual, communication, physical, and coordination task intensities. CZs are grouped into seven equally sized bins; darker shades indicate greater exposure. Exposure is the average within-occupation change in standard deviation units relative to the 2008 employment-weighted mean.

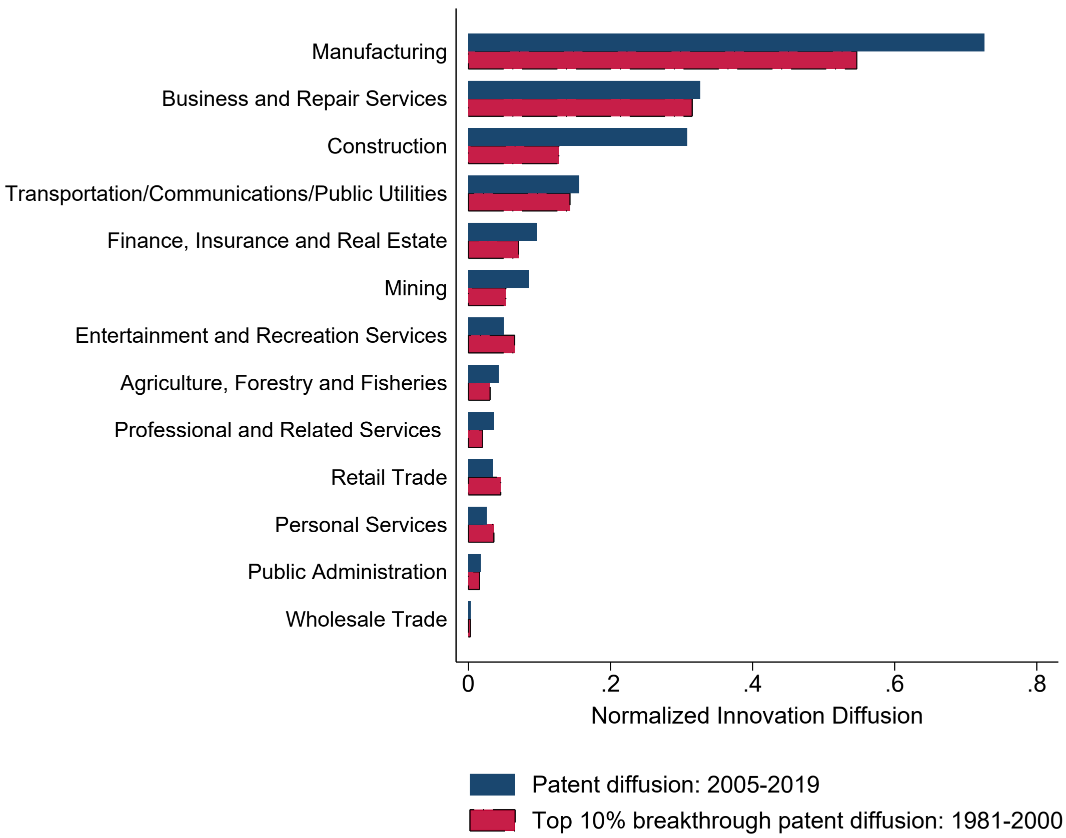
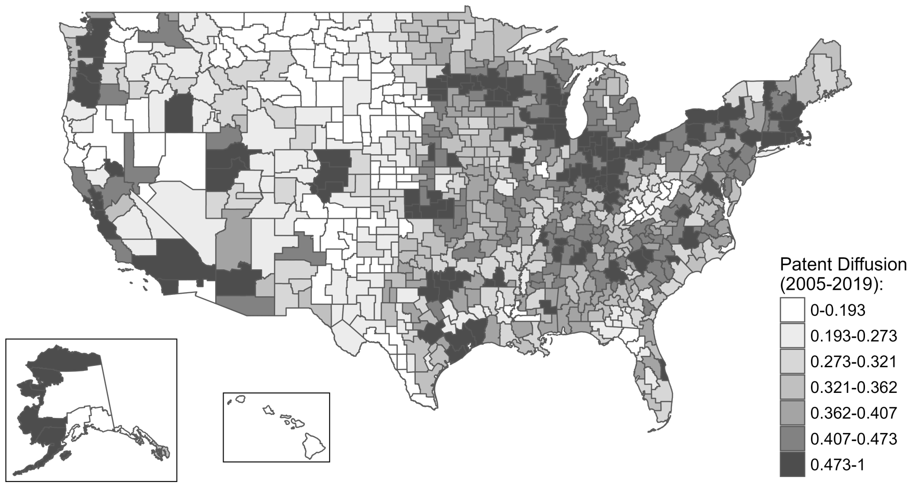


Figure E.2: Broad Industries' Patent and Breakthrough Patent Diffusion

Notes: Detailed industries are grouped into 13 broader categories based on the 1990 Census Bureau industrial classification system. Each detailed industry's patent diffusion is calculated as described in Section 3.1. The diffusion measure is first normalized at the detailed industry level, then averaged across all industries within the same broader group to ensure comparability between the two diffusion indicators. The contemporary patent diffusion measure (blue) is based on all utility patents granted between 2005 and 2019, using industry employment shares from 2005–07. The lagged breakthrough patent diffusion measure (red) includes the top 10% of breakthrough patents identified by Kelly et al. (2021) for the period 1981–2000, combined with industry employment shares from the 2000 Census.



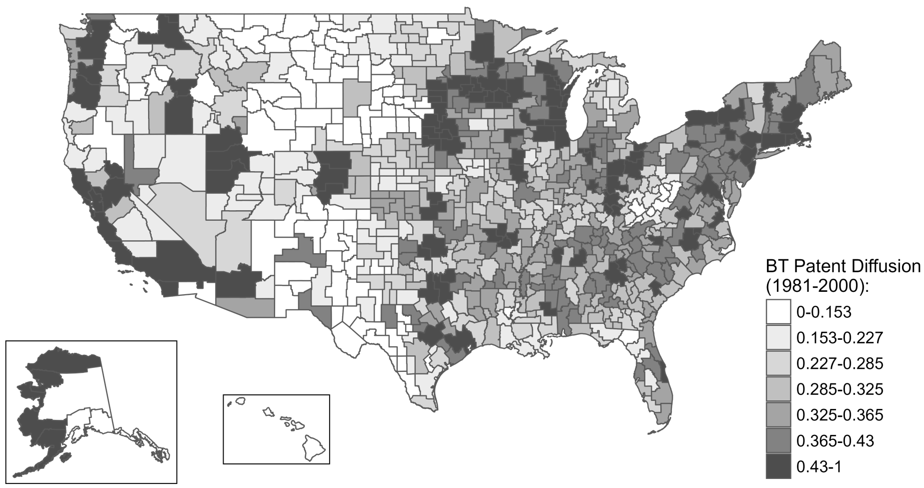


Figure E.3: The Diffusion of Patents and Breakthrough Patents into Local Labour Markets

Notes: The map displays 741 CZs based on the classification of Tolbert and Sizer (1996), covering the entire United States. Alaska and Hawaii are shown separately in the bottom left due to their geographic distance. The CZ-level innovation diffusion measure is constructed using equation 5 in Section 3.1. CZs are grouped into seven equally sized bins; darker shades indicate greater diffusion. The top map presents the normalized log diffusion of all utility patents granted between 2005 and 2019, based on CZs' industrial composition in 2005–07. The bottom map shows the normalized log diffusion of the top 10% of breakthrough patents identified by Kelly et al. (2021) for the period 1981–2000, using industry employment shares from the 2000 Census.

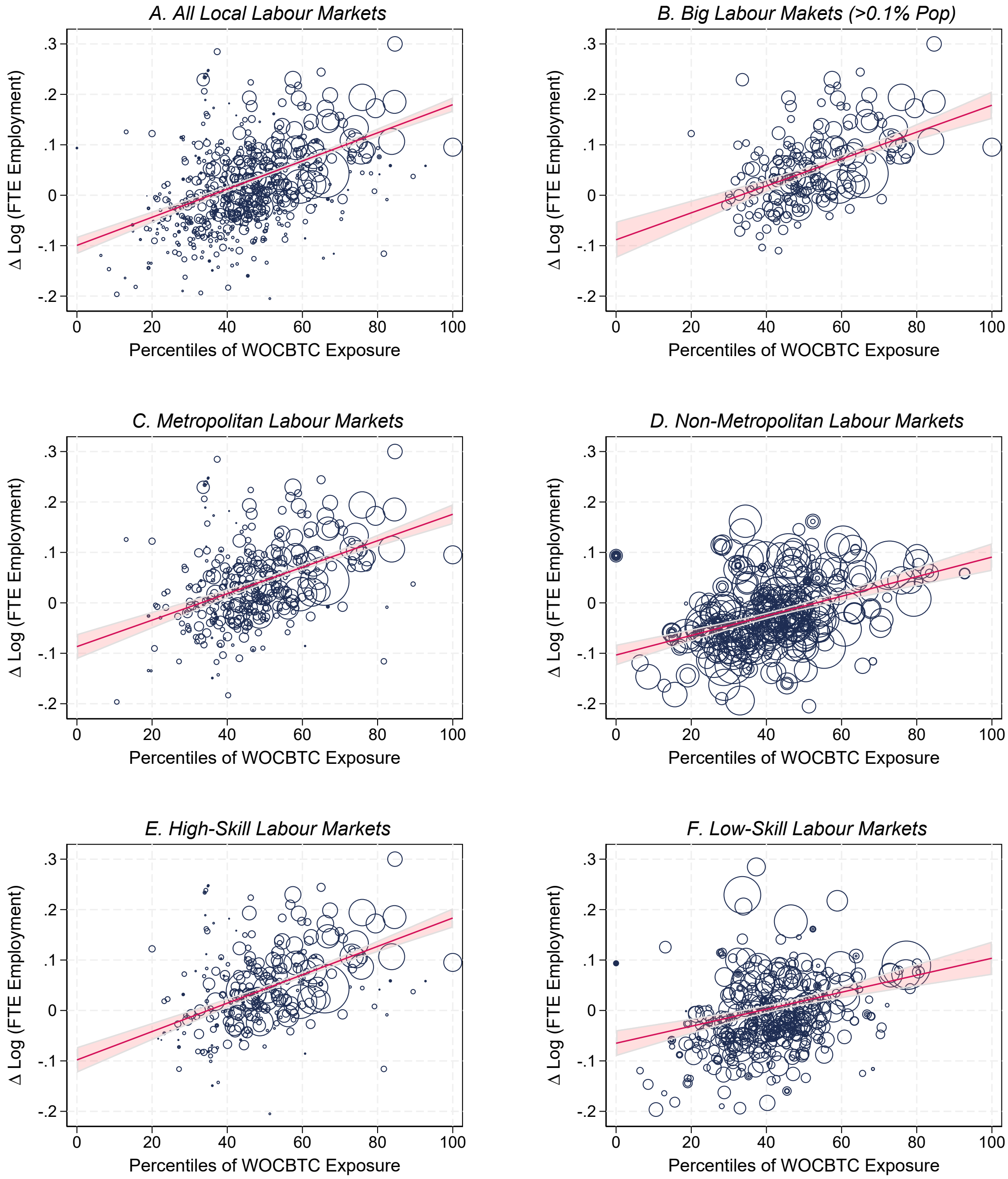


Figure E.4: WOCBTC and FTE Employment Growth across Local Labour Markets

Notes: CZs are sorted into percentiles based on their exposure to WOCBTC and the decennial log change in FTE employment. Panel A includes all 741 CZs. Panel B includes CZs with at least 0.1% of the U.S. population. In Panels C and D, CZs are classified as metropolitan if their population in 2005–07 lived at least partly in a Census-defined metropolitan area; otherwise, they are classified as non-metropolitan. Panels E and F split the sample into low- and high-skill labor markets using the median CZ-level college share (0.183) in 2005–07 as the threshold. CZs are weighted by their population shares in the baseline period (2005–07).

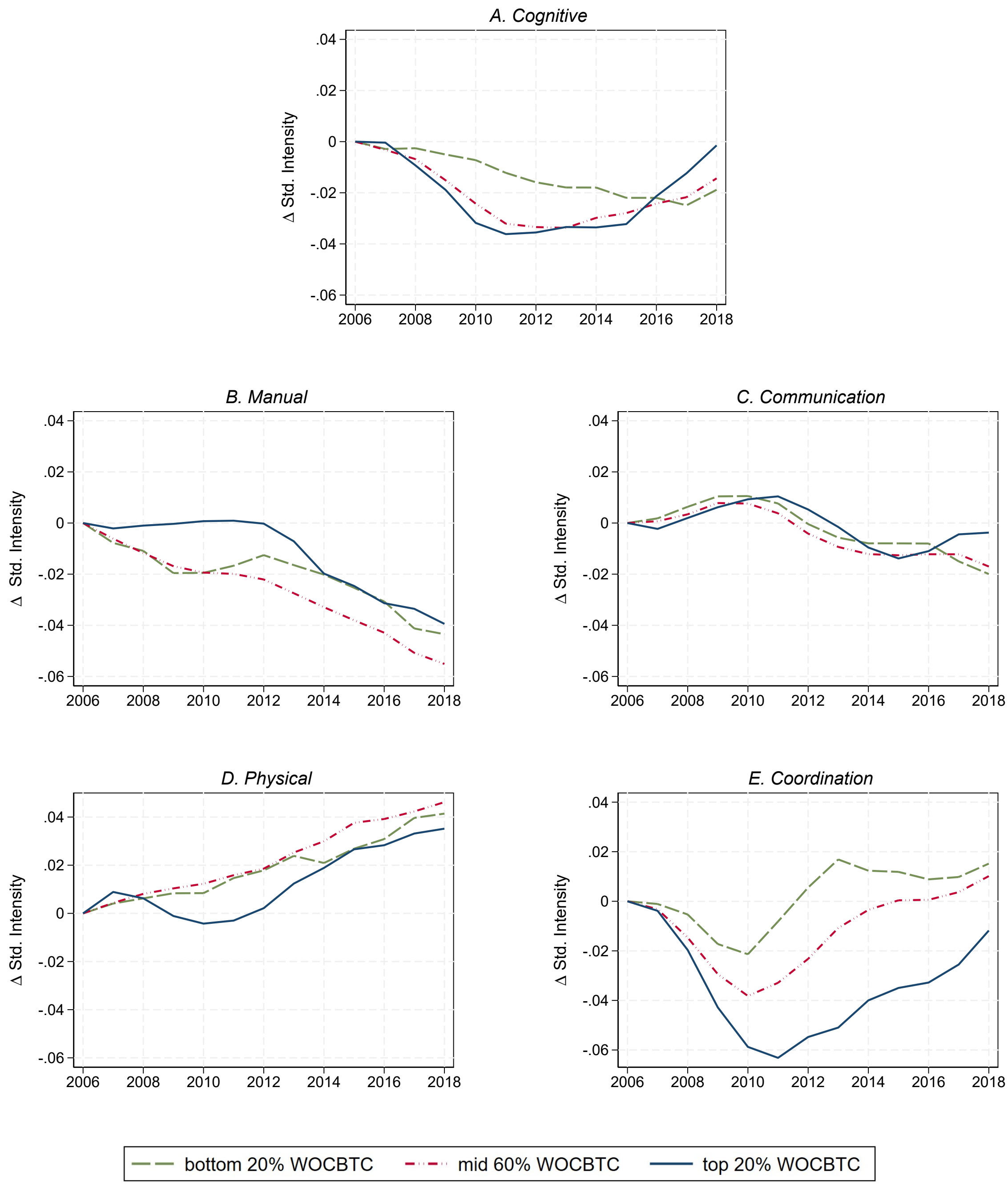


Figure E.5: Low-Skilled Workers' Task Intensity Evolutions through Occupational Re-sorting between Local Labour Markets with Different WOCBTC Exposure

Notes: The 741 CZs are ranked by their exposure to WOCBTC in 2005–07 and classified into three groups: bottom 20%, middle 60%, and top 20%. For each exposure group, low-skilled workers (high school graduates and dropouts without college experience) who are employed full-time and year-round (working more than 35 hours per week and more than 40 weeks per year) are pooled. Their average task intensities are calculated for each year from 2006 to 2018 using the standardized occupation-level task intensities derived via factor analysis in Section 2.2, weighted by year-specific employment shares across 430 occupations. Task intensities within occupations are held constant over time. A three-year moving average is applied to smooth the graphical trends in the five task intensity measures.

F Occupation Panel Crosswalk

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
	Management Occupations					
10	Chief executives/legislators	10	10	10	10	10
		30	10	10	10	10
20	General and operations	20	20	20	20	20
40	Advertising/promotions	40	40	40	40	40
50	Marketing/sales	50	50	50	50	51
						52
60	Public relations	60	60	60	60	60
100	Admin. services	100	100	100	100	101
						102
110	Computer/info. systems	110	110	110	110	110
120	Financial	120	120	120	120	120
130	Human resources	130	130	135	135	135
				136	136	136
				137	137	137
140	Industrial production	140	140	140	140	140
150	Purchasing	150	150	150	150	150
160	Transport./storage/distribution	160	160	160	160	160
205	Farmers/ranchers/agricultural	200	200	205	205	205
		210	210			
220	Construction	220	220	220	220	220
230	Education admin.	230	230	230	230	230
300	Architectural/engineering	300	300	300	300	300
310	Food service	310	310	310	310	310
330	Entertainment/recreation	330	330	330	330	335
340	Lodging	340	340	340	340	340
350	Medical/health services	350	350	350	350	350
360	Natural sciences	360	360	360	360	360
410	Property/real estate/community assoc.	410	410	410	410	410
420	Social/community service	420	420	420	420	420
430	Managers, nec	400	430	430	430	440
		430				705
	Business and Financial Operations Occupations					
500	Agents of artists/perform./athletes	500	500	500	500	500
510	Purchasing agents, farm products	510	510	510	510	510
520	Retail buyers, exc. farm products	520	520	520	520	520
530	Purchasing agents, exc. retail/farm	530	530	530	530	530
540	Claims adjusters/appraisers/examiners	540	540	540	540	540
560	Compliance officers	560	560	565	565	565
600	Cost estimators	600	600	600	600	600
620	Human resources specialists	620	620	630	630	630
				640	640	640
				650	650	650
700	Logisticians	700	700	700	700	700

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
710	Management analysts	710	710	710	710	710
720	Meeting/convention/event planners	720	720	725	725	725
740	Business operations specialists, nec	730	730	425	425	425
				740	740	750
800	Accountants/auditors	800	800	800	800	800
810	Property appraisers/assessors	810	810	810	810	810
820	Budget analysts	820	820	820	820	820
830	Credit analysts	830	830	830	830	830
840	Financial analysts	840	840	840	840	845
850	Personal financial advisors	850	850	850	850	850
860	Insurance underwriters	860	860	860	860	860
900	Financial examiners	900	900	900	900	900
910	Loan counselors/officers	910	910	910	910	910
930	Tax examiners/collectors/revenue agents	930	930	930	930	930
940	Tax prepares	940	940	940	940	940
950	Financial specialists, nec	950	950	950	950	960
	Computer and Mathematical Occupations					
1000	Computer scientists/systems analysts	1000	1000	1005	1005	1005
		5800	5800	1006	1006	1006
				1107	1107	1108
				5800	5800	
1010	Computer programmers	1010	1010	1010	1010	1010
1020	Software developers	1020	1020	1020	1020	1021
						1022
1060	Database admin.	1060	1060	1060	1060	1065
1100	Network/computer systems admin.	1040	1040	1050	1050	1050
		1100	1100	1105	1105	1105
		1110	1110	1007	1007	1007
				1106	1106	1106
				1030	1030	1031
						1032
1200	Actuaries	1200	1200	1200	1200	1200
1220	Operations research analysts	1220	1220	1220	1220	1220
1240	Mathematicians/statisticians	1210	1240	1240	1240	1240
		1230				
		1240				
	Architecture and Engineering Occupations					
1300	Architects, exc. naval	1300	1300	1300	1300	1305
						1306
1310	Surveyors/cartographers/photogrammetrists	1310	1310	1310	1310	1310
1320	Aerospace engineers	1320	1320	1320	1320	1320
1340	Agricultural/biomedical engineers	1330	1340	1340	1340	1340
		1340				
1350	Chemical engineers	1350	1350	1350	1350	1350
1360	Civil engineers	1360	1360	1360	1360	1360
1400	Computer hardware engineers	1400	1400	1400	1400	1400

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
1410	Electrical/electronic engineers	1410	1410	1410	1410	1410
1420	Environmental engineers	1420	1420	1420	1420	1420
1430	Industrial engineers	1430	1430	1430	1430	1430
1440	Marine engineers	1440	1440	1440	1440	1440
1450	Materials engineers	1450	1450	1450	1450	1450
1460	Mechanical engineers	1460	1460	1460	1460	1460
1520	Petroleum/mining/geological engineers	1500	1520	1520	1520	1520
		1520				
1530	Engineers, nec	1510	1530	1530	1530	1530
		1530				
1540	Drafters	1540	1540	1540	1540	1541
						1545
1550	Engineering technicians, exc. drafters	1550	1550	1550	1550	1551
						1555
1560	Surveying/mapping technicians	1560	1560	1560	1560	1560
	Life, Physical, and Social science Occupations					
1600	Agricultural/food scientists	1600	1600	1600	1600	1600
1610	Biological scientists	1610	1610	1610	1610	1610
1640	Conservation scientists/foresters	1640	1640	1640	1640	1640
1650	Medical scientists	1650	1650	1650	1650	1650
1700	Astronomers/physicists	1700	1700	1700	1700	1700
1710	Atmospheric/space scientists	1710	1710	1710	1710	1710
1720	Chemists/materials scientists	1720	1720	1720	1720	1720
1740	Environmental scientists	1740	1740	1740	1740	1745
						1750
1760	Physical scientists, nec	1760	1760	1760	1760	1760
1800	Economists	1800	1800	1800	1800	1800
1810	Market/survey researchers	1810	1810	735	735	735
				1815	1815	
1820	Psychologists	1820	1820	1820	1820	1821
						1822
						1825
1840	Urban/regional planners	1840	1840	1840	1840	1840
1860	Sociologists/social scientists, nec	1830	1860	1860	1860	1860
		1860				
1900	Agricultural/food science techs	1900	1900	1900	1900	1900
1910	Biological techs	1910	1910	1910	1910	1910
1920	Chemical techs	1920	1920	1920	1920	1920
1970	Life/physical/social science techs, nec	1930	1930	1930	1930	1935
		1940	1940	1940	1940	1970
		1960	1960	1950	1950	
				1965	1965	
	Community and Social Service Occupations					
2000	Counselors	2000	2000	2000	2000	2001
						2002
						2003

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
						2004
						2005
						2006
2010	Social workers	2010	2010	2010	2010	2011
						2012
						2013
						2014
2020	Community/social service specialists, nec	2020	2020	2015	2015	2015
				2016	2016	2016
				2025	2025	2025
2040	Clergy	2040	2040	2040	2040	2040
2050	Directors, religious activities/education	2050	2050	2050	2050	2050
2060	Religious workers, nec	2060	2060	2060	2060	2060
	Legal Occupations					
2100	Lawyers/judges/magistrates	2100	2100	2100	2100	2100
		2110				
2160	Legal support workers	2140	2140	2105	2105	2105
		2150	2150	2145	2145	2145
				2160	2160	2170
						2180
						2862
	Education, Training, and Library Occupations					
2200	Postsecondary teachers	2200	2200	2200	2200	2205
2300	Preschool/kindergarten teachers	2300	2300	2300	2300	2300
2310	Elementary/middle school teachers	2310	2310	2310	2310	2310
2320	Secondary school teachers	2320	2320	2320	2320	2320
2330	Special education teachers	2330	2330	2330	2330	2330
2340	Teachers and instructors, nec	2340	2340	2340	2340	2350
						2360
2400	Archivists/curators/museum techs	2400	2400	2400	2400	2400
2430	Librarians	2430	2430	2430	2430	2435
2440	Library techs	2440	2440	2440	2440	2440
2540	Teacher assistants	2540	2540	2540	2540	2545
2550	Education/training/library workers, nec	2550	2550	2550	2550	2555
	Arts, Design, Entertainment, Sports, and Media Occupations					
2600	Artists	2600	2600	2600	2600	2600
2630	Designers	2630	2630	2630	2630	2631
						2632
						2633
						2334
						2335
						2336
						2340
2700	Actors	2700	2700	2700	2700	2700

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
2710	Producers/directors	2710	2710	2710	2710	2710
2720	Athletes/coaches/umpires	2720	2720	2720	2720	2721
						2722
						2723
2740	Dancers/choreographers	2740	2740	2740	2740	2740
2750	Musicians/singers	2750	2750	2750	2750	2751
						2752
2760	Entertainers/performers, nec	2760	2760	2760	2760	2755
						2770
2800	Announcers	2800	2800	2800	2800	2805
2810	News analysts/reporters/correspondents	2810	2810	2810	2810	2810
2820	Public relations specialists	2820	2820	2825	2825	2825
2830	Editors	2830	2830	2830	2830	2830
2840	Technical writers	2840	2840	2840	2840	2840
2850	Writers/authors	2850	2850	2850	2850	2850
2860	Media/communication workers, nec	2860	2860	2860	2860	2861
						2865
2905	Broadcast/sound engineering techs	2900	2900	2900	2900	2905
		2960				
2910	Photographers	2910	2910	2910	2910	2910
2920	Television/video camera operators/editors	2920	2920	2920	2920	2920
	Healthcare Practitioners and Technical Occupations					
3000	Chiropractors	3000	3000	3000	3000	3000
3010	Dentists	3010	3010	3010	3010	3010
3030	Dietitians/nutritionists	3030	3030	3030	3030	3030
3040	Optometrists	3040	3040	3040	3040	3040
3050	Pharmacists	3050	3050	3050	3050	3050
3060	Physicians/surgeons	3060	3060	3060	3060	3090
						3100
3110	Physician assistants	3110	3110	3110	3110	3110
3120	Podiatrists	3120	3120	3120	3120	3120
3130	Nurses	3130	3130	3255	3255	3255
				3256	3256	3256
				3258	3258	3258
3140	Audiologists	3140	3140	3140	3140	3140
3150	Occupational therapists	3150	3150	3150	3150	3150
3160	Physical therapists	3160	3160	3160	3160	3160
3200	Radiation therapists	3200	3200	3200	3200	3200
3210	Recreational therapists	3210	3210	3210	3210	3210
3220	Respiratory therapists	3220	3220	3220	3220	3220
3230	Speech-language pathologists	3230	3230	3230	3230	3230
3245	Therapists, nec	3240	3240	3245	3245	3245
3250	Veterinarians	3250	3250	3250	3250	3250
3260	Health diagnosing/treating, nec	3260	3260	3260	3260	3261
						3270
3300	Clinical laboratory techs	3300	3300	3300	3300	3300
3310	Dental hygienists	3310	3310	3310	3310	3310

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
3320	Diagnostic related techs	3320	3320	3320	3320	3321
						3322
						3323
						3324
						3330
3400	Emergency medical techs/paramedics	3400	3400	3400	3400	3401
						3402
3420	Health practitioner support techs	3410	3410	3420	3420	3421
						3422
						4323
						3424
						3430
3500	Licensed practical/vocational nurses	3500	3500	3500	3500	3500
3510	Medical records/health information techs	3510	3510	3510	3510	3515
3520	Opticians, dispensing	3520	3520	3520	3520	3520
3530	Health techs, nec	3530	3530	3535	3535	3545
3540	Healthcare practitioners, nec	3540	3540	3540	3540	1980
						3550
	Healthcare Support Occupations					
3600	Nursing/psychiatric/home health aides	3600	3600	3600	3600	3601
						3603
						3605
3610	Occupational therapist assistants	3610	3610	3610	3610	3610
3620	Physical therapist assistants	3620	3620	3620	3620	3620
3630	Massage therapists	3630	3630	3630	3630	3630
3640	Dental assistants	3640	3640	3640	3640	3640
3650	Medical assistants, nec	3650	3650	3645	3645	3645
				3646	3646	3646
				3647	3647	3647
				3648	3648	3648
				3649	3649	3649
				3655	3655	3655
	Protective Service Occupations					
3700	Supervisors of correctional officers	3700	3700	3700	3700	3700
3710	Supervisors of police/detectives	3710	3710	3710	3710	3710
3720	Supervisors of fire fighters	3720	3720	3720	3720	3720
3730	Supervisors of protective services, nec	3730	3730	3730	3730	3725
3740	Fire fighters	3740	3740	3740	3740	3740
3750	Fire inspectors	3750	3750	3750	3750	3750
3800	Bailiffs/correctional officers/jailers	3800	3800	3800	3800	3801
						3802
3820	Detectives/criminal investigators	3820	3820	3820	3820	3820
3840	Law enforcement officers	3830	3840	3840	3840	3840
		3840				
3870	Police officers	3850	3850	3850	3850	3870
		3860				

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
3900	Animal control workers	N/A	3900	3900	3900	3900
3910	Private detectives/investigators	3910	3910	3910	3910	3910
3930	Security guards/gaming surveillance	3920	3920	3930	3930	3930
3940	Crossing guards	3940	3940	3940	3940	3940
3950	Protective service workers, nec	3950	3950	3945	3945	3945
				3955	3955	3946
						3960
	Food Preparation and Serving Related Occupations					
4000	Chefs/head cooks	4000	4000	4000	4000	4000
4010	Supervisors of food serving workers	4010	4010	4010	4010	4010
4020	Cooks	4020	4020	4020	4020	4020
4030	Food preparation workers	4030	4030	4030	4030	4030
4040	Bartenders	4040	4040	4040	4040	4040
4055	Fast food/counter workers	4050	4050	4050	4050	4055
		4060	4060	4060	4060	
4110	Waiters/waitresses	4110	4110	4110	4110	4110
4120	Food servers, non-restaurant	4120	4120	4120	4120	4120
4140	Dishwashers	4140	4140	4140	4140	4140
4150	Hosts and hostesses, restaurant	4150	4150	4150	4150	4150
4160	Food preparation/serving workers, nec	4130	4130	4130	4130	4130
		4160				4160
	Building and Grounds Cleaning and Maintenance Occupations					
4200	Supervisors of janitorial workers	4200	4200	4200	4200	4200
4210	Supervisors of landscaping workers	4210	4210	4210	4210	4210
4220	Janitors/building cleaners	4220	4220	4220	4220	4220
4230	Maids/housekeeping cleaners	4230	4230	4230	4230	4230
4240	Pest control workers	4240	4240	4240	4240	4240
4250	Grounds maintenance workers	4250	4250	4250	4250	4251
						4252
						4153
	Personal Care and Service Occupations					
4330	Supervisors of personal care workers	4300	4300	4300	4300	4330
		4320	4320	4320	4320	
4340	Animal trainers	4340	4340	4340	4340	4340
4350	Non-farm animal caretakers	4350	4350	4350	4350	4350
4400	Gaming services workers	4400	4400	4400	4400	4400
4420	Ushers/lobby attendants/ticket takers	4420	4420	4420	4420	4420
4435	Entertainment attendants, nec	4430	4410	4410	4410	4435
			4430	4430	4430	
4460	Embalmers/crematory operators	4460	4460	4460	4460	4461
4465	Morticians/undertakers/funeral directors	320	320	4465	4465	4465
4500	Barbers	4500	4500	4500	4500	4500
4510	Hairdressers/hairstylists/cosmetologists	4510	4510	4510	4510	4510
4520	Personal appearance workers, nec	4520	4520	4520	4520	4521

occ2010fr	Occupation Group and Title	ACS Occupation Codes 2000	2005	2010	2012	2018
						4522
						4525
4530	Baggage porters/bellhops/concierges	4530	4530	4530	4530	4530
4540	Tour/travel guides	4540	4540	4540	4540	4540
4600	Childcare workers	4600	4600	4600	4600	4600
4610	Personal/home care aides	4610	4610	4610	4610	3602
4620	Recreation/fitness workers	4620	4620	4620	4620	4621
						4622
4640	Residential advisors	4640	4640	4640	4640	4640
4650	Personal care/service workers, nec	4650	4650	4650	4650	4655
	Sales and Related Occupations					
4700	Supervisors of retail sales	4700	4700	4700	4700	4700
4710	Supervisors of non-retail sales	4710	4710	4710	4710	4710
4720	Cashiers	4720	4720	4720	4720	4720
4740	Counter/rental clerks	4740	4740	4740	4740	4740
4750	Parts salespersons	4750	4750	4750	4750	4750
4760	Retail salespersons	4760	4760	4760	4760	4760
4800	Advertising sales agents	4800	4800	4800	4800	4800
4810	Insurance sales agents	4810	4810	4810	4810	4810
4820	Securities/commodities/financial sales agents	4820	4820	4820	4820	4820
4830	Travel agents	4830	4830	4830	4830	4830
4840	Sales representatives. of services, nec	4840	4840	4840	4840	4840
4850	Sales representatives, wholesale/manufacturing	4850	4850	4850	4850	4850
4900	Models/demonstrators/product promoters	4900	4900	4900	4900	4900
4920	Real estate brokers/sales agents	4920	4920	4920	4920	4920
4930	Sales engineers	4930	4930	4930	4930	4930
4940	Telemarketers	4940	4940	4940	4940	4940
4950	Door-to-door sales/news/street vendors	4950	4950	4950	4950	4950
4960	Sales workers, nec	4960	4960	726	726	726
				4965	4965	4965
	Office and Administrative Support Occupations					
5000	Supervisors of office/admin. support	5000	5000	5000	5000	5000
5010	Switchboard operators	5010	5010	5010	5010	5010
5020	Telephone operators	5020	5020	5020	5020	5020
5030	Communications equipment operators, nec	5030	5030	5030	5030	5040
5100	Bill/account collectors	5100	5100	5100	5100	5100
5110	Billing/posting clerks	5110	5110	5110	5110	5110
5120	Bookkeeping/accounting/auditing clerks	5120	5120	5120	5120	5120
5140	Payroll/timekeeping clerks	5140	5140	5140	5140	5140
5150	Procurement clerks	5150	5150	5150	5150	5150
5160	Tellers	5160	5160	5160	5160	5160
5220	Court/municipal/license clerks	5220	5220	5220	5220	5220
5230	Credit authorizers/checkers/clerks	5230	5230	5230	5230	5230
5240	Customer service representatives	5240	5240	5240	5240	5240
5250	Eligibility interviewers, govt programs	5250	5250	5250	5250	5250
5260	File Clerks	5260	5260	5260	5260	5260

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
5300	Hotel/motel/re-sort desk clerks	5300	5300	5300	5300	5300
5310	Interviewers, exc. eligibility/loan	5310	5310	5310	5310	5310
5320	Library assistants, clerical	5320	5320	5320	5320	5320
5330	Loan interviewers/clerks	5330	5330	5330	5330	5330
5340	New accounts clerks	5340	5340	5340	5340	5340
5350	Correspondence/order clerks	5210 5350	5350	5350	5350	5350
5360	Human resources assistants, exc. payroll	5360	5360	5360	5360	5360
5400	Receptionists/information clerks	5400	5400	5400	5400	5400
5410	Reservation/transportation agents	5410	5410	5410	5410	5410
5420	Information/record clerks, nec	5200 5420	5200 5420	5200 5420	5200 5420	5420
5500	Cargo/freight agents	5500	5500	5500	5500	5500
5510	Couriers/messengers	5510	5510	5510	5510	5510
5520	Dispatchers	5520	5520	5520	5520	5521 5522
5530	Meter readers, utilities	5530	5530	5530	5530	5530
5540	Postal service clerks	5540	5540	5540	5540	5540
5550	Postal service mail carriers	5550	5550	5550	5550	5550
5560	Postal service mail sorters/operators	5560	5560	5560	5560	5560
5600	Production/planning/expediting clerks	5600	5600	5600	5600	5600
5610	Shipping/receiving/traffic clerks	5610	5610	5610	5610	5610
5620	Stock clerks/order fillers	5620	5620	5620	5620	9645
5630	Weighers/measurers/checkers/samplers	5630	5630	5630	5630	5630
5700	Secretaries/administrative assistants	5700	5700	5700	5700	5710 5720 5730 5740
5810	Data entry keyers	5810	5810	5810	5810	5810
5820	Word processors/typists	5820	5820	5820	5820	5820
5840	Insurance claims/policy processing clerks	5840	5840	5840	5840	5840
5850	Mail clerks/machine operators, exc. postal	5850	5850	5850	5850	5850
5860	Office clerks, general	5860	5860	5860	5860	5860
5900	Office machine operators, exc. computer	5900	5900	5900	5900	5900
5910	Proofreaders/copy markers	5910	5910	5910	5910	5910
5920	Statistical assistants	5920	5920	5920	5920	5920
5930	Office/administrative support, nec	5130 5830 5930	5130 5930	5130 5165 5940	5130 5165 5940	5165 5940
	Farming, Fishing, and Forestry Occupations					
6000	Supervisors of farming/fishing/forestry	6000	6000	6005	6005	6005
6010	Agricultural inspectors	6010	6010	6010	6010	6010
6040	Graders/sorters, agricultural products	6040	6040	6040	6040	6040
6050	Agricultural workers, nec	6020 6050	6050	6050	6050	6050
6115	Fishing/hunting workers	6100 6110	6100	6100	6100	6115

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
6120	Forest/conservation workers	6120	6120	6120	6120	6120
6130	Logging workers	6130	6130	6130	6130	6130
	Construction and Extraction Occupations					
6200	Supervisors of construction/extraction	6200	6200	6200	6200	6200
6210	Boilermakers	6210	6210	6210	6210	6210
6220	Brickmasons/blockmasons/stonemasons	6220	6220	6220	6220	6220
		6500	6500	6500		
6230	Carpenters	6230	6230	6230	6230	6230
6240	Carpet/floor/tile installers	6240	6240	6240	6240	6240
6250	Cement masons/terrazzo workers	6250	6250	6250	6250	6250
6260	Construction laborers	6260	6260	6260	6260	6260
6305	Construction equip. operators	6300	6300	6300	6300	6305
		6310	6320	6320	6320	
		6320				
6330	Drywall/ceiling tile installers/tapers	6330	6330	6330	6330	6330
6350	Electricians	6350	6350	6355	6355	6355
6360	Glaziers	6360	6360	6360	6360	6360
6400	Insulation workers	6400	6400	6400	6400	6400
6410	Painters/paperhangers	6420	6420	6420	6420	6410
		6430	6430	6430		
6440	Pipelayers/plumbers/pipefitters	6440	6440	6440	6440	6441
						6442
6460	Plasterers/stucco masons	6460	6460	6460	6460	6460
6510	Roofers	6510	6510	6515	6515	6515
6520	Sheet metal workers	6520	6520	6520	6520	6520
6530	Structural iron/steel workers	6530	6540	6530	6530	6530
6600	Helpers, construction trades	6600	6600	6600	6600	6600
6660	Construction/building inspectors	6660	6660	6660	6660	6660
6700	Elevator installers/repairers	6700	6700	6700	6700	6700
6710	Fence erectors	6710	6710	6710	6710	6710
6720	Hazardous materials removal workers	6720	6720	6720	6720	6720
6730	Highway maintenance workers	6730	6730	6730	6730	6730
6740	Rail-track laying/maintenance operators	6740	6740	6740	6740	6740
6760	Construction workers, nec	6750	6760	6540	6540	6540
		6760		6765	6765	6765
6800	Derrick operators, oil/gas/mining	6800	6800	6800	6800	6800
		6920				
6820	Earth drillers, except oil/gas	6820	6820	6820	6820	6825
6830	Explosives workers	6830	6830	6830	6830	6835
6850	Underground mining operators	6840	6840	6840	6840	6850
		9730				
6950	Extraction workers, nec	6910	6940	6940	6940	6950
		6930				
		6940				
	Installation, Maintenance, and Repair Occupations					
7000	Supervisors of mechanics/repairers	7000	7000	7000	7000	7000

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
7010	Computer/automated teller repairers	7010	7010	7010	7010	7010
7020	Radio/tele equip. repairers	7020	7020	7020	7020	7020
7030	Avionics techs	7030	7030	7030	7030	7030
7040	Electric motor/power tool repairers	7040	7040	7040	7040	7040
7100	Electrical repairers, industrial/utility/vehicles	7050	7100	7100	7100	7100
		7100	7110	7110	7110	
		7110				
7120	Electronic home entertain equip. installers	7120	7120	7120	7120	7120
7130	Security/fire alarm systems installers	7130	7130	7130	7130	7130
7140	Aircraft mechanics/service techs	7140	7140	7140	7140	7140
7150	Automotive body repairers	7150	7150	7150	7150	7150
7160	Automotive glass installers	7160	7160	7160	7160	7160
7200	Automotive service techs/mechanics	7200	7200	7200	7200	7200
7210	Bus/truck/diesel engine mechanics	7210	7210	7210	7210	7210
7220	Heavy vehicle/mobile equipment mechanics	7220	7220	7220	7220	7220
7240	Small engine mechanics	7240	7240	7240	7240	7240
7260	Vehicle/mobile equip. mechanics/repairers, nec	7260	7260	7260	7260	7260
7300	Control/valve installers/repairers	7300	7300	7300	7300	7300
7310	Heating/air conditioning/refrigeration mechanics	7310	7310	7315	7315	7315
7320	Home appliance repairers	7320	7320	7320	7320	7320
7330	Industrial/refractory machinery mechanics	7330	7330	7330	7330	7330
7340	Maintenance/repair workers, general	7340	7340	7340	7340	7340
7350	Maintenance workers, machinery	7350	7350	7350	7350	7350
7360	Millwrights	7360	7360	7360	7360	7360
7410	Electrical power-line installers	7410	7410	7410	7410	7410
7420	Telecommunications line installers	7420	7420	7420	7420	7420
7430	Precision instrument/equipment repairers	7430	7430	7430	7430	7430
7510	Coin/vending/amusement machine repairers	7510	7510	7510	7510	7510
7540	Locksmiths/safe repairers	7540	7540	7540	7540	7540
7560	Riggers	7560	7560	7560	7560	7560
7610	Helpers - installation/maintenance/repair	7610	7610	7610	7610	7610
7640	Installation/maintenance/repair, nec	7520	7550	7550	7630	7640
		7550	7620	7630		
		7600				
		7620				
	Production Occupations					
7700	Supervisors of production workers	7700	7700	7700	7700	7700
7720	Electrical/electronics assemblers	7720	7720	7720	7720	7720
7730	Engine/machine assemblers	7730	7730	7730	7730	7730
7740	Structural metal fabricators/fitters	7740	7740	7740	7740	7740
7750	Assemblers/fabricators, nec	7710	7710	7710	7710	7750
		7750	7750	7750	7750	
7800	Bakers	7800	7800	7800	7800	7800
7810	Butchers/meat processing workers	7810	7810	7810	7810	7810
7830	Food/tobacco/baking operators	7830	7830	7830	7830	7830
7840	Food batchmakers	7840	7840	7840	7840	7840
7850	Food cooking machine operators	7850	7850	7850	7850	7850

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
7900	Computer control programmers, metal/plastic	7900	7900	7900	7900	7905
7925	Forming machine operators, metal/plastic	7920	7920	7920	7920	7925
		7930	7930	7930	7930	
		7940	7940	7940	7940	
8025	Machine tool operators, metal/plastic, nec	7950	7950	7950	7950	7950
		7960	7960	7960		8000
		8000	8000	8000		8025
		8010	8010	8010		
		8020				
8030	Machinists	8030	8030	8030	8030	8030
8040	Metal furnace/kiln operators	8040	8040	8040	8040	8040
8100	Molders, metal/plastic	8060	8060	8060	8100	8100
		8100	8100	8100		
8130	Tool/die makers	8130	8130	8130	8130	8130
8140	Welding/soldering/brazing workers	8140	8140	8140	8140	8140
8225	Metal/plastic workers, nec	8120	8150	8150	8220	8225
		8150	8200	8200		
		8160	8210	8210		
		8200	8220	8220		
		8210				
		8220				
8250	Prepress techs/workers	8250	8250	8250	8250	8250
8260	Printing operators	8230	8230	8255	8255	8255
		8240	8240	8256	8256	8256
		8260	8260			
8300	Laundry/dry-cleaning workers	8300	8300	8300	8300	8300
8310	Pressers, textile/garment	8310	8310	8310	8310	8310
8320	Sewing machine operators	8320	8320	8320	8320	8320
8335	Shoe and leather workers/repairers	8330	8330	8330	8330	8335
		8340	8340	8340		
8350	Tailors/dressmakers/sewers	8350	8350	8350	8350	8350
8365	Textile machine setters/operators	8360	8400	8400	8400	8365
		8400	8410	8410	8410	
		8410	8420	8420	8420	
		8420				
8450	Upholsterers	8450	8450	8450	8450	8450
8465	Textile/apparel/furnishings workers, nec	8430	8460	8460	8460	8465
		8440				
		8460				
8500	Cabinetmakers/bench carpenters	8500	8500	8500	8500	8500
8510	Furniture finishers	8510	8510	8510	8510	8510
8530	Sawing machine operators, wood	8530	8530	8530	8530	8530
8540	Woodworking machine operators, exc. sawing	8540	8540	8540	8540	8540
8555	Woodworkers, nec	8520	8550	8550	8550	8555
		8550				
8600	Power plant operators	8600	8600	8600	8600	8600
8610	Stationary engineers/boiler operators	8610	8610	8610	8610	8610
8620	Water/liquid waste plant operators	8620	8620	8620	8620	8620
8630	Plant/system operators, nec	8630	8630	8630	8630	8630

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
8640	Chemical processing machine operators	8640	8640	8640	8640	8640
8650	Crushing/grinding/polishing workers	8650	8650	8650	8650	8650
8710	Cutting workers	8710	8710	8710	8710	8710
8720	Extruding/pressing machine operators	8720	8720	8720	8720	8720
8730	Furnace/kiln/oven/drier/kettle operators	8730	8730	8730	8730	8730
8740	Inspectors/testers/sorters/samplers	8740	8740	8740	8740	8740
8750	Precious stone/metal workers	8750	8750	8750	8750	8750
8760	Medical/dental/ophthalmic laboratory techs	8760	8760	8760	8760	8760
8800	Packaging/filling machine operators	8800	8800	8800	8800	8800
8810	Painting workers	8810	8810	8810	8810	8810
8830	Photographic process workers	8830	8830	8830	8830	8830
8850	Adhesive bonding machine operators	8850	8850	8850	8850	8850
8910	Etchers/engravers	8910	8910	8910	8910	8910
8920	Molders/shapers/casters, exc. metal/plastic	8920	8920	8920	8920	8920
8930	Paper goods machine operators	8930	8930	8930	8930	8930
8940	Tire builders	8940	8940	8940	8940	8940
8950	Helpers - production	8950	8950	8950	8950	8950
8990	Production workers, nec	8840	8860	7855	7855	7855
		8860	8960	8860	8965	8990
		8900		8965		
		8960				
	Transportation and Material Moving Occupationss					
9000	Supervisors of transportation/material moving	9000	9000	9000	9000	9005
9030	Aircraft pilots/flight engineers	9030	9030	9030	9030	9030
9040	Air traffic controllers/specialists	9040	9040	9040	9040	9040
9050	Transportation attendants	4550	4550	9050	9050	9050
				9415	9415	9415
9110	Ambulance drivers/attendants	N/A	9110	9110	9110	9110
9120	Bus drivers	9120	9120	9120	9120	9121
						9122
9130	Driver/sales workers and truck drivers	9130	9130	9130	9130	9130
9140	Taxi drivers/chauffeurs	9140	9140	9140	9140	9141
						9142
9150	Motor vehicle operators, nec	9150	9150	9150	9150	9150
9200	Locomotive engineers/operators	9200	9200	9200	9200	9210
9240	Railroad conductors/yardmasters	9240	9240	9240	9240	9240
9265	Rail transportation workers, nec	9230	9230	9230	9260	9265
		9260	9260	9260		
9300	Sailors/marine oilers/ship engineers	9300	9300	9300	9300	9300
		9330				
9310	Ship/boat captains/operators	9310	9310	9310	9310	9310
9350	Parking attendants	9350	9350	9350	9350	9350
9410	Transportation inspectors	9410	9410	9410	9410	9410
9430	Transportation workers, nec	9340	9360	9360	9360	9365
		9360	9420	9420	9420	9430
		9420				
9510	Crane/tower operators	9510	9510	9510	9510	9510

		ACS Occupation Codes				
occ2010fr	**Occupation Group and Title**	**2000**	**2005**	**2010**	**2012**	**2018**
9570	Conveyor/dredge/hoist/winch operators	9500	9520	9520	9520	9570
		9520	9560	9560	9560	
		9560				
9600	Industrial truck/tractor operators	9600	9600	9600	9600	9600
9610	Cleaners of vehicles/equipment	9610	9610	9610	9610	9610
9620	Laborers and freight/stock/material movers, hand	9620	9620	9620	9620	9620
9630	Machine feeders/offbearers	9630	9630	9630	9630	9630
9640	Packers/packagers, hand	9640	9640	9640	9640	9640
9650	Pumping station operators	9650	9650	9650	9650	9650
9720	Refuse/recyclable material collectors	9720	9720	9720	9720	9720
9760	Material moving workers, nec	9740	9750	9750	9750	9760
		9750				

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