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ABSTRACT

Trade-Induced Adoption of New Work*

I study the trade-induced restructuring process using a novel measure of new work that captures the firm's demand for jobs employing new knowledge, skills, and technologies. To construct measures of new work, I identify newly emerged job titles using word embedding models. Using both regional and firm-level analyses, I find that greater import exposure causes a persistent increase in new work in managerial occupations, but a decrease in new work in other occupations. Examining the activities performed in managerial new work, I find evidence of increased investments in post-production activities such as customer support, marketing, and sales. I further show that the trade-induced increase in managerial new work is driven by college-educated workers, thereby shedding light on the role of new work adoption in the distributional consequences of import shocks.

JEL Classification: F16, J23, O33, R12
Keywords: new work, trade adjustments, labor market inequality

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1 Introduction

Import competition poses a challenge to a firm's profitability and survival. Facing this type of adverse shock, some firms find it optimal or even necessary to restructure. Indeed, there exists substantial evidence of ongoing restructuring within surviving firms in the import competing sectors. Examples include refocusing on the firm's core competencies (Bernard and Fort, 2015), reallocating resources within-firm across establishments (Fort et al., 2018), reorganizing the firm hierarchy (Caliendo et al., 2020), and switching sectors to become more service-oriented (Bloom et al., 2019). This restructuring process can be broadly understood as changes in the composition of tasks performed in-house.

The literature on trade adjustments has mainly focused on understanding the compositional changes within existing tasks (e.g., decreasing the share of offshorable or routine tasks) and the consequences for productivity, welfare, and labor market inequality. However, less is known about the adjustment at the extensive margin – namely, through the adoption of *new tasks* – and about its impact on the broader economy. New work adoption occurs when a firm chooses to shift the production technology from the status quo to one that incorporates new tasks. Understanding new work adoption is important for the following reasons. First, new work adoption gives rise to an additional source of productivity growth as firms can choose from an increased set of production technologies to achieve higher profits. Second, it also provides information about the type of strategies firms focus on to escape competition and reshape comparative advantages. Third, transitions to implement new work that require specific skills can generate distributional consequences across worker groups, which sheds light on labor market inequality induced by post-shock restructuring strategies.

In this paper, I study the impact of trade-induced restructuring on new work adoption using a novel measure of new work. Using both regional and firm-level analyses, I provide evidence of increased new work shares in managerial jobs in response to import competition. Combining the new work measures with rich skills data in O*NET and Burning Glass Technologies' online vacancies, I find that increased demand of new work in managerial occupations accompanies skill requirements that relate to post-production activities such as customer support, marketing, and sales. I further show that a trade-induced increase in managerial new work is driven by college-educated workers, which highlights the role of new work adoption in the distributional consequences of import shocks.

Identifying *new work* in available data – essentially, measuring newness of a job – is challenging. For example, one could potentially use the changes in the occupational classification over time to identify new work. However, this approach can be misleading because merging and splitting of occupation codes may arise due to a growing supply of workers in particular jobs or due to revisions to improve the occupation classifications themselves. In this paper, I propose a novel measure of new work using the emergence of new job titles over time. This measure of new work is related to Lin (2011) but it has two important differences. First, I construct a continuous measure of newness for each job title using word embedding models, which compute the pairwise distance between job titles based on the context of their appearances in large texts. For each job title observed in the current period, I measure newness using the minimum of the pairwise distances with respect to all job titles (i.e., the closest match) in the previous period. Second, I include new work that emerged post 2000. This extension is crucial for studying the effects of important trade shocks that occurred after 2000, including China's integration into the global market, or what is often referred to as the China shock. Descriptive exercises of the skill content of new work that emerged after 2000 show that new work is concentrated in jobs with greater requirements in cognitive and social skills. New work is also intensive in skills that complement recent developments in technology and globalization, which substantially replace routine tasks. Furthermore, there is a significant wage premium associated with new work intensity.

Using these new work measures, I perform a series of analyses that relate import competition to new work adoption at both regional and firm levels. To identify import shocks, I follow Pierce and Schott (2016) and use the tariff gaps between the Normal Trade Relations (NTR) rates and the non-NTR rates generated due to the U.S. granting Permanent Normal Trade Relations (PNTR) to China at the end of 2000. With China gaining access to low tariff rates with certainty, industries that faced large gaps were more exposed to import shocks and local labor markets with heavy reliance on these industries were hit hard. I find a positive but statistically insignificant effect of import exposure on new work adoption when pooling all occupations; however, this estimate masks substantial heterogeneity across different occupation types.

To guide analysis on the heterogeneous effects, I group occupations into five categories: managerial, technological, clerical, production, and all others.[1] I find a significant increase in new work shares in managerial occupations, and the estimated effects also increase and persist over time. Comparing more exposed regions (90th percentile) to the less exposed ones (10th percentile), the difference in the change in new work shares reaches about three percentage points in 2015. The effects are statistically significant and negative for technological, clerical, and production occupations. I find similar heterogeneity by task type (Acemoglu and Autor, 2011), where the positive effects are concentrated in non-routine cognitive and analytical tasks, and the negative effects are most pronounced in routine tasks. The validity of the results is supported by including a host of controls on regional characteristics and a series of robustness tests on pre-existing trends, alternative measures of new work, and an alternative identification of import shocks.[2]

To better understand the nature of new work adopted in managerial occupations, I examine the types of activities performed in these jobs. I use O*NET's Knowledge data files for this exercise, which provide occupation-specific (8-digit SOC) knowledge requirements. I find that high-exposed regions show a significant increase in knowledge and skills requirements related to post-production stage (customer support, sales, marketing, and public relations) activities within managerial new work. In contrast, I find no such effect on existing work in managerial occupations, suggesting

[1] I use 2-digit SOC codes to classify occupations: managerial (11, 13, and 23), technological (15 and17), clerical (41 and 43), production (49, 51, and 53), and all others.

[2] For new work measures, I iterate the exercise using new work intensity measures based on O*NET's New and Emerging (N&E) occupations and the average new work intensity scores instead of employment shares. For import shocks, I follow Autor et al. (2013) and instrument U.S. imports from China with high-wage countries' imports.

that the results are not merely driven by an increase in certain managerial occupations requiring more post-production knowledge or skills. In addition, I do not find any significant effects on the demand for skills related to the management and organizational aspects of firm activities (human resources, legal, and management), or for those skills relevant to pre-production or main production stage activities. These findings collectively suggest that highly exposed regions disproportionately experience trade-induced restructuring that concentrates investments in post-production activities related to expanding firms' customer capital.

Next, I examine whether the positive effect on skill demands related to post-production activities are more pronounced in regions that experienced greater degrees of structural changes in the main production stage, namely offshoring and sectoral shifts to services. I use offshoring-led layoffs data in Trade Adjustment Assistance (TAA) petitions to construct regional measures of offshoring exposure. To measure sectoral shifts within firms, I use the sector information employers post in online job ads provided in Burning Glass Technologies (BGT), specifically focusing on shifts from manufacturing (2-digit NAICS 31 to 33) to professional services and wholesale (2-digit NAICS 42, 54, and 55). I find that the positive and significant results for skills related to post-production activities mainly hold for regions with high exposure to offshoring or sectoral shifts, which highlight important complementarities between post-production activities and structural changes in the main production stage. While shifting production modes can also induce investments in the pre-production stage (e.g., developing new product lines), note that these baseline exercises show negative effects when I examine technological new work. This is consistent with the findings of previous literature using patents as innovation measures in the U.S. (Autor et al., 2020; Hombert and Matray, 2018; Xu and Gong, 2017), though technological new work potentially corresponds to a broader notion of innovation than these conventional measures.[3]

What implications does the adjustment process have on workers and labor market inequality? To test for possible distributional effects and local labor market inequality related to new work demands, I conduct two exercises. First, I examine differences in the baseline findings for workers with and without college degrees and find that the effects of import shocks on managerial new work are driven mainly by college-educated workers. Second, I ask whether the demand for college-educated workers in new work is associated with a rise in local wage inequality. I find a statistically significant increase in the log wage differences between workers with and without college degrees ($\Delta(logw_c - logw_{nc})$) for new work in highly exposed regions relative to low-exposed ones. However, I do not find any significant effects for "existing" jobs. The findings highlight the role of new work adoption in the distributional consequences of the China shock. The differences in job opportunities induced by the restructuring process, shifting the demand towards high-skill workers with comparative advantages in performing new tasks, contribute to the substantial differences in post-shock earnings across worker groups. These wage gaps not only persist but become amplified over time.

[3]Import shocks can discourage product innovation as increased competition already reduces profits (Aghion et al., 2005). In addition, if foreign products easily substitute for domestic ones (Holmes and Stevens, 2014), there may be little room for developing new product lines particularly in industries that produce standardized goods.

While the regional results capture both the effects of import shocks on new work within surviving firms and any compositional effects from firm entry and exit, the firm analysis isolates the effects within surviving firms. Using a merged sample of publicly listed manufacturing firms in Compustat and online vacancies from BGT, I study the establishment-level responses to industry-level NTR gaps. Since BGT data is only accessible to this project starting in 2010, examining establishment- or firm-level changes in new work adoption relative to the pre-China shock period is not feasible. However, recall that the regional analysis shows that the China shock induced a steady increase in the managerial new work and new work involving non-routine tasks, both of which persist beyond 2010. I interpret the results of the BGT-based analysis under the assumption that the post-2010 dynamics reflect a continuation of pre-2010 adjustments to trade shocks.

The firm analysis complements the regional findings in three important ways. First, I confirm that the importance of managerial new work remains when examining within-establishment adoption of new work. I further find that the increase in demand for managerial new work is greater in high-revenue firms. Second, I document evidence of upskilling within managerial new work using college requirements employers list in BGT job ads. Further exploring the composition of college majors listed in job ads, I find a positive and significant demand for business-related majors but not for STEM degrees. The result shows that the increasing importance of managerial relative to technological new work remains pronounced even conditional on new work that requires college degrees. Third, I confirm the significant increase in skills related to post-production activities in managerial new work by examining skill intensity measures constructed using BGT skills data, which accounts for variations in skills within detailed occupation codes.[4] I also study whether the positive and significant effects persist after restricting the analysis to the following post-production skills: (i) ability to use information technology and (ii) ability to acquire or sell to consumers. I find suggestive evidence that trade-exposed firms are more likely to focus on post-production innovations that exhibit important complementarity with new technologies and focus on building customer capital.

This paper contributes to three strands of literature. First, it contributes to a small yet important branch of recent studies on "new work." Lin (2011) is the first to identify new work (1980-2000) using job titles by effectively combining information from Census revision documents and applying string matching methods. Atalay and Sarada (2020) identify new work (1940-2000) using the distribution of job title appearances in newspaper advertisements. Autor et al. (2021) examine new work (1900-2020) and constructs new work intensity by linking texts of patents and consumer demand surveys to job titles. Among these measures of new work, this paper's measure is closest in spirit to Lin (2011). However, my methodology – the use of word embedding models to construct new work – has both advantages in the way it classifies new work and is general enough to apply to job titles data retrieved from various sources. In addition, by examining the importance of trade in explaining the adoption of new work, I complement other studies that focus on the role of agglomeration Lin (2011) and foreign high-skill labor supply (Hanson, 2021).

[4] I also conduct robustness checks examining changes in firm-level expenditures of advertising and sales in Compustat data and confirm the importance of post-production activities in firm-level adjustments to trade shocks.

Second, this paper contributes to a burgeoning line of work studying job creation and destruction caused by trade shocks (Asquith et al., 2017; Bloom et al., 2019) and the trade-induced structural change where firms become factoryless (Bernard et al., 2017) and transform to become more service-oriented (Breinlich et al., 2018; Ding et al., 2020). Using the new work measures, I offer evidence of trade-induced adjustments at the extensive margin and document the rising importance of post-production investments. By further assessing the skill demands involved in new work adoptions, I show distributional effects of the restructuring process across worker groups. The results have implications for policies related to job training for current or displaced workers and human capital investments of future workers.

Lastly, this paper is also related to studies examining the impact of import competition on innovation. Investing in innovation activities, which can range from developing patents and upgrading production methods to implementing novel business strategies, is an important margin of firm-level adjustment to import shocks. Past literature has mainly focused on product innovation employing conventional measures such as R&D expenditure and patents using data from various countries and regions, including the U.S. (Autor et al., 2020; Hombert and Matray, 2018; Xu and Gong, 2017), Europe (Bloom et al., 2016), China (Brandt et al., 2017; Bombardini et al., 2018), and South Korea (Ahn et al., 2018).[5] I argue that new work adoption in part reflects firms' broader innovation efforts. Hence, by showing the baseline findings on the heterogeneous responses in new work adoption across occupation types, I provide complementary evidence on how firms innovate as they adjust to import competition.

2 Data and New Work Measures

2.1 Data

To construct measures of new work that serve as dependent variables of my analyses in sections 4 and 5, I use data on job titles collected from three sources: Dictionary of Occupation Titles (1980 and 1990), the Census Bureau's Classified Index of Industries and Occupations (2000), and the Sample of Reported Titles and Alternate Titles in the O*NET database (2016).[6] After classifying jobs as new, I aggregate the data by detailed occupation codes to merge with other data sources that record employment and vacancies at the detailed occupation level. For the regional analysis, I combine the new work measures with the Decennial Censuses 1980, 1990, and 2000 5 percent sample and the American Community Surveys (ACS, 2005-2018) (Ruggles et al., 2020). For the firm analysis, I combine the measures with a merged sample of publicly traded firms in Compustat and Burning Glass Technologies (henceforth, BGT), which provides the near-universe of U.S. online job ads (2010-2020) collected from around 40,000 job boards. I use detailed information on the job requirements for skills, education, college major, and certification in BGT data to study the skill and

[5] See Shu and Steinwender (2018) for an extensive review.

[6] Job titles processed by Lin (2011) for years 1980, 1990, and 2000 can be downloaded from: `https://sites.google.com/site/jeffrlin/newwork`.

task content of the new work that firms adopt as they adjust to import shocks.[7] To construct import exposures to the China shock, I use the historical tariff rates of U.S. trading partner countries. As in Pierce and Schott (2016), I exploit China's unprecedented emergence in the world economy in the early 2000s using industry-level variations in gaps in the Normal Trade Relations (NTR) rates and the non-NTR rates. For the regional analysis, I then use initial local industry compositions constructed using the County Business Patterns Data (1980, 1990, and 2000) as weights to apportion industry-level shocks to local labor markets. For the firm analysis, I use industry-level (4-digit SIC) NTR gaps.

2.2 New Work Measures

Job titles reflect tasks, skills, and responsibilities in the workplace, and thus, the emergence and disappearance of job titles provide important information about the changing nature of work over time.[8] In the pioneering work by Lin (2011), new job titles in each decade (1980-2000) are identified using information collected from revision documents and direct string matching methods. In this paper, I construct newness measured as distances from previous job titles based on the context of their appearances in large texts. Specifically, I use the Continuous Bag of Words (henceforth CBOW) model, one of the widely used Word2Vec algorithms, to generate word-specific vectors by predicting the appearance of target words in a job title based on the surrounding words in a sample of large texts.[9] This approach has advantages over direct string matching methods as it helps minimize misclassification of job titles due to relabeling over time.

To construct new work intensity of each job title $x \in X_t$ (the set of all job titles observed in period t), I use the job-title-specific vector $f(x)$ to then compute pairwise distances across all existing job titles in the past decade ($\forall y \in X_{t-1}$) using cosine similarity scores:

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

Note that, if $x \in X_{t-1}$ and $x \in X_t$, then $NWI_t(x) = 0$ immediately, which implies that x is not a new job based on a direct string match. Therefore, considering all elements of X_t is effectively the same as focusing only on $x \in X_t \setminus X_{t-1}$.

Before using the CBOW model, I edit the titles to remove unnecessary modifiers included in job titles for surveying purposes. This is important because the model can be sensitive to small differences in word combinations observed in some job titles, which translates into positive distances.

[7] Occupations and industries requiring greater skill are overrepresented in the data. See Figure A.1 for comparisons in the occupation and industry distributions with OES and JOLTS. While the aggregate number of job ads posted each year demonstrates an increasing trend, the occupation and industry distributions remain stable over time.

[8] Occupation titles, in comparison, deliver a more general idea of the job content (e.g., "Health Technician") than job titles (e.g., "Special Procedure Technologist, CT Scan"). Moreover, using changes in occupation classifications to examine the evolution of work can be misleading: merging and splitting of occupation codes may occur due to a growing supply of workers in particular jobs or revisions to improve the classifications.

[9] There is an increasing number of recent studies that conduct empirical analysis using data based on textual information for quantitative exercises (Atalay et al., 2018; Gentzkow et al., 2018; Hoberg and Phillips, 2016; Michaels et al., 2018; Gentzkow and Shapiro, 2010).

To further correct this issue after running the model, I also manually inspect the matched job titles and cosine similarity scores and draw a threshold above which I assign values of one, effectively setting the new work intensity scores to zero. I experiment with various threshold levels around 0.85 and examine differences in new work intensity scores aggregated by detailed occupations. Figures A.2 and A.3 show great similarity between the occupational new work intensity scores derived using thresholds of 0.85, 0.90, and 0.95.[10]

To test the performance of the CBOW model in identifying new job titles, I compare the new work measures with those obtained by Lin (2011) for the years 1990 and 2000. I begin by checking the correlation coefficients between the two measures. Table A.2 shows values ranging between 0.67 and 0.76. Comparing the measures more closely, I find that the two methods mostly agree on detecting job titles that existed in the past; however, for some job titles identified as new by Lin (2011), the CBOW model finds matching job titles from the past period. Through manual inspection, I find that direct string matching methods can be sensitive to the ordering of words, the punctuation used, and the use of conjunctions and abbreviations, among other slight differences in content. I investigate these divergences further by (i) classifying job titles into four categories similar to the confusion matrix in statistical classification and (ii) examining the share of "existing (new)" titles identified by CBOW in what Lin (2011) identifies as "new (existing)." Figure A.4 shows that about 10 percent of new job titles in Lin (2011) are identified as existing by CBOW in 1990 and 20 percent in 2000. Examining existing job titles, approximately 10 percent are reported as new by CBOW for both years.[11] Finally, I test whether the new work intensity scores are sensitive to implementing alternative word-embedding models. In particular, I use Glove and Fasttext to construct new work measures and check the pairwise correlations with the preferred CBOW measures. Figure A.6 and Table A.2 demonstrate significant and positive correlations between measures obtained using all three models.

In the empirical analysis of the paper, I use a binary indicator that classifies occupations in the top quartile of new work intensity scores as new work and assigns the rest as existing work. To test the robustness of my results to the quartile threshold, I compare them with results obtained using the continuous new work intensity scores.[12] I also verify results using an alternative measure of new work: "New and Emerging (N&E) Occupations" identified in the O*NET data released in 2006 and 2009. The N&E classification is defined as occupations that "involve significantly different work than performed by job incumbents of other occupations and are not adequately reflected by the existing occupational structure."[13] Because the matched data sets identify occupations by 3-digit occupation codes, I create an indicator for new work that is set to one if the 3-digit occupation code includes any of the 8-digit O*NET SOC codes listed as N&E.

[10]See Appendix A for further details of the algorithm, text cleaning, and comparisons of new work intensity scores across threshold values.

[11]Figure A.4 plots the shares against varying thresholds of new work intensity scores. The estimates I mention in the main text correspond to those when no threshold is applied.

[12]The benchmark threshold value for assigning zeros to job titles with low new work intensity is 0.85.

[13]See `https://www.onetcenter.org/reports/NewEmerging.html` for further details.

3 Descriptive Analysis

For illustrative purposes, Table B.1 lists examples of job titles with high values of new work intensity. The list reveals substantial heterogeneity, reflecting the various channels through which the demand for new work arises. For example, firms that adopt green technology are likely to hire "Green Building Energy Engineers" or "Solar Panel Technicians" whose skills complement the newly adopted machinery. Firms that take advantage of increased foreign market access may demand a "Global Supply Chain Director" or "International Trade Specialist." Also, the demand for "Internet Marketers," "Online Content Coordinators," and "Data Abstractors" can emerge as the use of information technology and artificial intelligence becomes critical in analyzing markets and branding products. Figure 1 provides a visual summary of the distributions of new work intensity by 2-digit SOC occupation codes. White-collar occupations (legal, education, technological, business/finance, and healthcare) tend to show higher average new work intensity than the blue-collar occupations (production and construction); however, there is significant variation in new work intensity within occupation groups. I use a variance decomposition exercise to examine the variation in new work intensity explained by within versus between occupations. Figure B.2 shows that about 60 percent of the aggregate variation is due to within-occupation variance.

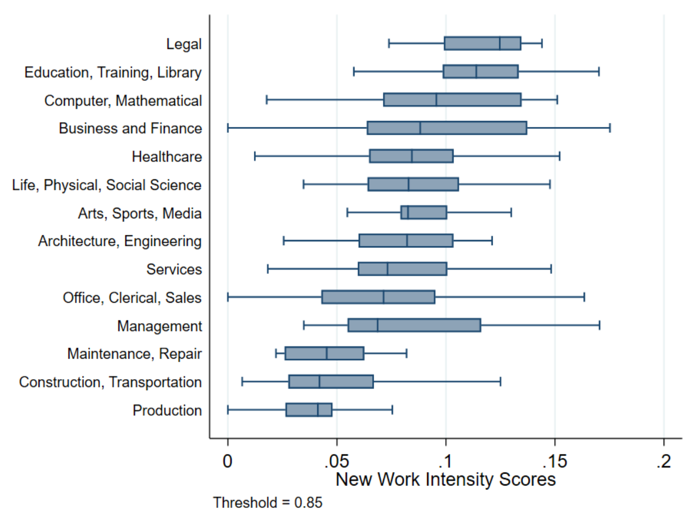

Figure 1: New Work Intensity by Occupations

Note: The box plot includes the minimum, maximum, median, top and bottom quartile values of the new work intensity scores by 2-digit SOC codes constructed using CBOW (threshold = 0.85) and aggregated at the 3-digit occupation level.

3.1 Skill Content of New Work

To describe the skill content of new work, I follow Deming and Kahn (2018) and search for keywords and phrases in BGT job ads related to skills that employers generally recognize as important: cognitive, social, character, writing, customer service, project management, people management, financial, and computer. For each of these skill dimensions, I then estimate the relative skill intensity of new work. Specifically, I run a series of bivariate ordinary least squares regressions for different skill categories using the 3-digit Census detailed occupations as the unit of analysis. The dependent variable is the share of job ads with the corresponding skill requirement. The explanatory variable is a binary indicator identifying the top quartile of the new work intensity scores obtained using CBOW. There are two main takeaways. First, occupations classified as new work require greater cognitive and interpersonal skills. However, the estimated differences for skills related to customer services, which also show little correlation with problem-solving or writing skills, are insignificant (Figure 2, left). The results suggest that the complementarity between cognitive and social skills documented in recent studies (Deming, 2017) is also found in the skill content of new work that emerged post 2000. Second, job ads listing new work intensive occupations are more likely to require skills related to information technology. The result implies that new work complements skills related to recent developments in technology (Acemoglu and Restrepo, 2018).

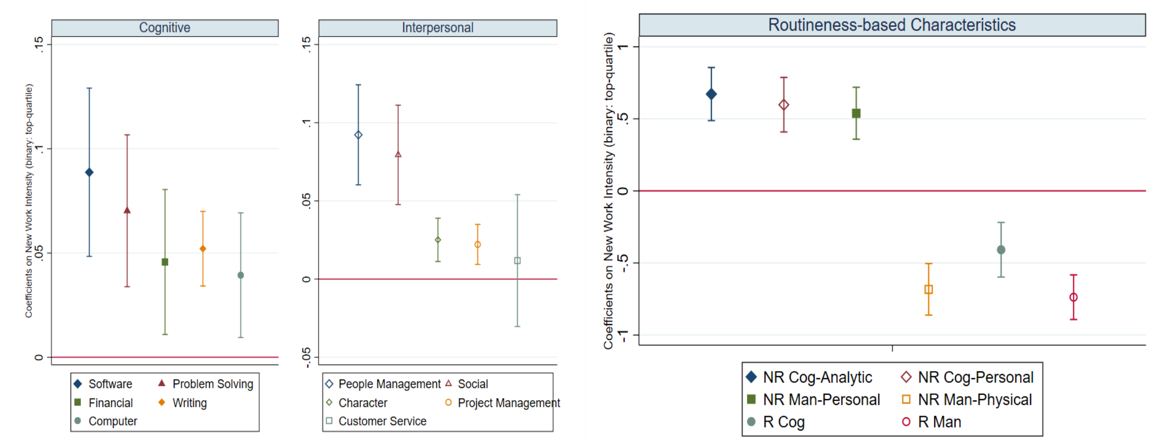

Figure 2: Skill Characteristics of New Work Post 2000

Note: Each estimated coefficient and 95% confidence interval are obtained using separate regressions of skill/task intensities on a binary indicator of new work (top-quartile) constructed using CBOW (threshold = 0.85). On the left, the dependent variable is the share of job ads with the corresponding skill requirement for each occupation-skill pair constructed using BGT skill requirements in 2010. On the right, the dependent variable is the average task intensity score for each occupation-task pair constructed using O*NET's skill descriptors.

I further study the second point by quantifying the skill content of new work based on technology-related task characteristics. I repeat the regression exercise for six task categories (non-routine cognitive, non-routine analytical, non-routine manual, non-routine interpersonal, routine cognitive, and routine manual), which I construct following Acemoglu and Autor (2011). The dependent variables are the average task intensity scores in each category. As shown in Figure 2 (right), new work that emerged post 2000 shows greater intensity in non-routine cognitive, analytical, and interpersonal tasks compared to existing work; these emerging jobs are relatively less intensive in routine or manual tasks. Figure B.6 also includes a set of parallel results for new work that emerged between 1990 and 2000. The results are qualitatively similar between the two decades; however, the magnitudes of the coefficients are greater in all skill categories for the analysis of new work that emerged after 2000. The findings are consistent with previous studies documenting significant shifts from routine and manual tasks to non-routine analytic and interactive ones in U.S. labor market demand over recent decades (Atalay et al., 2019).

3.2 Wage Premium of New Work

The analysis thus far implies that new work is relatively skill intensive and involves tasks that complement recent technological changes. Consistent with this, analyses of microdata using IPUMS-USA on worker education levels and earnings show that both demonstrate a strong positive relationship with new work intensity of the occupations that employ them. Figure B.7 shows the share of workers with a college education and above in new work employment has increased since 2000 and exceeded 50 percent in 2015.[14] Figure B.8 shows a strong positive correlation between occupational new work intensity scores and average wages and average wage growth.[15] Consistent with prior research discussing the importance of skill demand in the evolution of labor market inequality (Katz and Murphy, 1992; Autor et al., 2005), the result suggests that the growth in the demand for skills required to perform new work outpaces supply. Thus, new work adoption may be an important contributor to the rise in earnings inequality.

To further examine the extent to which new work explains variations in wages, I regress individual log(wages) on a binary measure of new work intensity. Table B.3 reports coefficients on new work intensity from models that include no controls other than year fixed effects (odd columns) and specifications that include both industry fixed effects and a set of controls (even columns). Columns (1) and (2) pool all years between 2005 and 2018, while columns (3) to (6) focus on a single year. Standard errors are clustered at the 3-digit Census occupation level. I find a positive and significant relationship between occupational new work intensity and individual wages across all specifications.[16] The coefficient estimate in column (2) implies that new work intensive occupations are associated with a 13.7 percent increase in wages for otherwise observationally similar workers. Comparisons of columns (4) and (6) show that the estimated wage premium is larger in 2015 (14.5 percent) compared to 2010 (13.1 percent).[17]

The wage premium and skill demands of new work highlight the distributional effects of new work adoption across workers. In the context of the trade-induced adjustment process, if new work adoption is an important channel through which firms restructure to escape import competition, then the corresponding shifts in skill demand potentially aggravate the inequality in job opportunities and earnings already generated by the initial import shock. Therefore, in the

[14]In Figure B.7, I also show the distribution of new work across different demographic groups.

[15]To construct wages, I divide earnings (*incwage*) by the product of weeks worked (*wkswork2*) and the usual weekly hours worked (*uhrswork*). I then CPI-adjust wages using 2000 as the base year. The average wage growth uses log changes between 2000 and 2015.

[16]Controls include binary indicators for gender, marital status, nativity, migration status, race (White, Black, Hispanic, Asian, and others), education (less than high school, high school, college, some college, and beyond college), and age (16-19, 20-29, 30-39, 40-49, and 50-70). Table B.4 reports results applying a threshold of 0.85 to new work intensity scores. Table B.5 reports estimation results using a continuous new work intensity score.

[17]In Tables B.6, I include results using the IPUMS-USA Decennial Census samples for 1990 and 2000, employing new work that emerged between 1980 to 1990 and 1990 to 2000, respectively.

following sections, I use the new work measures to examine the causal effects of import competition on new work adoption and further study the role of new work adoption in understanding labor market consequences of trade-induced restructuring and adjustments.

4 Regional Analysis

In this section, I take a local labor market approach using commuting zones (Tolbert and Sizer, 1996) and study the effects of import competition on new work adoption using regional variations in exposures to China's unprecedented emergence in the world economy in the early 2000s. Similar to Pierce and Schott (2020), I employ a Bartik-style instrument using the industry-level gaps in the Normal Trade Relations (NTR) rates and the non-NTR rates.[18] Upon China's accession to the WTO at the end of 2001, the U.S. granted the Permanent Normal Trade Relations (PNTR) to China. It removed uncertainty associated with annual renewals of import tariff rates on Chinese goods, otherwise subject to higher rates initially set under the Smoot-Hawley Act of 1930. The impact of China's entry into the world market was greater in industries with larger NTR gaps. Consequently, local labor markets with heavy reliance on these hard-hit industries were more exposed to the shock.

The regional import exposures are constructed by apportioning trade shocks using initial local industry compositions,

$$\text{NTR Gap}_{i,1999} = \sum_{j \in T} \frac{L_{ij0}}{L_{i0}} \times \text{NTR Gap}_{j,1999} \tag{2}$$

where $\text{NTR Gap}_{j,1999}$ is the difference between the non-NTR rate and the NTR rate for industry j in 1999 and is weighted by the industry shares in the tradable sector in commuting zone i in year 2000.[19] The average NTR gap across commuting zones is 0.08 with a standard deviation of 0.03; and the difference between commuting zones at the 90th (0.12) and 10th (0.04) percentiles is 0.08. Endogeneity concerns are mitigated as variations in the NTR gap are driven by the initial rates set in 1930 (Pierce and Schott, 2016).

To benchmark the patterns in my data against the findings of others, I regress changes in the share of local manufacturing employment and average wages on the local exposures to NTR gaps. For this exercise only, I use the Quarterly Census of Employment and Wages (1990 to 2019) to obtain data on local labor markets for additional pre-shock years. I run the regression separately for each year and include commuting zone characteristics in 2000 and state fixed effects. The coefficients and confidence intervals for these regressions are plotted in Figure 3. Similar to prior work studying the China shock on manufacturing (e.g., Autor et al., 2013; Pierce and Schott, 2016), I find statistically significant and negative effects on local manufacturing employment and wages.

[18] This is similar to the research design employed in the seminal China shock study by Autor et al. (2013) but differs in industry-level measure of import exposure. Rather than instrumenting import penetration using Chinese imports of other high-wage countries, the strategy focuses on the removal of uncertainty in U.S. tariff policy regarding China.

[19] Other studies that constructs regional exposures using tariff rates to examine local labor market effects of trade shocks include Topalova (2010); Kovak (2013), and Hakobyan and McLaren (2016).

I find no evidence that either effect was driven by pre-existing trends. Consistent with previous evidence that the China shock has induced firms to become factoryless (Bernard and Fort, 2015) and even transition to the service sector Bloom et al. (2019), I find that manufacturing employment share continues to decline for two decades following the initial shock.

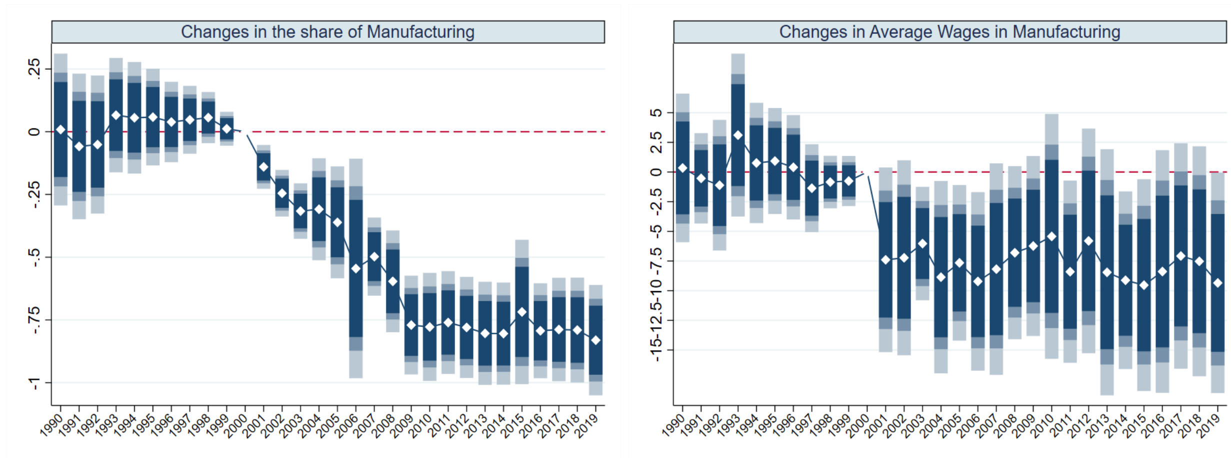

Figure 3: Changes in Manufacturing Employment and Wages (Data Source: QCEW 1990-2019)

Note: I run the following for each year: $\Delta y_{it,2000} = \beta_0 + \beta_{1t}\text{NTR Gap}_{i,1999} + \mathbf{X}'_{i,2000}\gamma_t + \eta_S + e_{it}$. Each graph plots the point estimates of β_{1t}'s and includes 90, 95, and 99 percent confidence intervals. The unit of analysis is a commuting zone-year pair. The dependent variables are the change in the share of manufacturing employment (left) and average log wages (right) in commuting zone i relative to that in year 2000. Controls include initial characteristics of local labor markets. State fixed effects are included. Robust standard errors are clustered on state.

4.1 Empirical Specification

The baseline specification to examine the effects of import exposures on new work adoption is,

$$\Delta y_{iot,2000} = \beta_0 + \sum_t \beta_{1t}\mathbb{1}(\text{year} = t) \times \text{NTR Gap}_{i,1999} + \mathbf{X}'_{i,2000}\gamma + \eta_t + \eta_R + e_{iot}. \tag{3}$$

I define y_{iot} as the share of workers hired in occupations with high new work intensity (top-quartile) in occupation o (2-digit SOC codes) in commuting zone (henceforth, CZ) i in year t. I use the new work intensity scores constructed using CBOW (threshold = 0.85). The dependent variable $\Delta y_{iot,2000}$ is the difference in regional new work shares between 2000 and year t. The sample period includes 2005 to 2018.[20] The time-invariant import exposure measure NTR Gap$_{i,1999}$ is interacted with a full set of year dummies. The coefficients of interests, β_{1t}, capture the effect of local import shocks on changes in new work adoption within a local labor market relative to the base year. Using the difference specification, I control for any time-invariant factors at the CZ-occupation pair level. Thus, comparing the estimated β_{1t}'s across the sample period allows me to test for the persistence of trends in new work adoption induced by the China shock. I also control for CZ-specific characteristics related to education, gender, age, race, marital status, migration, and

[20] ACS lacks CZ-level data on employment and wages for years from 2001 to 2004.

other economic indicators in 2000.[21] I add year fixed effects to absorb macroeconomic trends, and I also include Census region fixed effects. I weight observations by the size of the labor force in 2000 in each CZ. Robust standard errors are clustered on state.

Since the impact of import competition on new work adoption likely varies across different occupation types depending on the type of innovation that is induced, I investigate this heterogeneity using the following:

$$\begin{aligned}\Delta y_{iot,2000} = \beta_0 &+ \sum_t \beta_{1t} \mathbb{1}(\text{year} = t) \times \text{NTR Gap}_{i,1999} \\ &+ \sum_{t,s} \beta_{2st} \mathbb{1}(\text{year} = t, \text{type} = s) \times \text{NTR Gap}_{i,1999} + \mathbf{X}'_{i,2000}\gamma + \eta_t + \eta_R + e_{iot}.\end{aligned} \tag{4}$$

Compared to equation (3), I add triple interactions between occupation type, local import exposure measures, and year. I construct occupation types in two ways. First, I classify occupations into five broad categories (2-digit SOC): managerial (11, 13, and 23), technological (15 and 17), clerical (41 and 43), manual production (49, 51, and 53), and all others. The triple interactions are additive across occupation types and each estimate for β_{2st} captures the additional changes in new work employment shares for occupation type s compared to the reference occupation group in each year.[22] Second, I study heterogeneous responses by occupational task characteristics. Following Acemoglu and Autor (2011), I construct indicators based on six task intensity measures: non-routine cognitive, non-routine analytical, non-routine manual, non-routine interpersonal, routine cognitive, and routine manual. For each categorization, I set the indicator equal to one if occupation o is in the top quartile of task intensity scores. In this case, I include triple interactions between the indicator, local import exposure measures, and year. Each β_{2st}'s estimated using separate regressions for each task category capture the additional changes in new work employment shares for occupations with high intensity in each task compared to those with low intensity.

Identification rests on the assumption that pre-existing trends in the occupation-specific new work demands across local labor markets are uncorrelated with regional NTR Gaps. The assumption could be violated if an increased demand for new work in a particular occupation group in the pre-China shock period is more prevalent in regions with an industry composition that is more (or less) vulnerable to the removal of uncertainty in tariffs imposed on U.S. imports from China. To mitigate concerns related to pre-existing trends and possible confounding factors, I show that the results are robust to (i) including a host of variables related to pre-shock local characteristics; and (ii) adding past changes in the new work share (1980 to 1990, 1990 to 2000) as controls. I also perform falsification exercises, which I describe below.

[21] Controls include education (the share of population with less than high-school, high-school graduates, some college, college graduates, beyond college), gender, age (the share of those younger than 20, between 21 and 29, between 30 and 39, between 40 and 49, older than 49), race (the share of White, Black, Hispanic, Asian and others), marital status, migration, and economic indicators (employment status and average wage).

[22] The reference occupation group consists of occupations classified as "all others."

4.2 Main Results

Figure 4 summarizes the estimation results for equation (3). Each bar graph plots the point estimates of the coefficients of interests β_{1t} and the 90, 95 and 99 percent confidence intervals of each year in the sample period. The estimated effects of the China shock on within-occupation changes in local labor market adoption of new work are positive; however, the estimates lack precision in most years. Next, I examine heterogeneity in the effects across different occupation types using equation (4). To guide interpretation of the results, I plot the estimated total effects ($\beta_{1st} + \beta_{2st}$) for four different occupation types (Figure 5). Beginning with managerial jobs (top left panel), the coefficients near the value of zero and insignificant from 2005 to 2010. However, the coefficients become positive and significant in 2011, a trend that persists in subsequent years with the exception of 2012. A one standard deviation increase in import exposure leads to an increase in the share of new work by 1.11 ppt in 2015. Comparing CZs that are more exposed (90th percentile) to the less exposed (10th percentile) in terms of local NTR gaps (0.08), the difference in the change in new work shares is about 3 ppt in 2015. The results substantially differ for changes in new work adoption in technological jobs (top right panel). The estimated effects show a negative trend until 2011 and then fluctuates in the subsequent years.

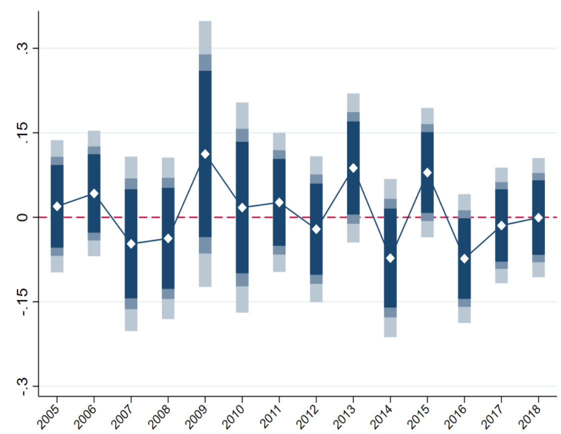

Figure 4: Changes in the Share of New Work within Occupation

Note: Each bar graph plots the point estimates of the coefficient of interest (β_{1t}) in equation (3) and includes 90, 95, and 99 percent confidence intervals for each year in the sample period. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Controls include initial characteristics of local labor markets. Census region fixed effects and time fixed effects are included. Robust standard errors are clustered on state.

On the bottom panel, I report the results for clerical (left) and production (right) work. The estimated effects are negative and statistically significant throughout the sample period, with the exception of a few years. A one standard deviation increase in import exposure leads to a decrease in the share of new work by 1.02 ppt in 2015 and 1.65 ppt in 2018 for clerical work; and 0.33 ppt and 0.81 ppt for production work. The estimated coefficients in 2010 and 2011 increase in magnitude by more than 100 percent in 2018 for clerical work. For production work, the estimates remain relatively stable until 2015, before increasing in magnitude by 170 percent in 2018. Compared to

CZs with relatively low import exposure (10th percentile), the more exposed ones (90th percentile) show a decrease in new work shares by 4.96 ppt and 2.72 ppt in 2018 for clerical and production work, respectively.

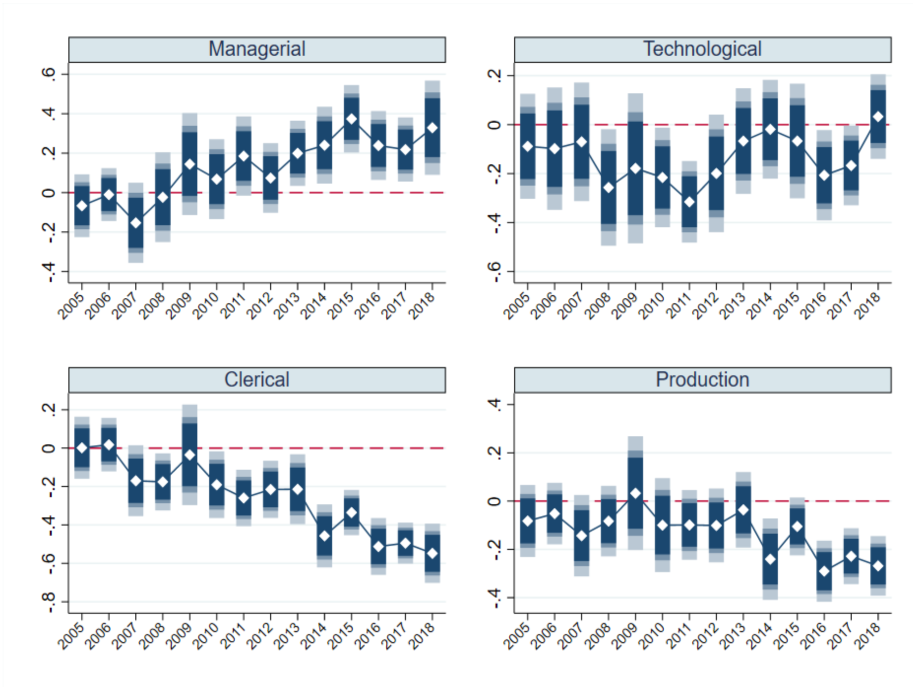

Figure 5: Changes in the Share of New Work by Occupation Type

Note: Each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) in equation (4) and includes 90, 95, and 99 percent confidence intervals. Occupation types are defined as broad categories (2-digit SOC): managerial (11, 13, and 23), technological (15 and 17), clerical (41 and 43), and manual production (49, 51, and 53). The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Controls include initial characteristics of local labor markets. Census region fixed effects and time fixed effects are included. Robust standard errors are clustered on state.

I turn to studying variations in the effects across occupation groups categorized using task types. Figure 6 reports estimated coefficients (β_{2st}) obtained by running separate regressions for each task type. The coefficients indicate the additional change in new work adoption that occurs in occupations intensive in task s relative to those that are not. The top panel reports the estimated results for three tasks types – non-routine cognitive analytical, interpersonal, and non-routine manual interpersonal – that demonstrate positive trends over time. Note that these positive effects are mainly concentrated in task types common to new work-intensive occupations (section 3.1). The bottom panel, on the other hand, demonstrates contrasting results, with negative trends for tasks that are non-routine manual physical and routine manual. While the estimates lack precision for routine cognitive tasks, there are several years near the end of the sample period (2015 to 2018) with statistically significant and negative effects.

Comparing with the baseline results (Figure 5), the positive estimates in managerial occupations, which show high intensity in non-routine cognitive tasks, are consistent with the first two graphs in the top panel of Figure 6. The negative estimates in production work, which are intensive in routine manual tasks, exhibit similar results with the bottom right graph of Figure 6. The estimated effects further show considerable persistence in several task types. As for occupations intensive in non-routine cognitive interpersonal tasks, one standard deviation in the NTR gaps causes an increase in the relative share of new work by 0.33 ppt in 2010, which remains significant throughout the sample period and increases in magnitude over time. For occupations intensive in non-routine cognitive analytical tasks, most of the significant change takes place in 2014 and the effects remain significant in subsequent years. Furthermore, for occupations intensive in routine manual tasks, the estimated coefficients in 2005 increase in magnitude by more than three times in 2018.

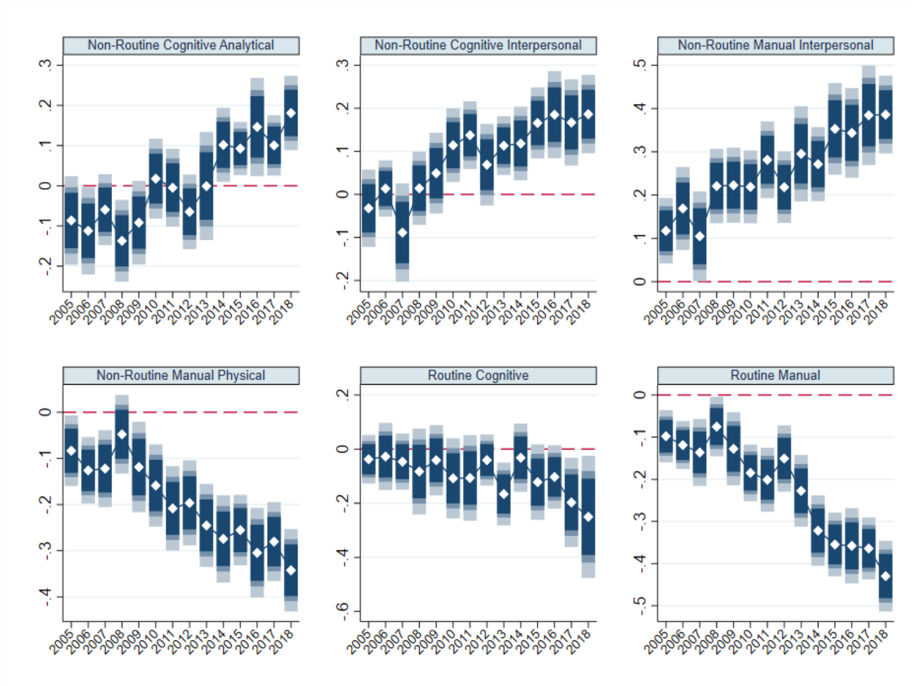

Figure 6: Relative Changes in the Share of New Work by Task Type

Note: Each graph plots the point estimates of the relative effects (β_{2st}) in equation (4) including 90, 95, and 99 percent confidence intervals. Occupations are categorized using a binary indicator for each task type: non-routine cognitive, non-routine analytical, non-routine manual, non-routine interpersonal, routine cognitive, and routine manual. Regressions are run *separately* for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Controls include initial characteristics of local labor markets. Census region fixed effects and time fixed effects are included. Robust standard errors are clustered on state.

To mitigate concerns that the estimated effects might be driven by pre-existing trends in the demand for new work, I show in Figure C.1 that the results are robust to including a host of variables related to local characteristics obtained from 1990 instead of 2000 and adding past changes in the local labor market adoption of new work shares (1980 to 1990, 1990 to 2000). To test whether the results are driven by time-varying industry-level shocks such as technological change, Figure C.2 examines equation (4) using the unit of analysis at the quartet of CZ-industry(2-digit NAICS)-occupation-year and adding industry fixed effects. There is an overall increase in the level of the estimated coefficients compared to Figure 5, but the overall interpretation of the baseline results are robust to this exercise.[23] The key results are qualitatively the same compared to Figure 6,

[23] For example, estimates in the early period for clerical work are positive and ultimately become negative in later

except that there is a starker decreasing trend in the estimated relative effects for routine cognitive jobs. I also check whether the results are driven by occupation-specific national trends. Figure C.3 shows that the positive trends shown in managerial work are not sensitive to including occupation trends as additional controls.[24] To test whether the estimated effects using new work shares are due to changes in the employment levels of existing work, I use new work employment in each occupation category normalized by CZ employment and find qualitatively similar results (Figure C.4).

I also perform a placebo test to check whether the effects are driven by contemporaneous changes in the demand for specific groups of occupations, rather than new work. To do this, I focus on occupations identified as new work in the 1990s, which are treated as existing work in the sample period, instead of new work that emerged post 2000. I compute the change in employment share in these jobs, which I use as the dependent variable in equation (4). Figure C.11 confirms that my results are not merely picking up long-run trends in the demand for specific jobs. I also conduct a falsification exercise by regressing past changes in the employment share of new work (1980 to 2000 and 1990 to 2000) on measures of future import exposures from China. I try using the full sample of CZs as well as focusing on the quartile of those with high import exposures. Table C.2 shows that most of the results are either reversed or insignificant. The exercise does not rule out all possible confounding factors that affect both changes in the share of new work and local labor market exposure to Chinese imports. However, it suggests that the main findings capture period-specific effects of import shocks on new work adoption.

The validity of the results thus far is also supported by a series of robustness tests using alternative measures of new work. Figure C.5 repeats the analysis using new work intensity measures based on O*NET's New and Emerging (N&E) Occupations.[25] Figure C.6 replaces the binary variable (indicator for top-quartile of new work intensity scores) with continuous measures. Specifically, I weight the new work intensity score by employment shares to obtain the average new work intensities. The dependent variable in the regression analysis becomes the change in new work intensities in CZ i for occupation group o. Both analyses produce results very similar to the baseline. Figure C.9 uses the new work intensity measures without applying the threshold (0.85) discussed in section 2.2 and shows the results are not sensitive to applying thresholds in the new work measure construction.[26] Finally, I show that the baseline results are robust to alternative identification strategy of import shocks. I follow Autor et al. (2013) and use changes in industry-level U.S. imports from China between 2000 and 2007 per worker weighted by the local industry mix, which is instrumented using import penetration of Chinese imports to other high-wage countries. Appendix

years. Estimates are insignificant in some years for technological and production work.

[24] I include interaction terms of occupation dummies for 2-digit SOC codes with the year variable.

[25] In O*NET, occupations that "involve significantly different work than performed by job incumbents of other occupations and are not adequately reflected by the existing occupational structure" are classified in this category. As discussed in section 2.2, I create an indicator variable for new work at the Census occupation-level, which indicates whether any of the detailed occupation codes (O*NET SOC 8 digits) listed as N&E are included in each Census occupation code.

[26] In section 2.2, I discuss how I implement a threshold rule in the new work measure construction.

C.3 shows that the estimated effects remain consistent employing an alternative identification strategy of import shocks. The magnitudes of the coefficients are greater compared to the main result as the measure of import exposures differs in scale.

4.3 Discussion

Thus far, I have presented evidence on the heterogeneous effects of import shocks on new work adoption across different occupation types. The adverse effects on technological new work are consistent with the findings of previous work using patents as innovation measures in the U.S. (Autor et al., 2020; Hombert and Matray, 2018; Xu and Gong, 2017). Although technological new work potentially corresponds to a broader notion of innovation than these conventional measures, both results suggest that import shocks deter innovations in pre-production activities, including product design, patent development, and research.[27] While a few technological leaders in a given industry might increase innovation activities to escape competition, firms that are far from the technology frontier would decrease innovation as increased competition already reduces profits (Aghion et al., 2005). If the source of rising competition is due to foreign firms manufacturing products that are substitutes for domestic ones (Holmes and Stevens, 2014), there may be little room for developing new product lines particularly in industries that produce standardized goods.

The results for production work and routine manual tasks further suggest investments in the main production activities that accompany new work adoption respond negatively to import shocks. This persistent and negative effect is consistent with firms replacing routine manual tasks through new machinery adoption and outsourcing/offshoring production (Bernard and Fort, 2015) and becoming more service-oriented (Breinlich et al., 2018; Ding et al., 2020). The positive effects of import shocks on new work adoption are mainly concentrated in managerial, legal, and business occupations and in occupations with non-routine cognitive tasks. The results potentially reflect firms' efforts to improve management (Bloom and Van Reenen, 2007, 2010; Bloom et al., 2013), reduce managerial slack (Chen and Steinwender, 2017), invest in post-production activities such as marketing and sales (Porter, 1985), and expand their customer capital (Klette and Kortum, 2004). In addition, structural changes in the main production stage discussed above may further induce new work adoption in managerial work (e.g., changes in the production mode require managers to oversee the production unit). Not to mention, reorganizing production or switching industries is accompanied by considerable restructuring of firm hierarchy (Caliendo et al., 2020), which usually includes managerial work gaining particular importance.

4.3.1 Mechanisms

While the current data does not allow me to assess how each channel spurs innovation in managerial work, learning more about the types of activities performed in these jobs is informative of the

[27] Empirical work using data from other countries and regions find positive effects, including in Europe (Bloom et al., 2016), China (Brandt et al., 2017; Bombardini et al., 2018), and South Korea (Ahn et al., 2018). Autor et al. (2020) explains the opposite findings using the mechanisms discussed in Aghion et al. (2005), in which innovation incentives depend on the distribution of technological advancements across firms.

underlying mechanism. I use O*NET's Knowledge data files for this exercise, which provide occupation-specific (8-digit SOC) knowledge requirements. After classifying 33 items into 12 knowledge categories relevant to firm activities, I construct mean intensity scores of each category for CZ-occupation(2-digit SOC) pair in each year, which serves as the dependent variables. I examine equation (3) for 2015 and 2016 separately and focus on managerial occupation types. I also try pooling both years to check whether the results are sensitive to selecting a single year. Figure 7 shows that, within managerial new work, import shocks cause an increase in knowledge requirements related to the post-production stage (customer support and business) and have no significant effect on those related to management and organizational aspect of firm activities (human resources, legal, and management). Although the results do not fully rule out other channels, the estimates lend support to import shocks inducing innovation activities in the post-production stage. The same effect is not present in existing work (indicated by the hollow red symbols), which suggests that the results are not merely driven by an increase in certain managerial occupations requiring more post-production knowledge.

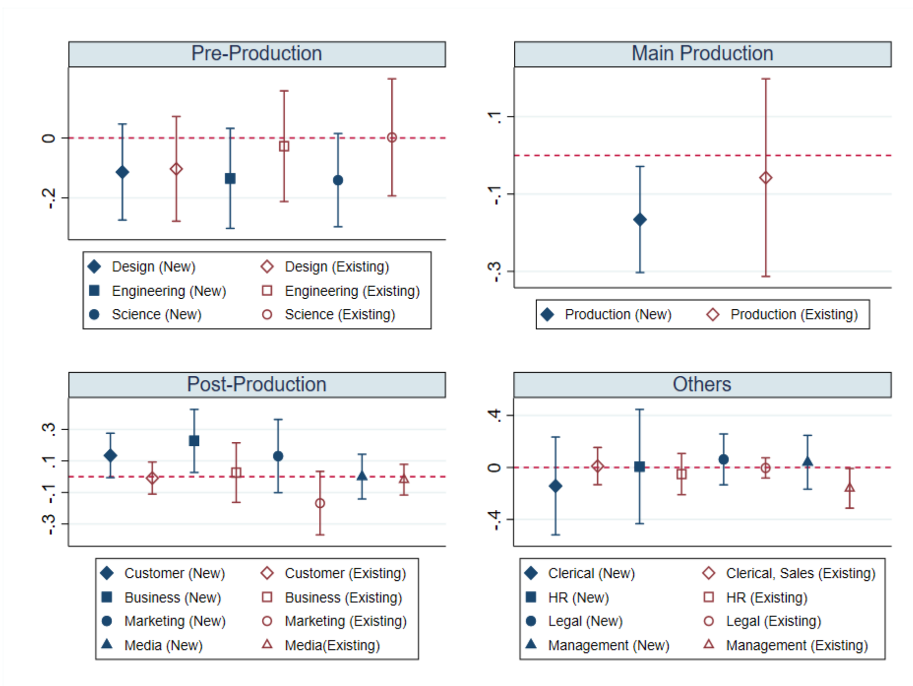

Figure 7: Change in Knowledge Requirements in Managerial Work

Note: Each graph plots the point estimates of β_1 in equation (3) pooling years 2015 and 2016 and includes 95 percent confidence intervals. The regression is run separately for each knowledge category. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Estimates with the solid blue symbols are new work; those with the hollow red symbols are existing work.

Since O*NET provides a snapshot of the knowledge requirements for detailed occupations, the results in Figure 7 are primarily driven by changes in occupational compositions within managerial occupations. However, as documented in previous research (e.g., Deming and Kahn, 2018; Atalay et al., 2019, etc.), there are substantial variations in skills within detailed occupation codes. To explore this intensive margin, I repeat the above exercise using BGT data. Each BGT job ad lists multiple skills with detailed information on the content of required skills, software, and technologies, which is available in the raw texts of job ads or the processed skills files by BGT. To construct skill intensity measures, I classify detailed skills data into 15 broad categories and use the number of mentions in a given skill category normalized by the total number of mentions of a given skill for each job ad. I then aggregate the intensity scores at the level of CZ-occupation (2-digit SOC) pair each year.[28] Since the data is only available from 2010, I construct dependent variables by deriving changes in skill intensities relative to 2010. The preferred estimates in Figure C.12 are obtained by examining overlapping five-year differences (2010-2015 and 2011-2016) with period-specific effects; the results do not qualitatively change when examining each period separately.[29] The results are qualitatively similar to those based on O*NET data. Regions that are more exposed to the China shock show an increase in skill demands in post-production activities (marketing and public relations).

Next, I study the extent to which structural changes in the main production stage discussed in section 4.3 show complementarities with the post-production activities. In particular, I examine whether regions that experienced more offshoring activities have a higher concentration of trade-induced investments in post-production activities. To construct regional measures of offshoring exposure, I use the Trade Adjustment Assistance (TAA) petitions data and aggregate the number of workers laid off due to offshoring. Following Monarch et al. (2017), I focus on certified petitions related to (i) company imports (the company replaced in-house tasks with imports); and (ii) production shift (the company replaced tasks with activities at its own subsidiaries abroad). I compute the regional growth rates in offshoring-induced layoffs between the early 2000s (2000 to 2002) and later years (2008 to 2010); and assign regions with growth rates above the median as highly exposed. I run the same regressions as in Figure 7, but separately for the high- and low-exposed local labor markets. Figure C.13 (top panel) shows that the positive and significant results for skills related to post-production activities mainly hold only for regions with high exposure to offshoring. In fact, the estimates are greater in magnitude compared to those in Figure 7.

I repeat the exercise by comparing regions that differ in the extent to which local manufacturing firms become service-oriented. To do this, I construct the regional measures of transitioning to the service industry, using the sector information employers post in BGT job ads. Focusing on establishments that continue to post jobs online, I identify those whose share of job ads shift from manufacturing (2-digit NAICS 31 to 33) to services (2-digit NAICS 42, 54, and 55). To the extent that the strategic changes in the core business activity through servitization are reflected in the job demands, the measure helps identify the degrees of structural changes manufacturing firms undertake. Admittedly, in the presence of multi-establishment firms that restructure by reallocating

[28]The 15 categories are: Business; Customer and Client Support; Design; Engineering; Finance and Legal; Human Resources; Industry Knowledge; Information Technology; Maintenance; Repair; and Installation; Manufacturing and Production; Marketing and Public Relations; Sales and Administration; Science and Research; Social Science and Research; and Supply Chain and Logistics.

[29]Bloom et al. (2016) and Xu and Gong (2017) also use overlapping five-year differences in their main empirical specifications to maximize the use of the data.

resources across establishments and increasing the degree of specialization by location, the measure will only partly capture the magnitude of the restructuring process. Similar to the previous exercise, I compute the regional growth rates in the number of establishments that become more service-intensive and identify regions with growth rates above the median as highly exposed.[30] Figure C.13 (bottom panel) shows qualitatively similar results, confirming that trade-induced investments in the post-production stage are more pronounced in areas where greater degrees of structural changes in the main production stage takes place.

4.3.2 Labor Market Inequality

What implications does the adjustment process have for workers? To investigate the possible distributional effects of the documented changes in demand for new work, I conduct two exercises. First, I examine differences in the baseline findings for workers with and without college degrees by estimating equation (4) separately for workers in each education group. Figure C.14 shows that the positive effects of new work adoption in managerial work and occupations intensive in non-routine cognitive tasks (both analytical and interpersonal) are primarily driven by college-educated workers. In fact, the effects are either insignificant or negative for workers without college degrees in these occupations. The contrasting results between the two worker groups also hold for occupations in production work or those intensive in routine manual tasks. Here, the negative effects are mainly driven by college-educated workers.

Second, I study whether the demand for college-educated workers in new work is associated with a rise in local wage inequality. Here, I run equation (3) using changes in the log wage differences between workers with and without college degrees ($\Delta(logw_c - logw_{nc})$) as dependent variables. I examine this regression separately for new and existing work. Table C.3 (column 1) shows that there is a significant increase in the wage gap between workers employed in new work in the year 2014, which persists until the end of the sample period; however, there are no significant effects for non-new jobs (column 2). I additionally check whether the wage differences between workers hired into new work jobs and those hired into existing work jobs within the same education group ($\Delta(logw_{new} - logw_{ex})$) increase. While there are significant differences for college-educated workers in 2014 and 2015 (columns 3), the estimates lack precision in other years. The findings highlight the role of new work adoption in the distributional consequences of the China shock. The differences in job opportunities induced by the restructuring process, shifting the demand towards high-skill workers with comparative advantages in performing new tasks, potentially contribute to the substantial differences in post-shock earnings across worker groups that persist and become amplified over time.

[30] More specifically, I identify establishments that (i) post more jobs in manufacturing than services between 2010 and 2012, and (ii) post more jobs in service than in manufacturing between 2016 and 2018.

5 Establishment and Firm Analysis

The regional results capture both the effects of import shocks on new work within surviving firms and any compositional effects from firm entry and exit.[31] This section examines firm-level evidence of trade-induced new work adoption by focusing on the surviving firms. I use a merged sample of publicly listed manufacturing firms in Compustat and online vacancies from BGT data. Leveraging information on the location (city and state) of jobs in BGT data, I identify different establishments within firms and conduct the baseline analysis at the establishment level. As discussed earlier, BGT data only covers years from 2010 on, so examining establishment- or firm-level changes in new work adoption relative to the pre-China shock period is infeasible. To the extent that the adjustments continue after 2010 and do not show a (reversed) v-shaped pattern (e.g., changes from 2000 to 2010 and 2010 to 2015 show negative correlations), examining changes relative to 2010 would still have important implications for understanding within-firm restructuring and adjustments through new work adoption. Recall that the results in Figures 5 and 6 demonstrate a steady increase in the relative importance of new work in managerial jobs or non-routine tasks induced by the China shock over time. I also compare the magnitude of changes in new work adoption for 2000 to 2010 and 2010 to 2015 by separately examining equation (4) without the time fixed effects and interactions with the time dummies. Figure C.15 confirms that significant changes occur post-2010 for managerial occupations.[32]

To study establishment-level trade-induced adjustments, I examine the following specification separately for each occupation type:

$$\Delta y_{koj} = \beta_0 + \beta_1 \text{NTR Gap}_{j,1999} + \mathbf{X}'_{i,2010}\gamma + \eta_{j'} + e_{koj}, \tag{5}$$

I define y_{koj} as outcome measures in occupation o (2-digit SOC codes) in establishment k, industry j. Δy_{koj} is the change in y_{koj} between 2010 and 2015. The key outcome is the share of job ads posted in occupations with high new work intensity (top-quartile). NTR $\text{Gap}_{j,1999}$ is the difference between the non-NTR rate and the NTR rate for industry j in 1999. I control for firm characteristics (sales per worker, capital per worker, debt to equity ratio) in 2010 and include industry fixed effects at the 2-digit SIC level. I weight observations by firm size in 2010. Standard errors are clustered on 4-digit SIC industries. Using the difference specification, I control for any time-invariant factors at the establishment (k) and occupation (o) pair. The coefficient of interests β_1 captures the effect of industry-level import shocks on changes in establishment-level new work adoption. Due to the data limitation discussed above, I cannot check whether establishment-level changes in new work adoption in the pre-China shock period are correlated with the industry-level NTR Gaps. Instead, I construct past changes in new work at the industry level (1980 to 1990 and 1990 to 2000) and

[31] I test whether the estimates provide suggestive evidence of the role of establishment turnovers by additionally controlling for the entry and exit of establishments.

[32] Note that the estimates for technological occupations become insignificant in 2010 to 2015 and those for clerical and production occupations are similar between the two periods. Thus, there may not be enough variation observed for these occupation types in the firm analysis.

test whether the results are robust to adding these past changes as controls. To the extent that the industry-level changes are mainly driven by big firms, a significant portion of which are included in Compustat firms, the exercise helps mitigate concerns related to pre-existing trends.

Figure 8 reports the β_1 coefficients from equation (5) estimated separately for different occupation types. The effects of the initial exposure to the China shock on new work adoption in managerial occupations within the establishment-occupation pair are positive and statistically significant. The estimates are negative for technological ones and lack precision for other occupation types. I then study the effects by firm type (size, capital per worker, and sales per worker) and examine equation (5) separately for firms in the top quartile versus the rest, grouped by firm types. The solid red symbols in Figure 8 report estimates using firms in the top quartile group, while the hollow red symbols examine the rest of the firms. The positive demand for managerial new work is pronounced for firms with high per capita revenue: the value of the point estimates is significantly higher than estimates based on all firms. The estimates are negative and statistically significant for new work adoption in production occupations demanded in these firms. The results suggest the importance of the main production stage relative to other firm activities has decreased markedly among establishments in the top distribution of firms (in terms of revenue per worker), which highlights the firm heterogeneity in the adjustment process.

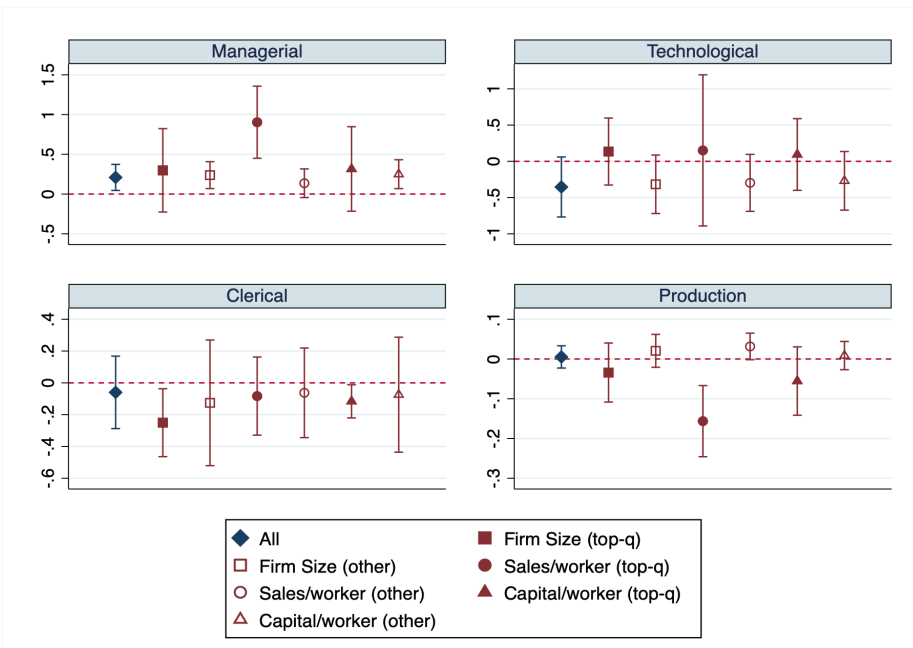

Figure 8: New Work Adoption by Occupation Type

Note: Each graph plots the point estimates of β_1's in equation (5) for year 2015 and includes 95 percent confidence intervals. The regression is run for each occupation type. The unit of analysis is a triplet of firm-occupation (2-digit SOC)-year. The solid blue symbols show estimates across all firms. The solid red symbols show firms in the top quartile group, and the hollow red symbols show the rest of the firms. Controls include initial characteristics of firms. Industry fixed effects (2-digit SIC) are included. Robust standard errors are clustered on 4-digit SIC industries.

Are firms more likely to seek college-educated workers in new work? To investigate evidence of upskilling within new work, I use the information on college requirements employers list in BGT job ads and study the demand for a college education in new work for each occupation type using equation (5). Figure D.3 (top panel) shows that upskilling within new work is statistically significant (at 90 percent confidence intervals) for managerial occupation types, but not for others. Not only do firms increase the demand for managerial new work, but they also are more likely to require college degrees within these jobs in response to trade shocks. Then, which types of college majors have become more in demand by employers? I use the CIP codes extracted from major/program information listed in BGT job ads and focus on two different major types: science, technology, engineering, and mathematics (STEM) and business-related degrees.[33] I examine equation (5) using establishment as the unit of analysis to understand the overall composition of in-house demands for college majors. Table D.1 reports a positive and significant demand for business-related majors but not for STEM degrees. The result suggests that the increasing importance of managerial relative to technological new work remains pronounced even conditional on new work that requires college degrees.

Next, I use skill intensity measures constructed using BGT skills data to learn more about the activity types performed in managerial new work.[34] Figure D.4 shows results that are qualitatively similar to the regional findings (Figure 7): the statistically significant and positive effects are mainly observed in skills related to post-production activities (customer support, marketing, and public relations). To investigate the nature of innovation pursued in marketing and sales, I examine whether the post-production skill types show complementarity with new technologies. For example, firms may invest in web-based marketing tools through digital platforms to be more effective in acquiring customers (e.g., Greenwood et al., 2021). I specifically test whether the positive and significant effects persist after restricting the analysis to post-production skills that use specialized computer software and digital platforms (search engine optimization, search engine marketing, social media, and web analytics, among others). Figure 9 (left) provides evidence of the complementarity with recent developments in information technology for customer support and marketing skills in managerial new work. The estimates lack precision when examining these skill demands in managerial work that is not new. I also test whether the post-production skills are more specific to building customer capital through advanced customer service, quality assurance, and more. Figure 9 (right) shows qualitatively similar results. The set of results using BGT skills data provides suggestive evidence that trade-exposed firms are more likely to focus on post-production investments that exhibit important complementarity with new technologies and focus on building customer capital.

While both regional and firm analyses provide evidence of the increased importance of post-

[33] I use the STEM Designated Degree Program list provided by the Department of Homeland Security to identify STEM degrees. I use Comprehensive Education Data and Research System (CEDARS) 's program areas information mapped to CIP codes to identify business-related degrees (CIP codes for "Business and Marketing Education"), most of which have the 2-digit CIP code 52.

[34] Similar to section 4.3, I classify detailed skills data into 15 broad categories and use the number of mentions in a given skill category normalized by the total number of skill mentions for each job ad. I then aggregate at firm-occupation (2-digit SOC) pair in each year.

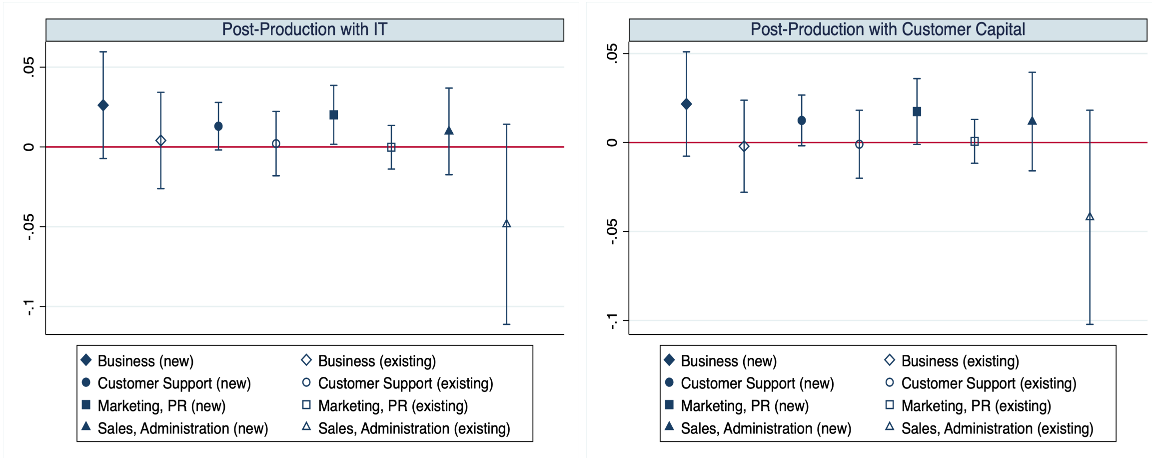

Figure 9: Post-production Skill Requirements in Managerial New Work

Note: Each graph plots the point estimates of β_1's in equation (5) for year 2015 and includes 95 percent confidence intervals. The unit of analysis is a triplet of firm-occupation (2-digit SOC)-year. Controls include initial characteristics of firms. Industry fixed effects (2-digit SIC) are included. Robust standard errors are clustered on 4-digit SIC industries.

production activities, I conduct robustness checks examining changes in firm-level expenditures of advertising and sales in Compustat data. The key benefit of the exercise lies in examining changes in the outcome measures relative to 2000 instead of 2010. To trace the effects over time, I use a dynamic version of equation (5) by interacting NTR $\text{Gap}_{j,1999}$ with the year dummies and include year fixed effects. The specification is similar to equation (4) using firm-year as the unit of analysis. The dependent variable is the change in log expenditures of advertisement between year t and 2000. Figure D.5 shows a statistically significant increase in these expenses for years before 2008, but the estimates are insignificant for subsequent years. I juxtapose results using changes in R&D expenditures, which demonstrate contrasting adverse effects throughout the period.[35] Using advertising expenses as a proxy for post-production investments does not capture innovation efforts in the same way that new work measures do; however, the results confirm the importance of post-production activities in firm-level adjustments to trade shocks.

Now, I will use a simple conceptual framework to describe a possible mechanism through which import shocks induce greater investments in new work related to post-production activities – namely, marketing and advertising – to acquire customers. The post-production investments can be thought of as a production function that uses two factor inputs, new tasks and existing tasks. One natural assumption for this production function is that the elasticity with respect to the new task is higher than that with the old task. This captures the notion of how the new technology is more efficient in reaching consumers than the existing one. As an example, the production function can take the following form, $Y = \left(x_E^{\alpha} + k x_N^{\beta}\right)^{\gamma}$ with $0 < \alpha < \beta < 1$, where x_E and x_N represent the quantity of input for existing tasks and new tasks, respectively. The budget constraint for marketing and advertising is given as $w_E x_E + w_N x_N \leq m$. I simply take as given the empirical result

[35]The results are both consistent using a sample of all Compustat manufacturing firms and a subset of them that are matched to BGT data.

that the industries that face greater import competition optimally spends a greater amount on post-production investments, implying a larger value of m. Since the ratio of new to existing tasks increase with m, ($\frac{\partial}{\partial m}\left(\frac{x_N}{x_E}\right) > 0$), it follows that the industries that face greater import competition adopts a greater share of new tasks in marketing and advertising.[36]

Considering the rising importance of strategic changes in the firm's core business product or activity recently documented in the manufacturing sector, I test whether the main findings on new work adoption and post-production skill demands are driven by sector-switching. For this exercise, I rely on the sector information firms list in BGT job ads and follow the definition of sector-switching or servitization described in section 4.3. To understand the importance of this channel, I first compare changes in the share of job ads in manufacturing and services in response to import shocks. Similar to the previous exercise, I examine a dynamic version of equation (5). I conduct the analysis both at the establishment and firm levels. Figure D.7 shows that at the firm-level, there is a significant decrease in the share of job ads in manufacturing (2-digit NAICS 31 to 33) but no significant changes in that of services (2-digit NAICS 42, 54, and 55). Examining establishment-level changes, I find a positive trend in the share of job ads in services before 2015; however, the estimates lack precision for that of manufacturing. Albeit weak, the results provide evidence of structural changes within manufacturing firms. Finally, I examine equation (5) excluding firms that switch sectors and confirm that the main findings on new work adoption and post-production skill demands remain consistent (Figures D.8 and D.9).

6 Conclusion

In this paper, I use new work adoption to study the trade-induced restructuring process. To construct new work measures, I use the emergence of new job titles identified through word embedding models. The newness of each job title represents how distant it is compared to all existing job titles observed in the prior decade based on the context of their appearances in large texts. Using these measures, I show that new work adoption in areas with greater exposure to import competition experience increases in new work in managerial occupations and decreases in all other occupation types (technological, clerical, and production). Examining the activities performed in managerial new work, I show that import shocks significantly increase investments in post-production activities such as customer support, marketing, and sales. What is more, the positive effects are more pronounced in areas with greater exposure to structural changes in the main production stage: offshoring and sector switching. These findings are qualitatively similar when examining the effects within surviving manufacturing firms in the firm analysis. Finally, I show that the positive effects of import shocks on managerial new work are driven mainly by college-educated workers, which sheds light on the role of new work adoption in the distributional

[36]Holding p_E/p_N fixed, the first order condition is $\alpha x_E(m)^{\alpha-1} = k\beta x_N(m)^{\beta-1}$. Differentiating both sides with respect to m and combining with this FOC itself yields $\frac{x_N'/x_N}{x_E'/x_E} = \frac{1-\alpha}{1-\beta} > 1$, which is equivalent to $\frac{\partial}{\partial m}\left(\frac{x_N}{x_E}\right) > 0$. Note that non-homotheticity ($\alpha \neq \beta$) is the key for generating this income effect.

consequences of import shocks.

There are several important implications of this paper that merit further research. First, building a model to see how the firm's restructuring decision at the extensive margin affects local labor market outcomes would serve as an important extension to quantify the magnitude of the new work adoption channel and explore general equilibrium effects. Second, further investigating whether the increased importance of post-production activities reshapes comparative advantages and affects productivity growth would help us understand the broader impacts of trade adjustments and post-shock restructuring. Third, examining how workers respond to new work adoption by altering their choice of human capital investments would be a valuable extension of the current exercises and provide policy implications for training current and future workers. Finally, constructing new work measures for different countries would be an important complement that could shed light on cross-country differences in the evolution of work.

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Appendices

Appendix A Data and Measures

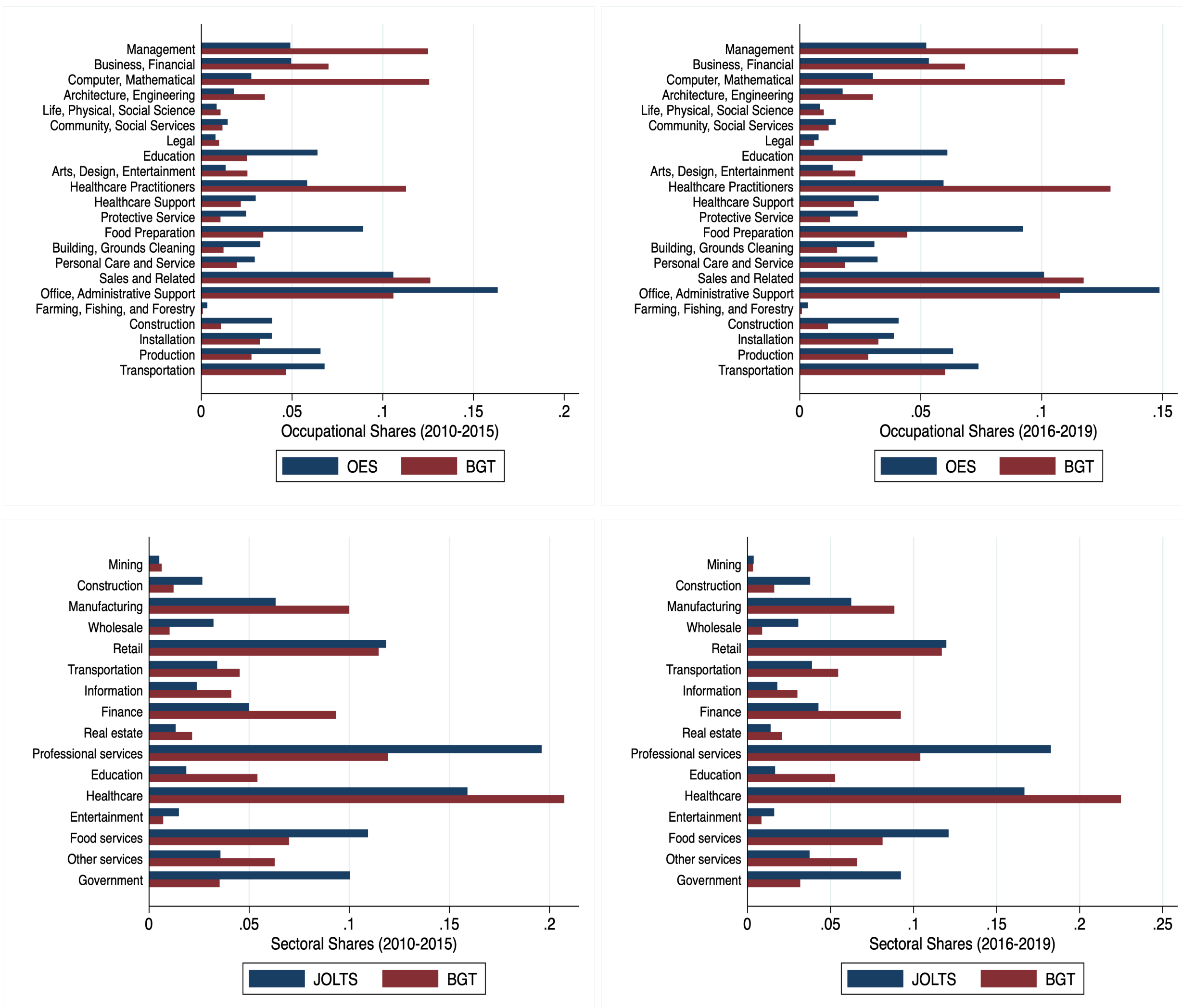

Figure A.1: Distribution of Occupations and Industries in BGT

Note: The two graphs on the top panel show the occupational distribution of job ads in BGT, compared to occupational employment shares obtained from Occupational Employment Survey (OES) data. The two graphs on the bottom panel show the industry distribution of job ads in BGT, compared to industry shares from Job Openings and Labor Turnover Survey (JOLTS) data. I combine data for years between 2010 and 2015 (left); and 2016 and 2019 (right).

Continuous Bag of Words Model The algorithm works as follows: (i) each word is characterized by a unique one-hot vector, which consists of zeros in all elements with the exception of one cell with the value of one; (ii) the neural network uses the one-hot vectors of the surrounding words and produces weights to predict the appearance of one-hot vector of the target word; (iii) errors are obtained and used to update weights as the process iterates, and the final weights are used to characterize each target word.[37]

Cleaning Job Titles Data Before employing the CBOW model, I clean the job titles data as follows. First, I remove specific words used solely for survey purposes or education requirement, which do not contribute to the nature of those occupations: 'specified activity', 'specified type', 'specified occupation', 'other specified type', 'specified type not listed', 'specified subject school level', 'activity not specified', 'subject level not specified', 'subject not listed', 'subject not specified', 'specified article not listed', 'all other type', 'bachelors degree', 'associate degree.' Second, I remove punctuation marks (e.g., dots, slashes, commas and parentheses) and unnecessary spaces between words. Finally, I convert all alphabets to lower cases.

Construction of New Work Intensity Scores To identify new work that emerged in each time period, I compare job titles published in the period of interest to those in the previous decade using the CBOW model. For new work that emerged in 1990, I compare job titles in the Dictionary of Occupation Titles (1990) to those in the Dictionary of Occupation Titles (1980). For 2000, I compare job titles in the Classified Index of Industries and Occupations (2000) to the combined set of job titles in the Dictionary of Occupation Titles (1990) and the Classified Index of Industries and Occupations (1990). For 2016, I compare job titles in the Sample of Reported Titles and Alternate Titles in the O*NET database (2016) to those in the Classified Index of Industries and Occupations (2000).

Data Source	Time Period	No. Titles	Mean	SD
Dictionary of Occupation Titles	1990	12,254	0.01	0.06
Classified Index of Industries and Occupations	2000	30,651	0.01	0.05
O*NET Alternative Job Titles	2016	59,958	0.06	0.11

Note: Mean and SD report the average and standard deviation of new work intensity scores of job titles after applying a threshold of 0.85. Job titles whose closest match have cosine similarity score greater than the threshold value are assigned a new work intensity score of zero.

Table A.1: Summary Statistics

[37] In Skip-gram, the target word is used to predict the surrounding words.

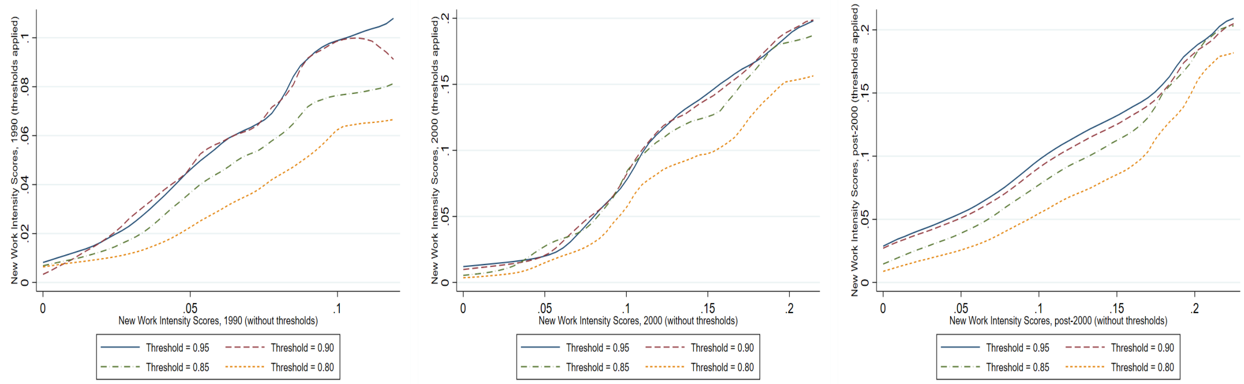

Figure A.2: Comparing New Work Intensity with Different Thresholds

Note: I plot the new work intensity scores aggregated to detailed census occupations (occ2010) without the thresholds against those with various levels of thresholds (0.80, 0.85, 0.90, 0.95) applied. For each threshold level, job titles whose closest match have cosine similarity score greater than the threshold value are assigned a new work intensity score of zero.

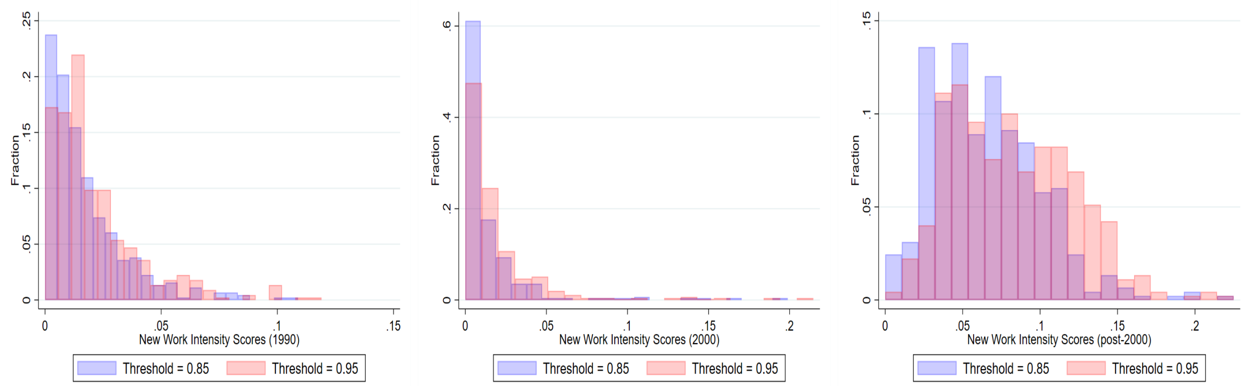

Figure A.3: Histogram of New Work Intensity (1990, 2000, 2016)

Note: The histograms provide comparisons of the average new work intensity scores aggregated to detailed census occupations (occ2010) with thresholds 0.85 and 0.95. For each threshold level (0.85, 0.95), job titles whose closest match have cosine similarity score greater than the threshold value are assigned a new work intensity score of zero.

Comparing Measures Lin (2011) constructs binary measures for new job titles by combining information from census revision documents and applying direct string matching methods. I classify job titles into a 2 by 2 matrix:

New (Lin, 2011), New (CBOW)	Existing (Lin, 2011), New (CBOW)
New (Lin, 2011), Existing (CBOW)	Existing (Lin, 2011), Existing (CBOW)

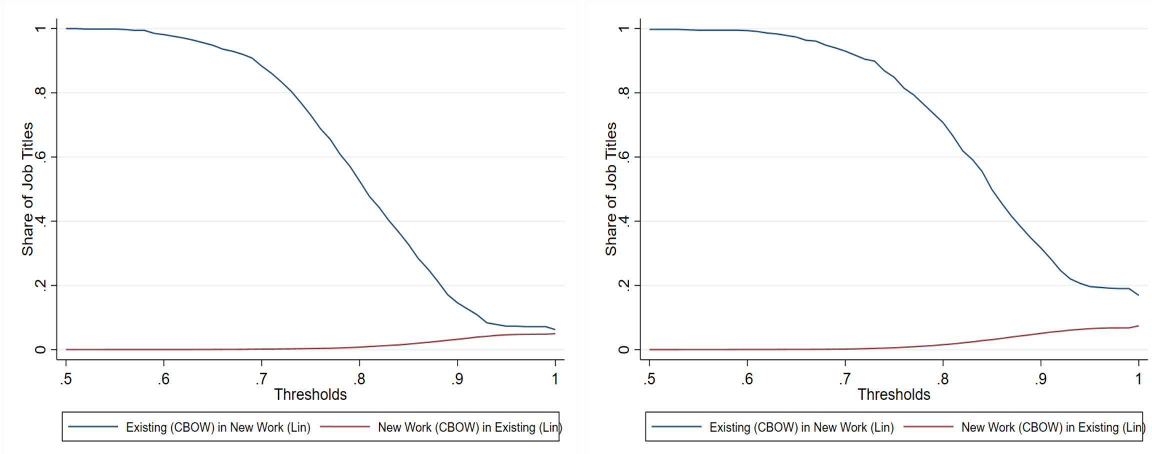

Figure A.4: Comparing Measures (Job Titles) with Lin (2011): Left (1990), Right (2000)

Note: "Existing (CBOW) in New Work (Lin)" plots the share of existing work identified by CBOW in what is identified as new work by Lin (2011); "New Work (Lin) in Existing (CBOW)" plots the share of new work identified by CBOW in what is identified as existing work by Lin (2011).

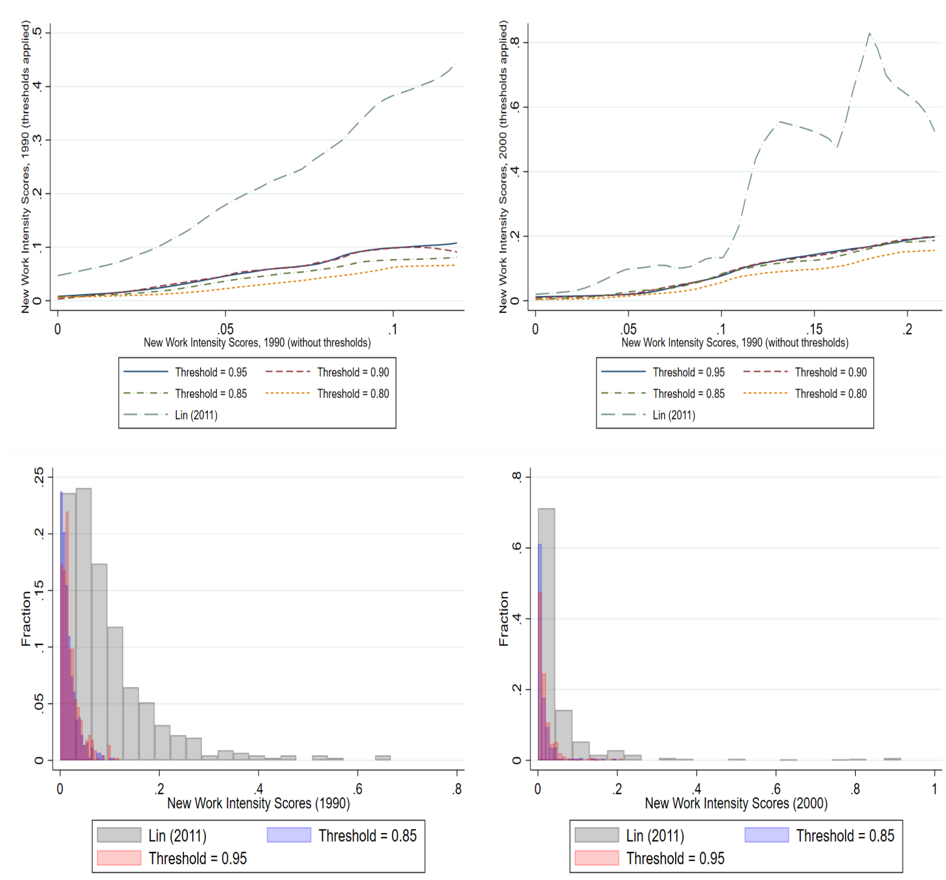

Figure A.5: Comparing Measures (Occupations) with Lin (2011): Left (1990), Right (2000)

Note: I compare measures aggregated at detailed census occupations by adding new work scores constructed by Lin (2011) to Figures A.2 and A.3.

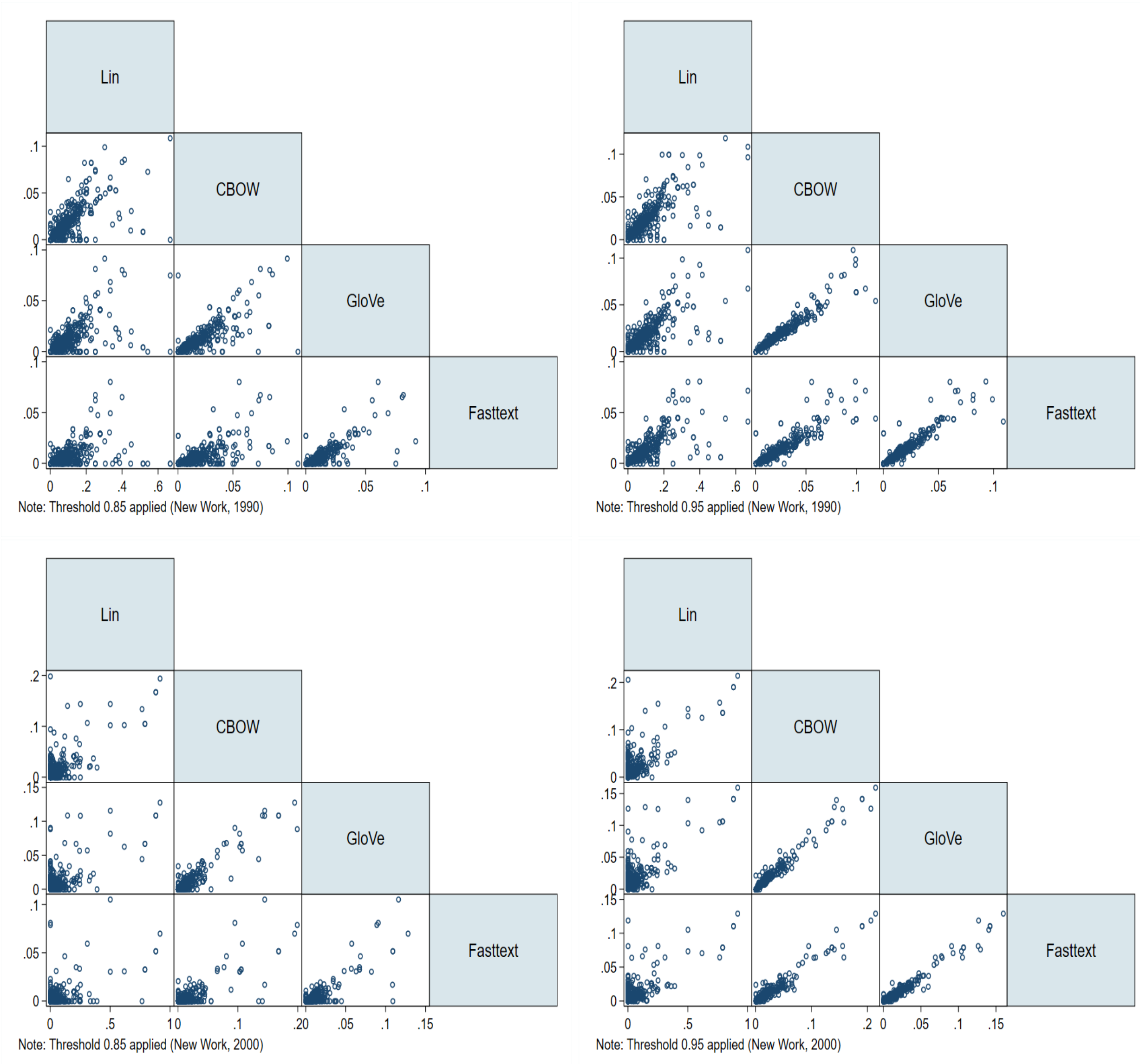

Figure A.6: Comparing Measures (job titles) with Lin (2011): Top (1990), Bottom (2000)

Note: I test sensitivity of the measure to the type of word embedding models employed by comparing the scores obtained using CBOW with those obtained from GloVe (pre-trained word vectors obtained using an "unsupervised learning algorithm for obtaining vector representations for words" (Pennington et al., 2014)) and Fasttext (pre-trained word vectors obtained using https://fasttext.cc/). The top panel provides data for 1990 and the bottom panel for 2000.

Model Type / Year (threshold)	1990 (0.85)	1990 (0.95)	2000 (0.85)	2000 (0.95)
CBOW	0.67*	0.76*	0.72*	0.75*
GloVe	0.58*	0.74*	0.66*	0.73*
Fasttext	0.43*	0.71*	0.55*	0.72*

Note: I test sensitivity of the measure to the type of word embedding models employed by comparing the scores obtained using CBOW with those obtained from GloVe (pre-trained word vectors obtained using an "unsupervised learning algorithm for obtaining vector representations for words" (Pennington et al., 2014)) and Fasttext (pre-trained word vectors obtained using https://fasttext.cc/). I use the average new work intensity scores aggregated to 3-digit census occupations.

Table A.2: Correlations with Measures by Lin (2011)

Appendix B Descriptive Analysis

Occupation Types	Example Job Titles Identified as New
Managerial	E-Learning Manager, Brownfield Redevelopment Specialist, Global Supply Chain Director, Green Material Value-Added Assessor, Sustainable Business Operations Specialist, International Trade Specialist, Life Care Planner, Data Abstractor
Technological	Pay-Per-Click Strategist, Search Engine Optimization Strategist, Data Warehouse Architect, Voice Over Internet Protocol Engineer, Softcopy Photogrammetrist Manufacturing Production Technician, Electronic Transaction Implementer
Clerical	Solar Energy Consultant and Designer, Internet Marketer, Online Content Coordinator Ocean Export Coordinator, Reprographics Technician, Debug Technician
Production	Solar Panel Technician, Immersion Metal cleaner, Digital Proofing and Platemaker

Note: Job titles whose closest match have cosine similarity score greater than 0.85 are assigned a new work intensity score of zero, which are aggregated at 3-digit occupations. Job titles are then grouped by 2-digit SOC codes then further classified into occupation types: managerial (11, 13, 23), technological (15, 17), clerical (41, 43), and production (49, 51, 53). For each occupation type, I include example job titles with high new work intensity obtained using CBOW on the O*NET job titles data and constructed following equation (1).

Table B.1: Example Job Titles with High New Work Intensity Scores by Occupation Types

Measures	Example New Job Titles	Corresponding Occupation Category
New & Emerging	Data Warehousing Specialists	Computer scientists and systems analysts
	Distance Learning Coordinators	Education administrators
	Neurodiagnostic Technologists	Health technologists and technicians, n.e.c.
	Geothermal Production Managers	Industrial Production Managers

Note: I provide example occupation titles included in O*NET's New and Emerging (N&E) Occupations.

Table B.2: Example New and Emerging Job Titles

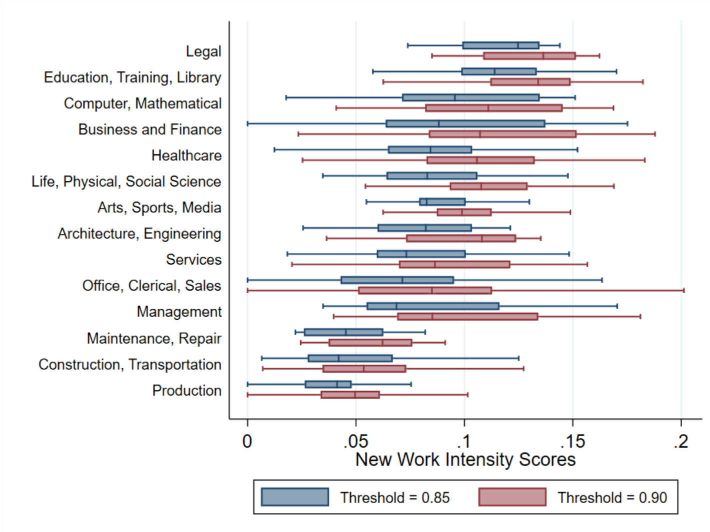

Figure B.1: New Work Intensity by Occupations

Note: The box plot includes the minimum, maximum, median, top and bottom quartile values of the new work intensity scores by 2-digit SOC occupations. For each threshold (0.85, 0.90), job titles whose closest match have cosine similarity score greater than the threshold value are assigned a new work intensity score of zero, which are aggregated at 3-digit occupations.

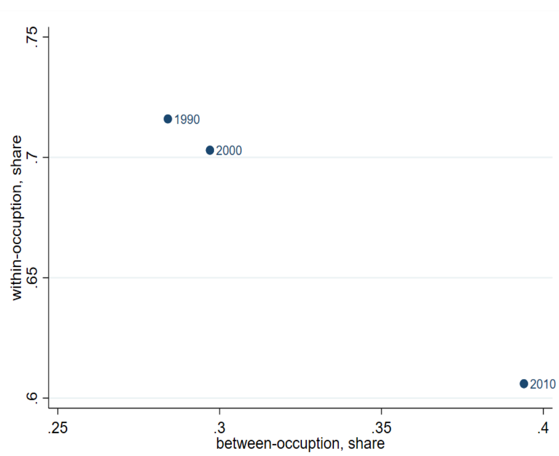

Figure B.2: Within-Between Occupation Variation in New Work

Note: For new work obtained across three decades, I conduct the following decomposition exercise: $(x_i - \overline{x})^2 = (x_i - \overline{x}_o)^2 + (\overline{x}_o - \overline{x})^2$ where x_i is the new work intensity score of each job title, $\overline{x}_o$ is the average score of 3-digit occupation, and $\overline{x}$ is the aggregate average. The graph illustrates the share of variation explained by within-occupation agains that by between-occupation. To construct new work intensity scores, job titles whose closest match have cosine similarity score greater than the threshold value of 0.85 are assigned a new work intensity score of zero, which are aggregated at 3-digit occupations.

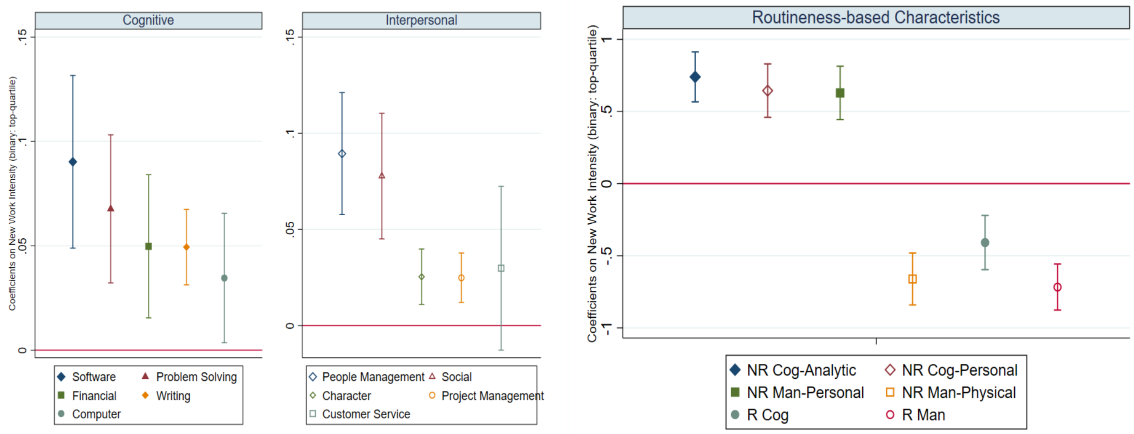

Figure B.3: Skill Characteristics of New Work Post 2000

Note: Both graphs plot the estimated coefficients and 95% confidence intervals obtained using a naive regression of the skill/task intensities on a binary indicator for being in the top quartile of the new work intensities constructed using CBOW (threshold = 0.90). On the left, I use BGT skill requirements in 2010 to construct the share of job ads with the corresponding skill requirement for each occupation-skill pair. On the right, I use O*NET skill descriptors to construct the average task intensity score for each occupation-task pair.

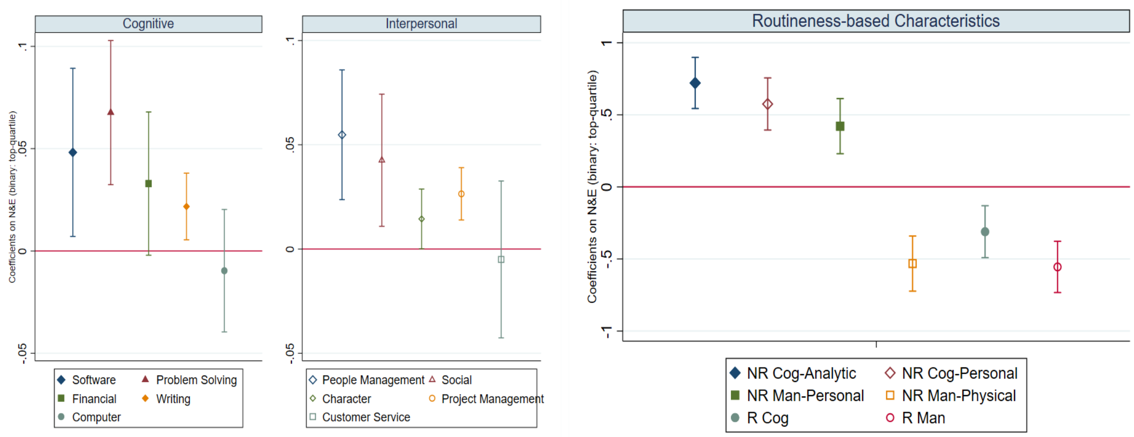

Figure B.4: Skill Characteristics of New and Emerging Occupations

Note: Both graphs plot the estimated coefficients and 95% confidence intervals obtained using a naive regression of the skill/task intensities on on the share of 8-digit SOC N&E occupations in 3-digit occupations. On the left, I use BGT skill requirements in 2010 to construct the share of job ads with the corresponding skill requirement for each occupation-skill pair. On the right, I use O*NET skill descriptors to construct the average task intensity score for each occupation-task pair.

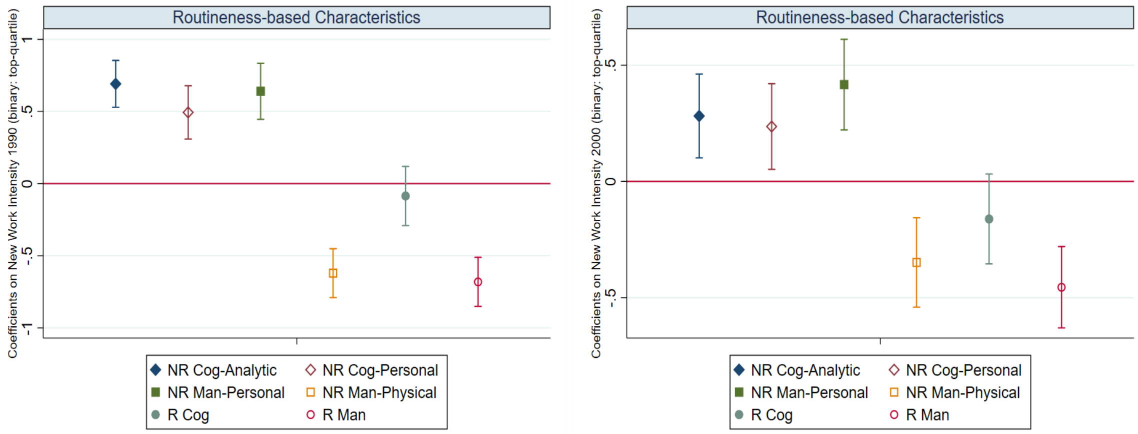

Figure B.5: Skill Characteristics of New work: Left (1990), Right (2000)

Note: Both graphs plot the estimated coefficients and 95% confidence intervals obtained using a naive regression of the skill/task intensities on a binary indicator for being in the top quartile of the new work intensities constructed using CBOW. I use O*NET skill descriptors to construct the average task intensity score for each occupation-task pair. I show results for new work that emerged in 1990 (left) and 2000 (right) respectively.

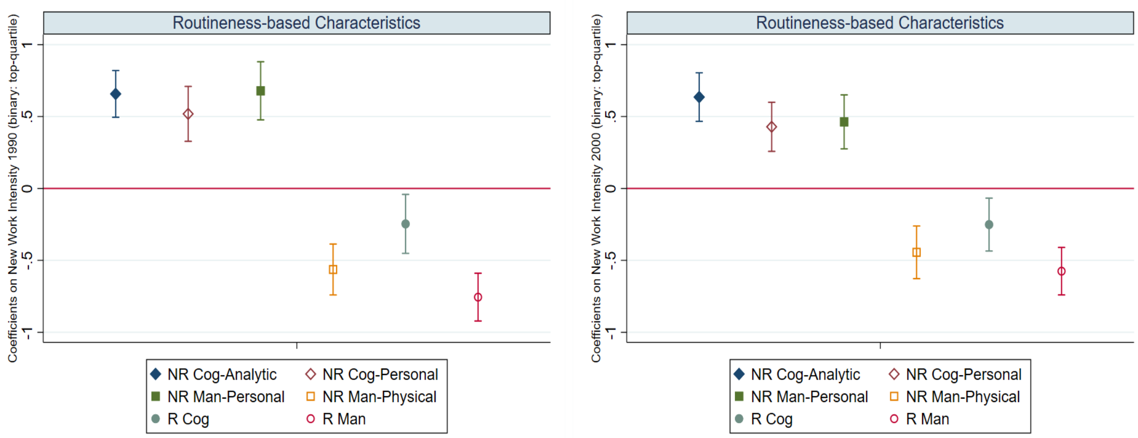

Figure B.6: Skill Characteristics of New work by Lin (2011): Left (1990), Right (2000)

Note: Both graphs plot the estimated coefficients and 95% confidence intervals obtained using a naive regression of the skill/task intensities on a binary indicator for being in the top quartile of the new work intensities constructed by Lin (2011). I use O*NET skill descriptors to construct the average task intensity score for each occupation-task pair. I show results for new work that emerged in 1990 (left) and 2000 (right) respectively.

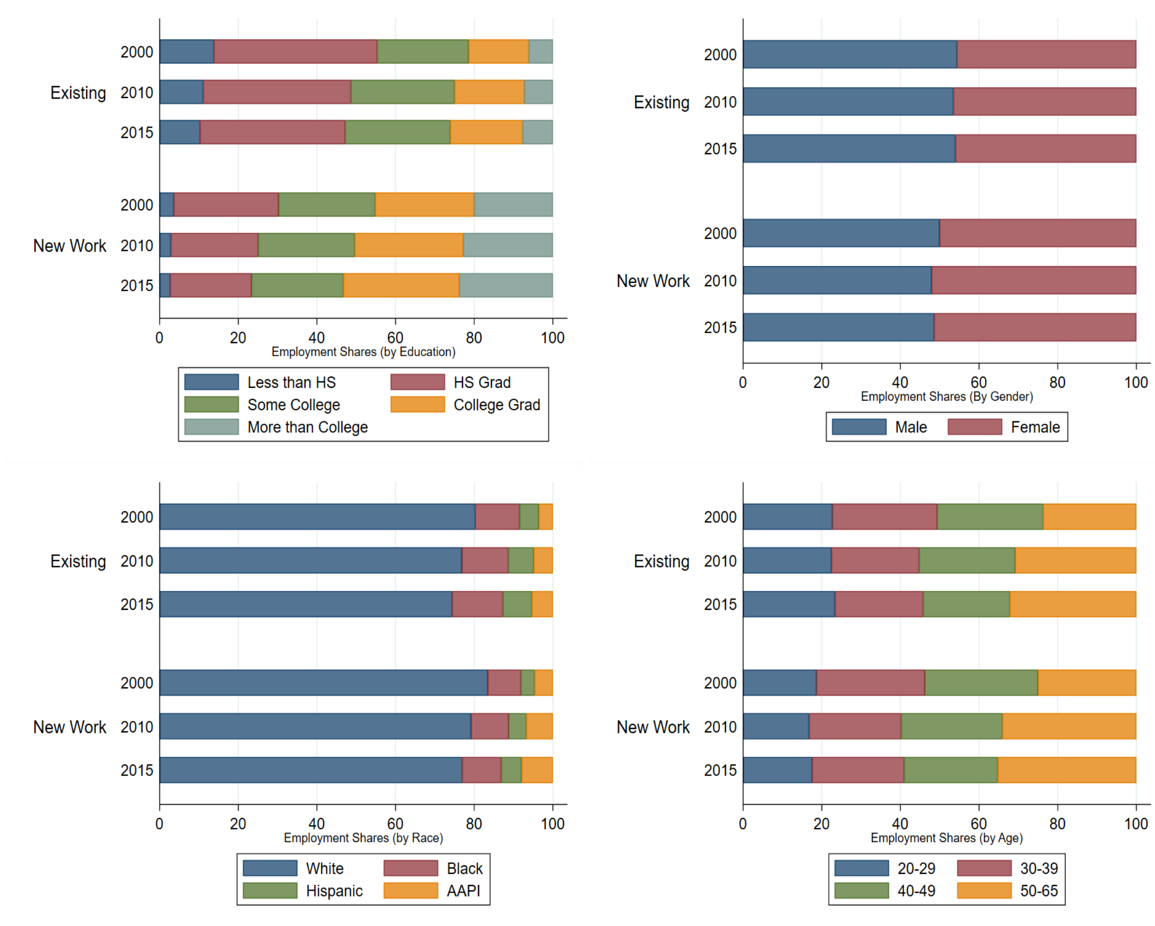

Figure B.7: Employment Shares of New and Existing Work by Group

Note: To obtain new work employment, I define respondents in IPUMS-USA as being employed in new work if their detailed occupation is the top quartile of new work intensities constructed using CBOW (threshold = 0.85).

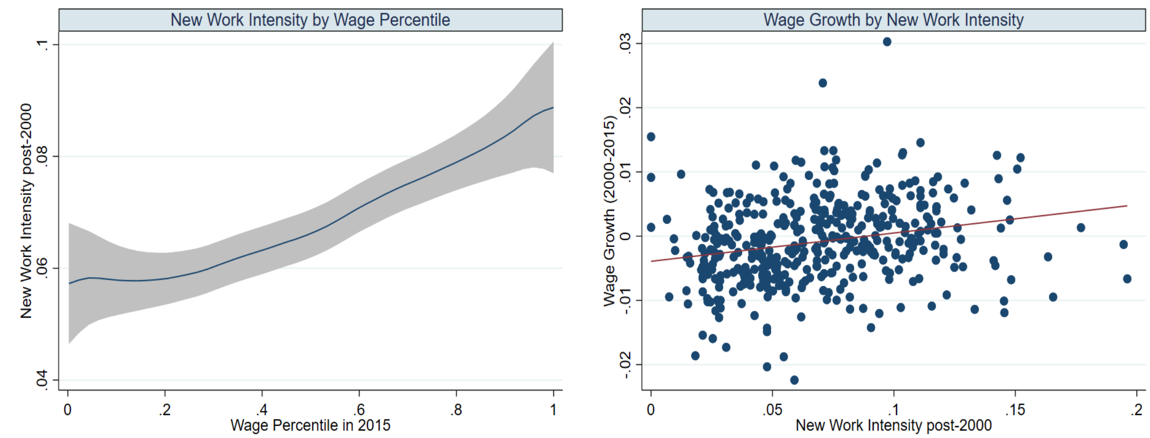

Figure B.8: New Work and Skill Percentile (left), Wage Growth (right)

Note: I use microdata from IPUMS-USA 2000 and 2015 and construct average wage for detailed census occupation codes (2010). On the left, I report the kernel-weighted local polynomial regression of occupational new work intensity (threshold = 0.85) on log wages with 95% confidence intervals. On the right, I show the average percentage change in log wage between 2000 and 2015 by occupational new work intensity (threshold = 0.85) with a fitted line of $\hat{y} = -0.004 + 0.044\hat{x}$.

	(1)	(2)	(3)	(4)	(5)	(6)
New Work (binary)	0.310***	0.137***	0.301***	0.131***	0.317***	0.145***
	(0.0806)	(0.0419)	(0.0801)	(0.0417)	(0.0821)	(0.0436)
Controls	N	Y	N	Y	N	Y
Industry FE	N	Y	N	Y	N	Y
Year FE	Y	Y	-	-	-	-
Sample Year(s)	2005-2018	2005-2018	2010	2010	2015	2015
Observations	31,916,771	31,916,771	1,979,230	1,979,230	2,556,162	2,556,162
R-squared	0.051	0.305	0.049	0.303	0.050	0.307

Note: A binary measure of new work intensity is employed (no threshold). All specifications include CZ fixed effects. Controls include binary indicators for gender, marital status, nativity, migration status, race, education, age. Parentheses contain robust standard errors clustered at the 3-digit census occupations (*** p<0.01, ** p<0.05, * p<0.1).

Table B.3: Wage Regressions for New Work Post 2000

	(1)	(2)	(3)	(4)	(5)	(6)
New Work (binary)	1.506***	0.102**	1.404***	0.0927**	1.591***	0.110**
	(0.464)	(0.0428)	(0.451)	(0.0418)	(0.481)	(0.0452)
Year FE	Y	Y	-	-	-	-
New Wok Measure	cont.	binary	cont.	binary	cont.	binary
Sample Year(s)	2005-2018	2005-2018	2010	2010	2015	2015
Observations	31,913,207	31,913,207	1,979,230	1,979,230	2,556,162	2,556,162
R-squared	0.302	0.302	0.301	0.301	0.304	0.304

Note: A binary measure of new work intensity is employed (threshold = 0.85). Controls include binary indicators for gender, marital status, nativity, migration status, race, education, age. All specifications include the full set of controls, CZ fixed effects and industry fixed effects. Parentheses contain robust standard errors clustered at the 3-digit census occupations (*** p<0.01, ** p<0.05, * p<0.1).

Table B.4: Wage Regressions for New Work Post 2000 (threshold applied)

	(1)	(2)	(3)	(4)	(5)	(6)
New Work (continuous)	4.222***	2.037***	4.177***	1.963***	4.234***	2.094***
	(0.792)	(0.427)	(0.788)	(0.428)	(0.807)	(0.434)
Controls	N	Y	N	Y	N	Y
Industry FE	N	Y	N	Y	N	Y
Year FE	Y	Y	-	-	-	-
Sample Year(s)	2005-2018	2005-2018	2010	2010	2015	2015
Observations	31,913,207	31,913,207	1,979,230	1,979,230	2,556,162	2,556,162
R-squared	0.056	0.306	0.056	0.304	0.054	0.308

Note: A continuous measure of new work intensity is employed. All specifications include CZ fixed effects. Controls include binary indicators for gender, marital status, nativity, migration status, race, education, age. Parentheses contain robust standard errors clustered at the 3-digit census occupations (*** p<0.01, ** p<0.05, * p<0.1).

Table B.5: Wage Regressions for New Work Post 2000 (continuous measure)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New Work (continuous)	2.266***	1.141***	0.820***	0.408***	2.470	1.729**	1.043***	0.414***
	(0.846)	(0.420)	(0.116)	(0.0601)	(1.709)	(0.826)	(0.337)	(0.132)
Controls	N	Y	N	Y	N	Y	N	Y
Industry FE	N	Y	N	Y	N	Y	N	Y
Sample Year(s)	2000	2000	2000	2000	1990	1990	1990	1990
New Work Construction	CBOW	CBOW	Lin	Lin	CBOW	CBOW	Lin	Lin
Observations	9,589,062	9,589,062	9,589,062	9,589,062	8,864,075	8,864,075	8,862,884	8,862,884
R-squared	0.028	0.269	0.039	0.271	0.035	0.274	0.039	0.278

Note: A continuous measure of new work intensity is employed. All specifications include CZ fixed effects. Controls include binary indicators for gender, marital status, nativity, migration status, race, education, age. Parentheses contain robust standard errors clustered at the 3-digit census occupations (*** p<0.01, ** p<0.05, * p<0.1).

Table B.6: Wage Regressions for New Work (2000, 1990; continuous measure)

Appendix C Regional Analysis

	Mean	SD	Min	Max		Mean	SD	Min	Max
					year = 2005				
NTR Gap	0.081	0.033	0.005	0.221	Δ NR Cognitive Analytical	0.003	0.163	-0.977	0.894
					Δ NR Cognitive Interpersonal	0.003	0.107	-0.574	0.509
					Δ NR Manual Physical	0.002	0.069	-0.406	0.537
year = 2005					Δ NR Manual Interpersonal	0.013	0.112	-0.574	0.546
Δ New Work Managerial	-0.005	0.156	-0.977	0.894	Δ Routine Cognitive	0.002	0.137	-0.977	0.894
Δ New Work Sales, Admin	0.004	0.053	-0.149	0.335	Δ Routine Manual	0.000	0.035	-0.158	0.288
Δ New Work Technological	-0.002	0.192	-0.886	0.722					
Δ New Work Production	-0.004	0.029	-0.110	0.193	year = 2010				
					Δ NR Cognitive Analytical	0.013	0.157	-1.000	0.894
					Δ NR Cognitive Interpersonal	0.021	0.100	-0.621	0.523
year = 2010					Δ NR Manual Physical	0.001	0.065	-0.342	0.593
Δ New Work Managerial	0.018	0.152	-1.000	0.894	Δ NR Manual Interpersonal	0.028	0.114	-0.621	0.593
Δ New Work Sales, Admin	-0.008	0.052	-0.148	0.323	Δ Routine Cognitive	0.003	0.132	-1.000	0.894
Δ New Work Technological	-0.002	0.192	-0.886	0.722	Δ Routine Manual	-0.000	0.037	-0.177	0.265
Δ New Work Production	0.000	0.035	-0.177	0.187					
					year = 2015				
					Δ NR Cognitive Analytical	0.025	0.148	-1.000	0.894
year = 2015					Δ NR Cognitive Interpersonal	0.034	0.098	-0.606	0.454
Δ New Work Managerial	0.049	0.147	-0.802	0.894	Δ NR Manual Physical	0.007	0.068	-0.334	0.638
Δ New Work Sales, Admin	-0.016	0.050	-0.171	0.196	Δ NR Manual Interpersonal	0.044	0.116	-0.606	0.761
Δ New Work Technological	0.006	0.174	-1.000	0.571	Δ Routine Cognitive	0.012	0.129	-0.802	0.894
Δ New Work Production	0.005	0.033	-0.161	0.209	Δ Routine Manual	-0.001	0.035	-0.161	0.209

Note: The table provides changes in the share of new work in each occupation groups. On the left panel, occupations are categorized into five mutually exclusive occupation types. On the right panel, occupations are categorized using a binary indicator of each task type.

Table C.1: Summary Statistics by Occupation Groups: Types (left), Tasks (right)

C.1 Robustness Checks

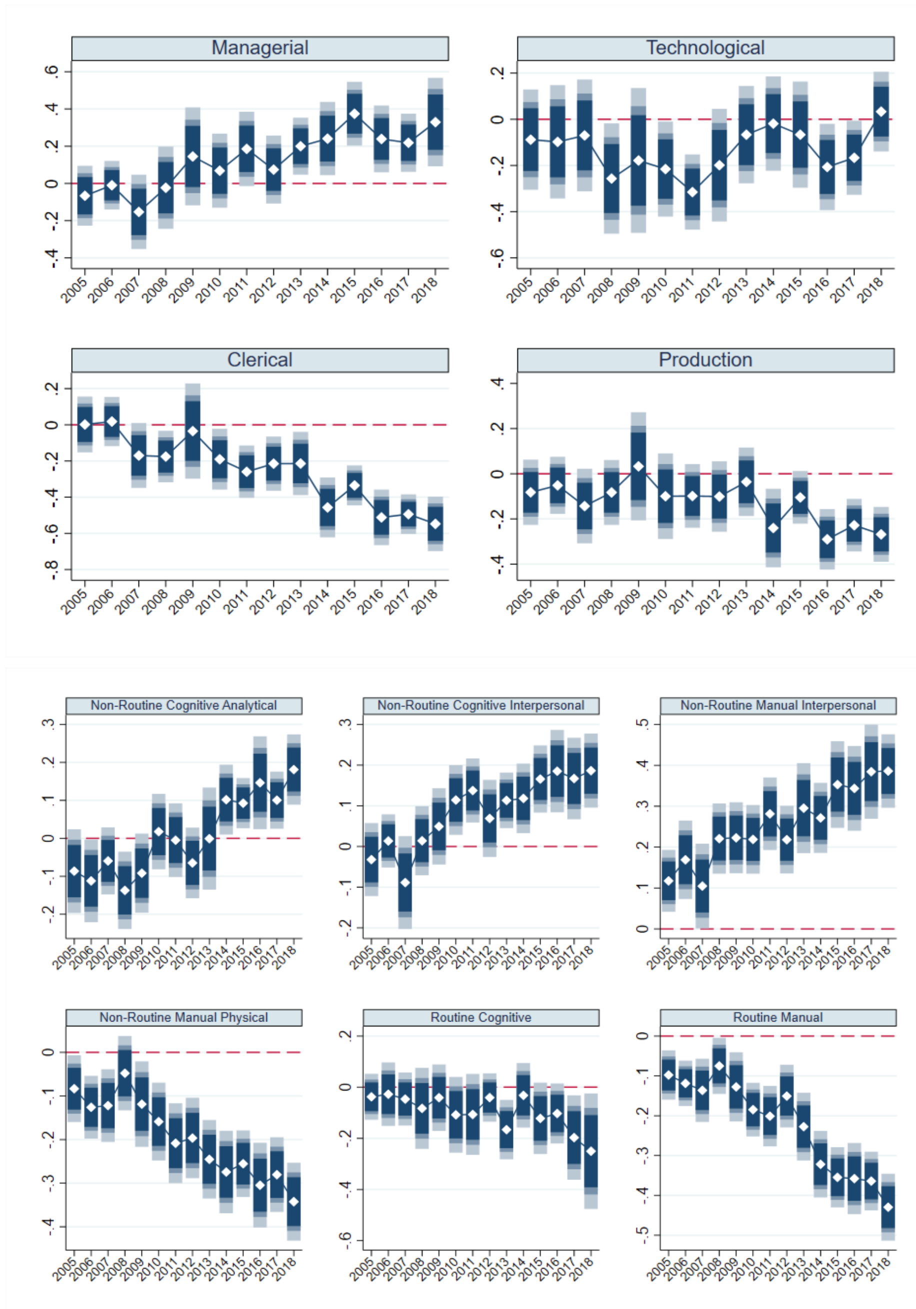

Figure C.1: Changes in New Work Shares: Additional Controls

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Compared to the baseline, past changes in the local labor market adoption of new work shares (1980-1990, 1990-2000) are included as additional controls.

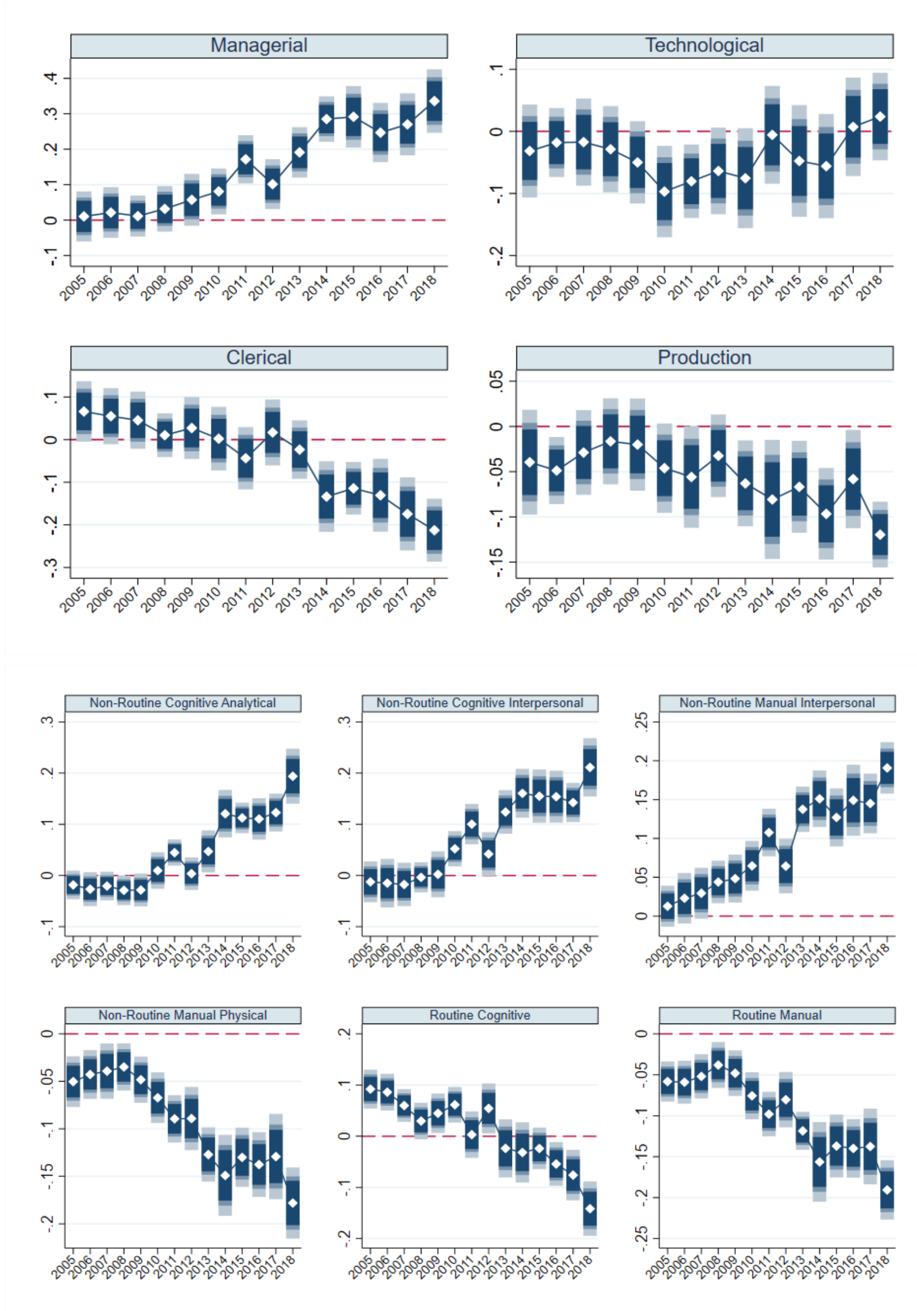

Figure C.2: Changes in New work Shares: within-Industry-Occupation

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Compared to the baseline, the unit of analysis is a quartet of CZ-industry (2-digit NAICS)-occupation-year and industry (2-digit NAICS) fixed effects are included.

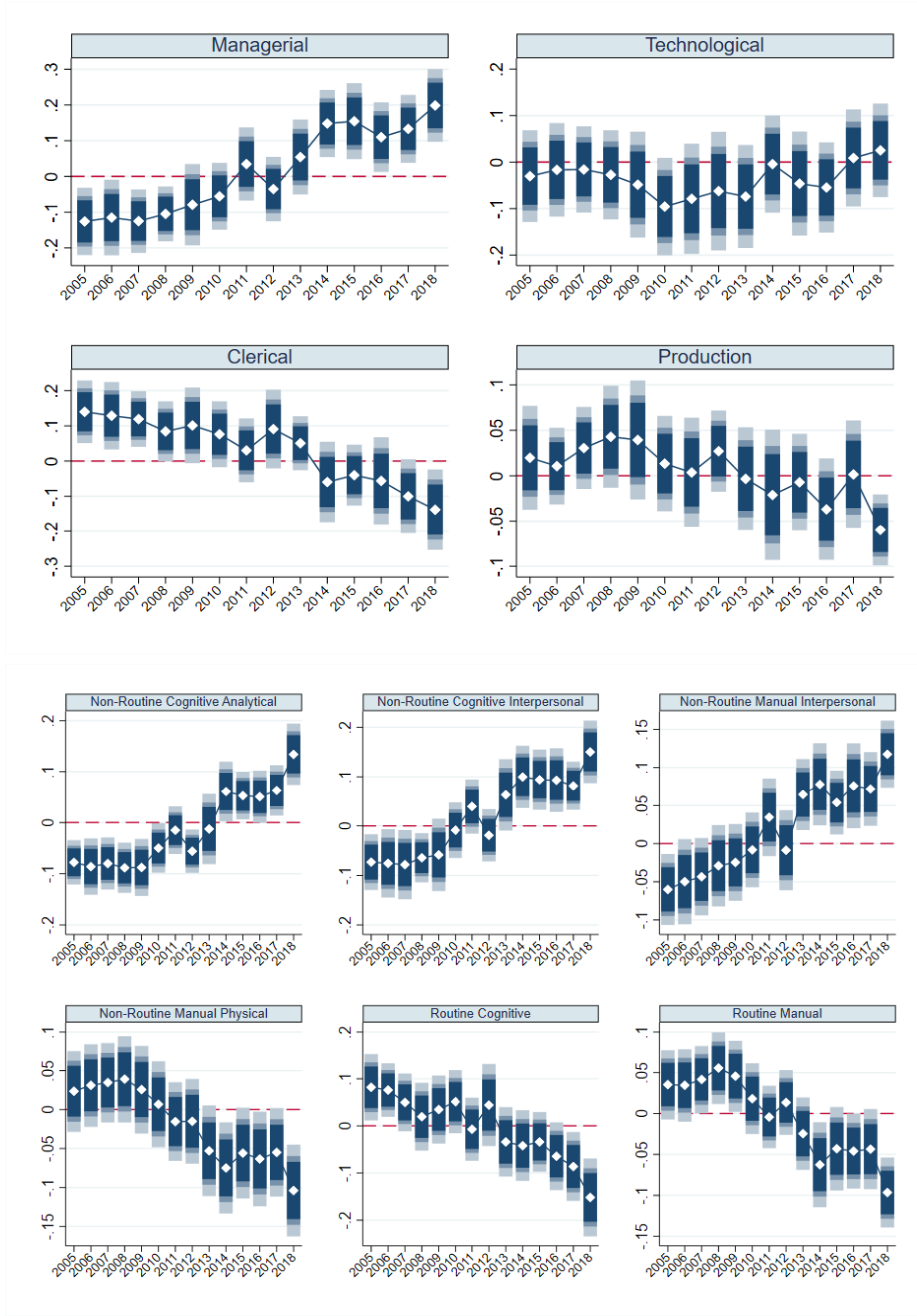

Figure C.3: Changes in New Work Shares: within-Industry-Occupation and Occupation Trends

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Compared to the baseline, the unit of analysis is a quartet of CZ-industry (2-digit NAICS)-occupation-year and industry (2-digit NAICS) fixed effects and occupation dummies interacted with the year variable are additionally included.

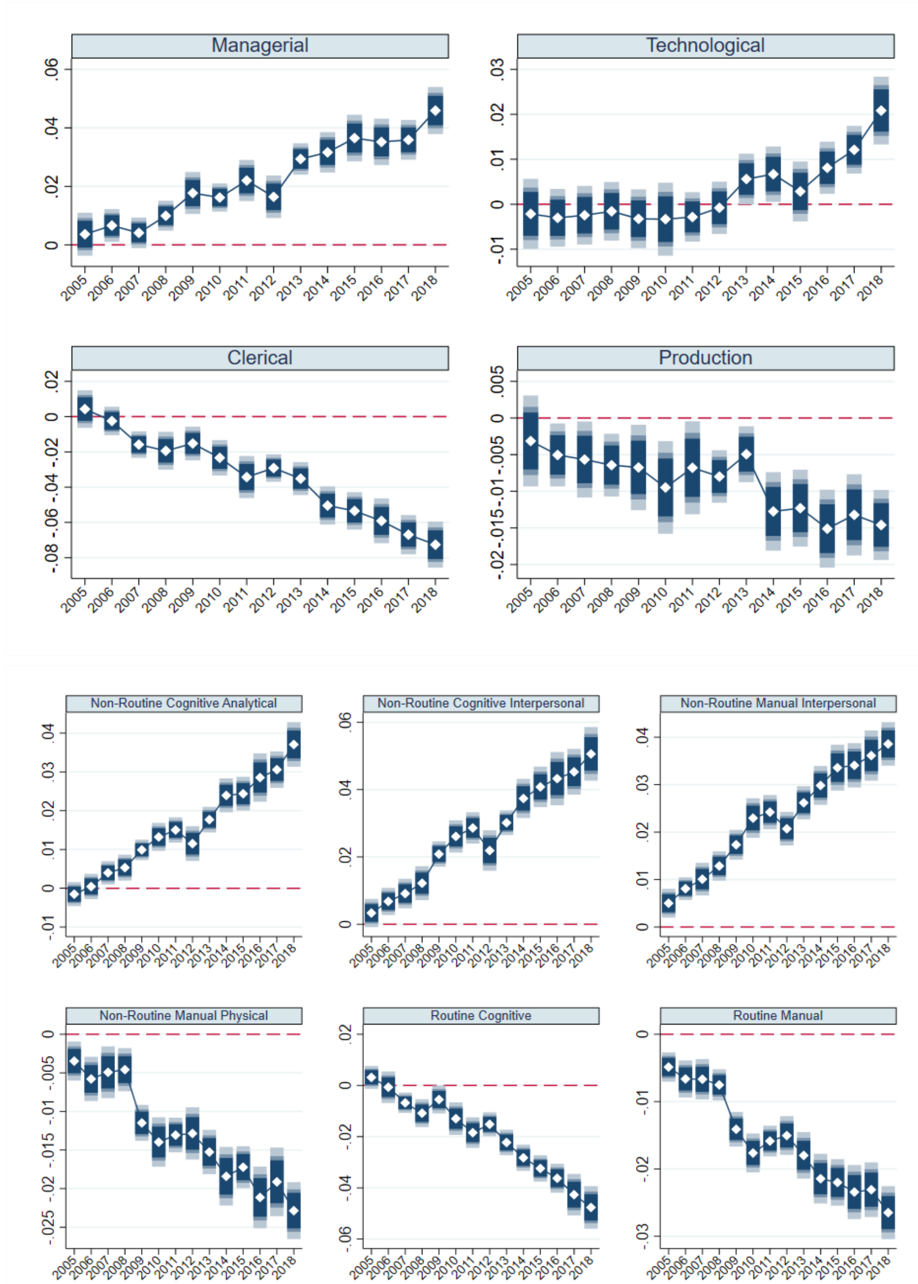

Figure C.4: Changes in New Work Shares: Employment Levels

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Compared to the baseline, occupation-specific new work is normalized by employment in CZs.

C.2 Alternative Measures

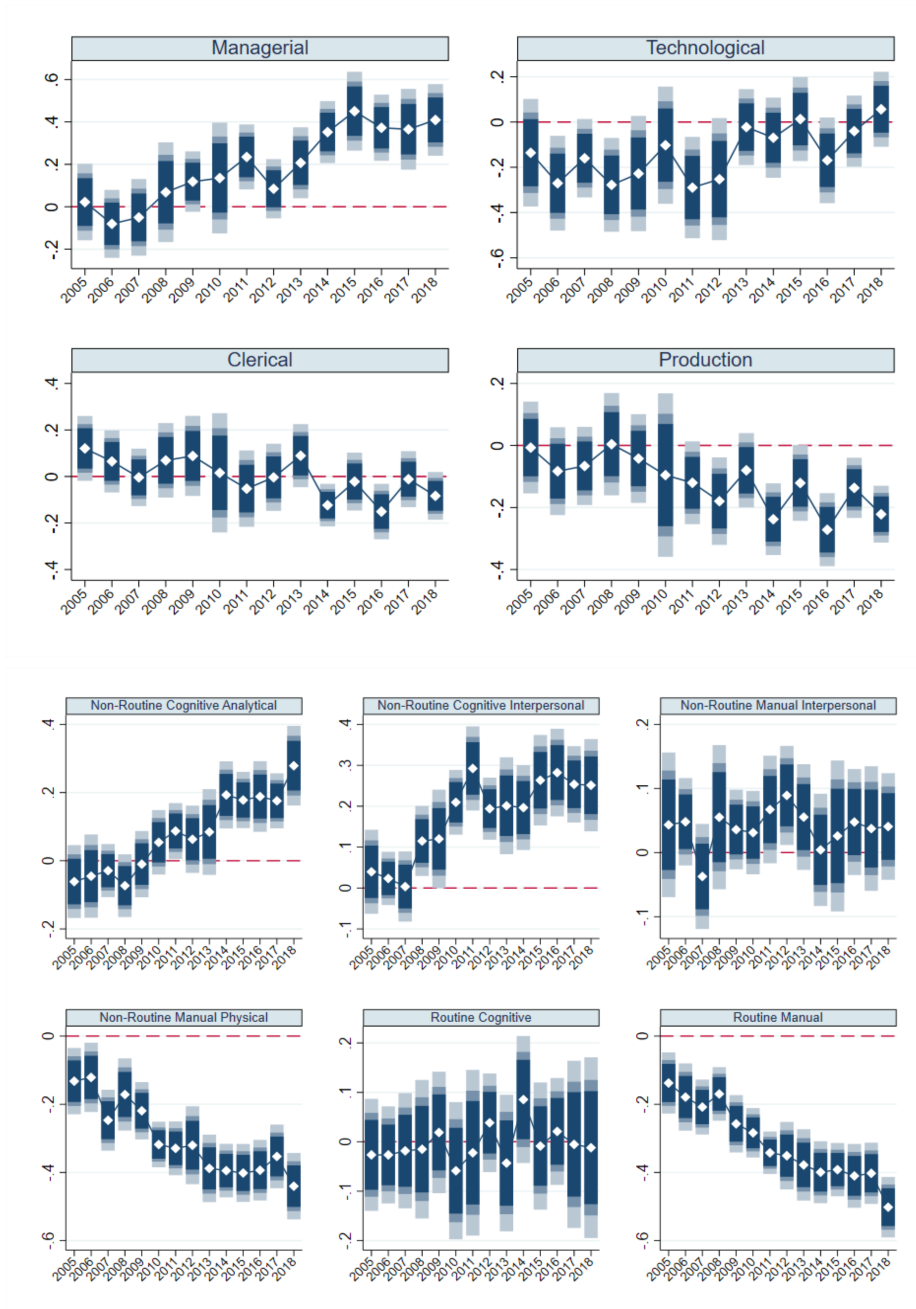

Figure C.5: Changes in New Work Shares: N&E Occupations

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Compared to the baseline, the dependent variable is constructed using N&E occupations.

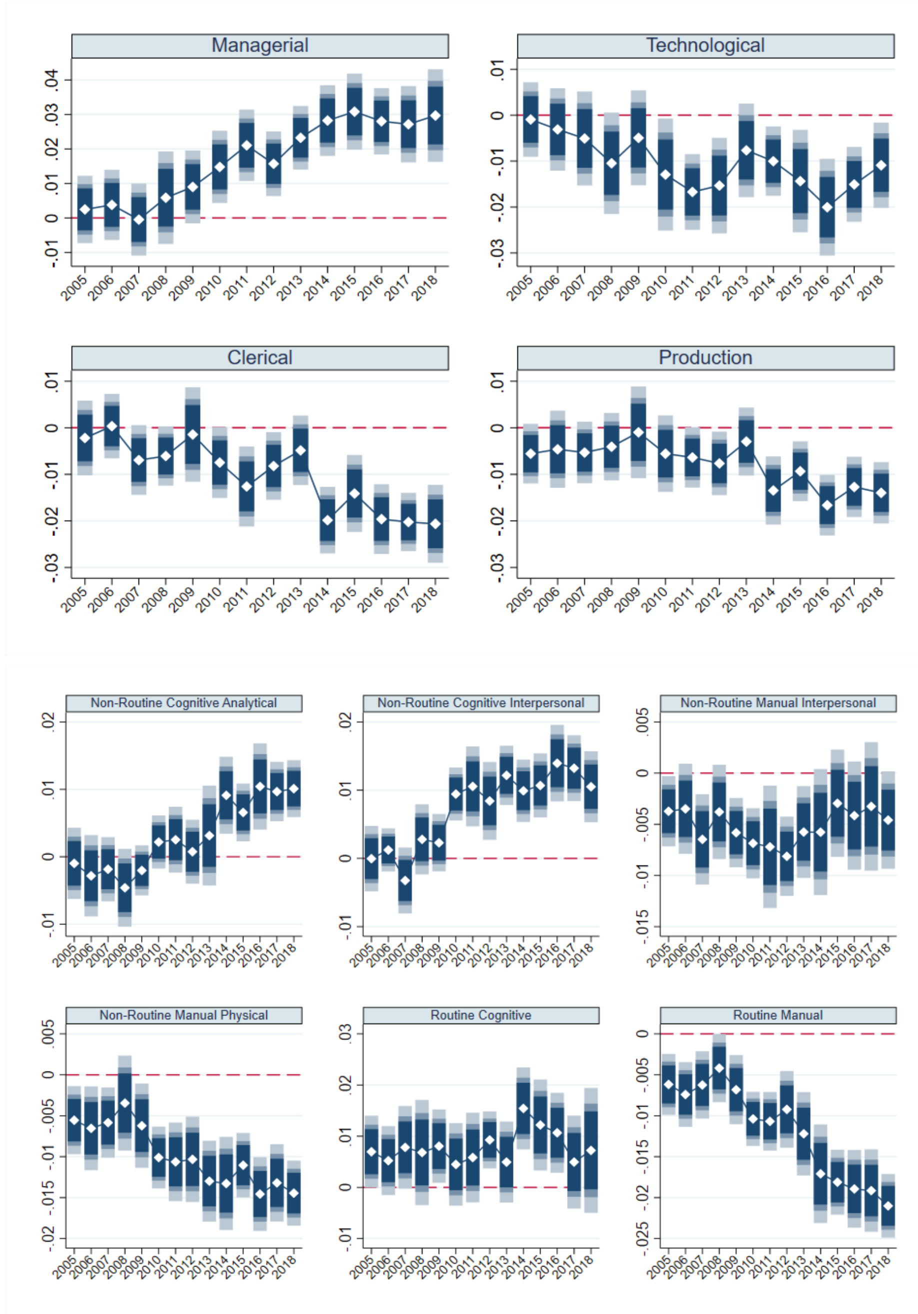

Figure C.6: Changes in New Work Shares: Continuous Measure of New Work

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Compared to the baseline, the dependent variable is constructed using a continuous measure of new work.

C.3 Alternative Identification of Import Shocks

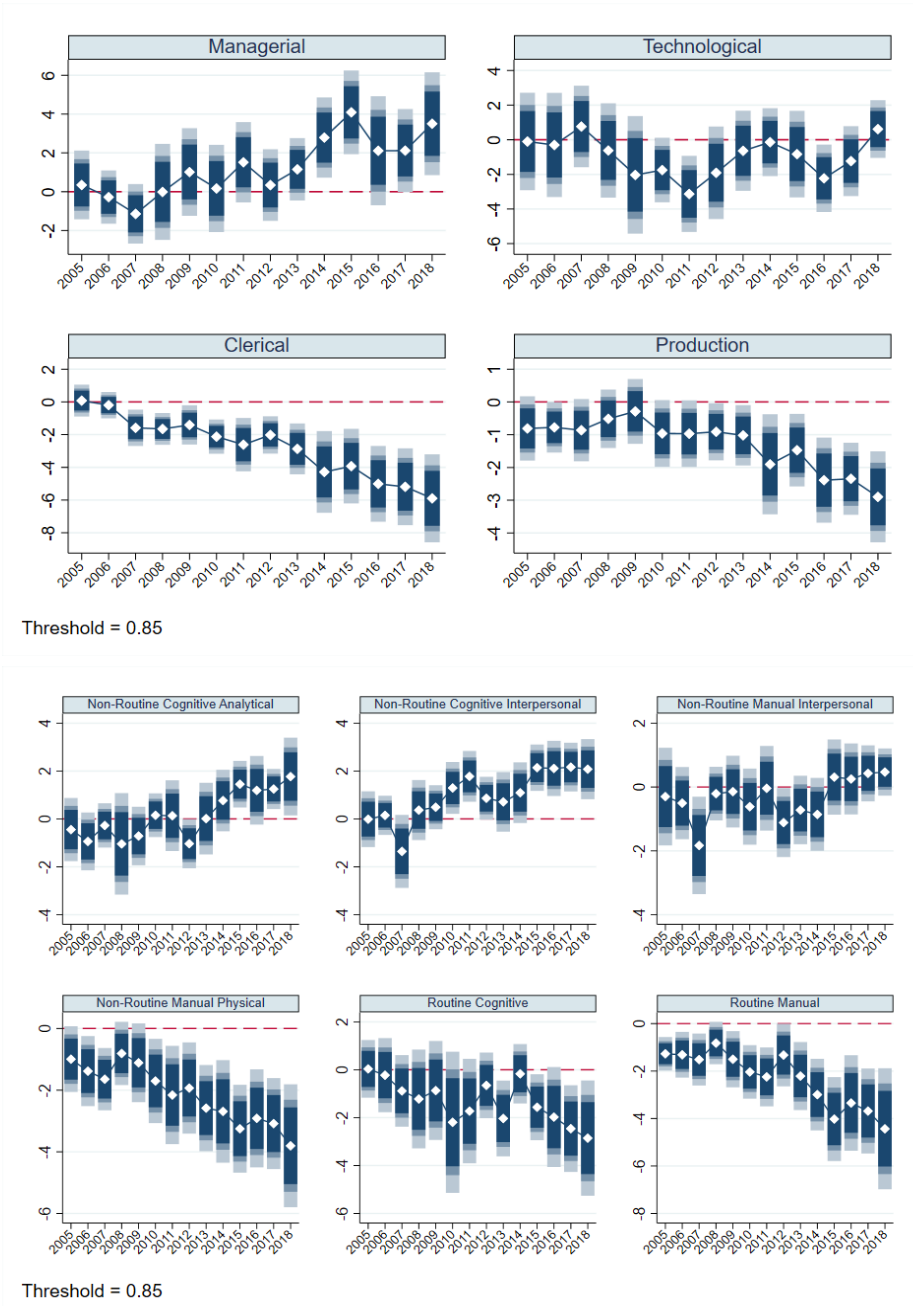

Figure C.7: Changes in New Work Shares: OLS Results

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Compared to the baseline, import shocks are measured using values of imports. I follow Autor et al. (2013) and use changes in the level of industry-level imports per worker weighted by the industry share in each region.

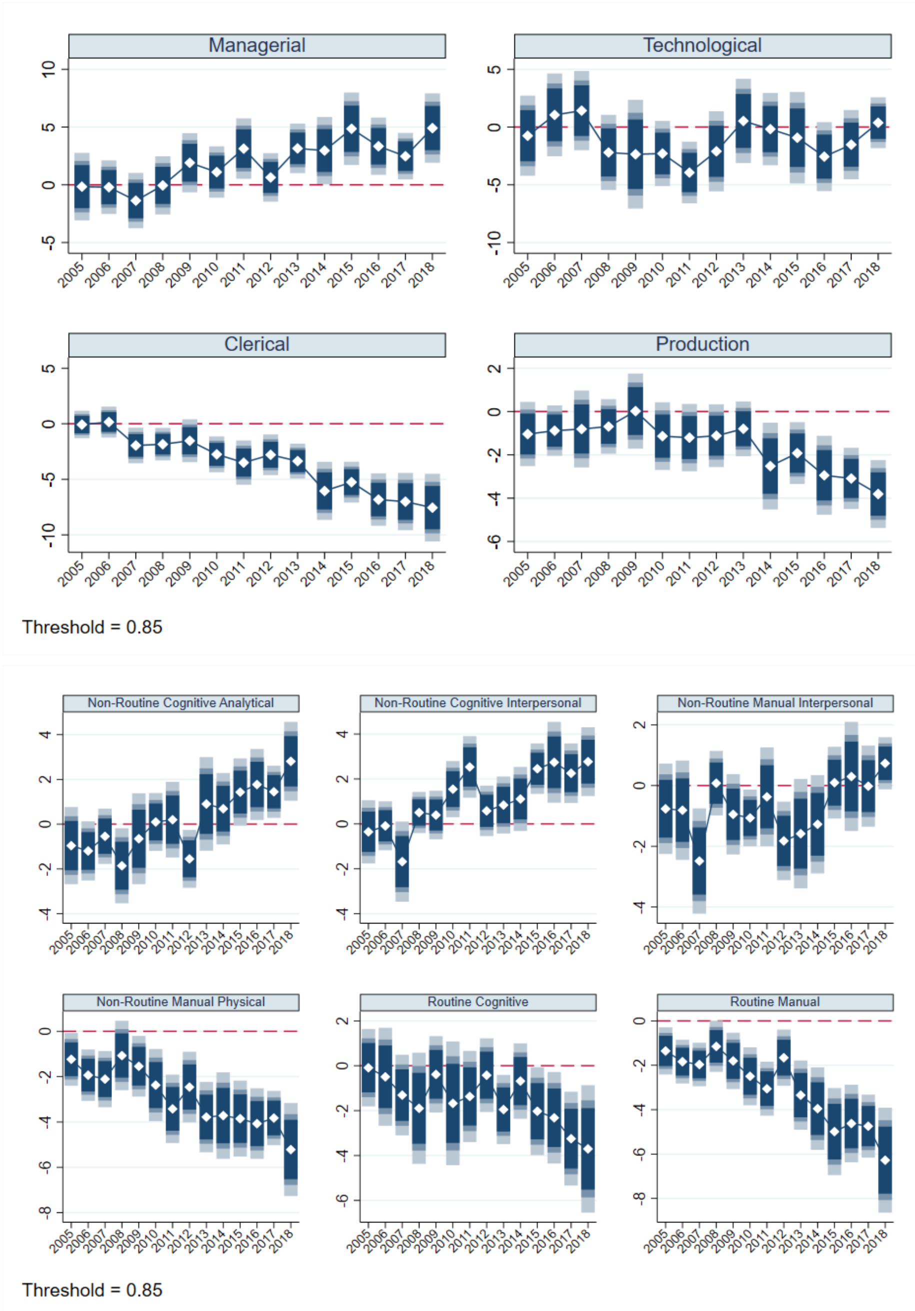

Figure C.8: Changes in New Work Shares: IV Results

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t}+\beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Compared to the baseline, import shocks are instrumented using Chinese imports from high-wage countries. I follow Autor et al. (2013) and use the instrument variable approach of the their work and use high-wage countries' imports from China weighted by the industry composition and employment in the previous period in each region.The list of countries includes Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

C.4 Alternative Specification

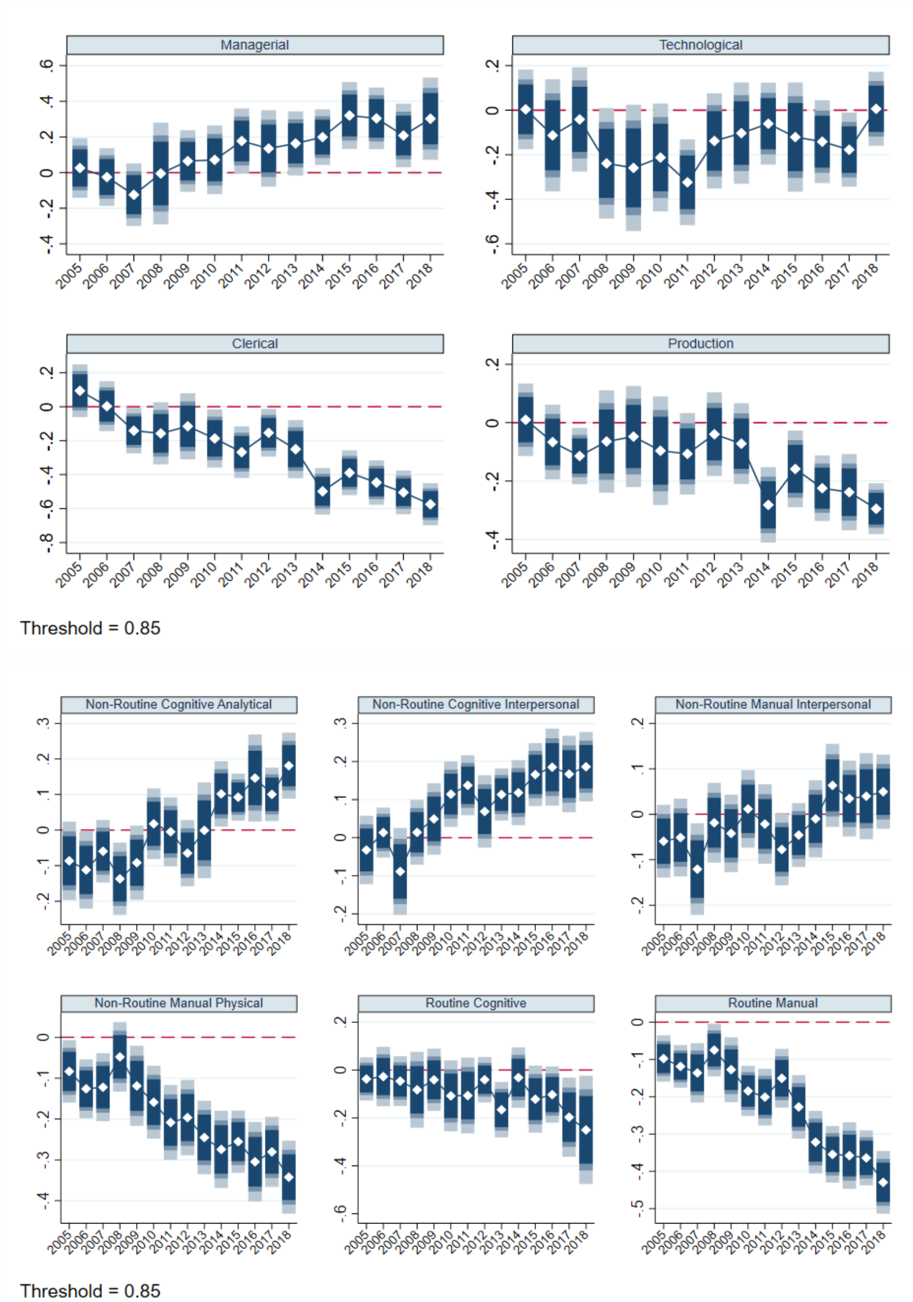

Figure C.9: Changes in New Work Shares: Estimation by Year

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Compared to the baseline, the regression specification of equation (4) is run separately for each year.

C.5 Comparison with BGT

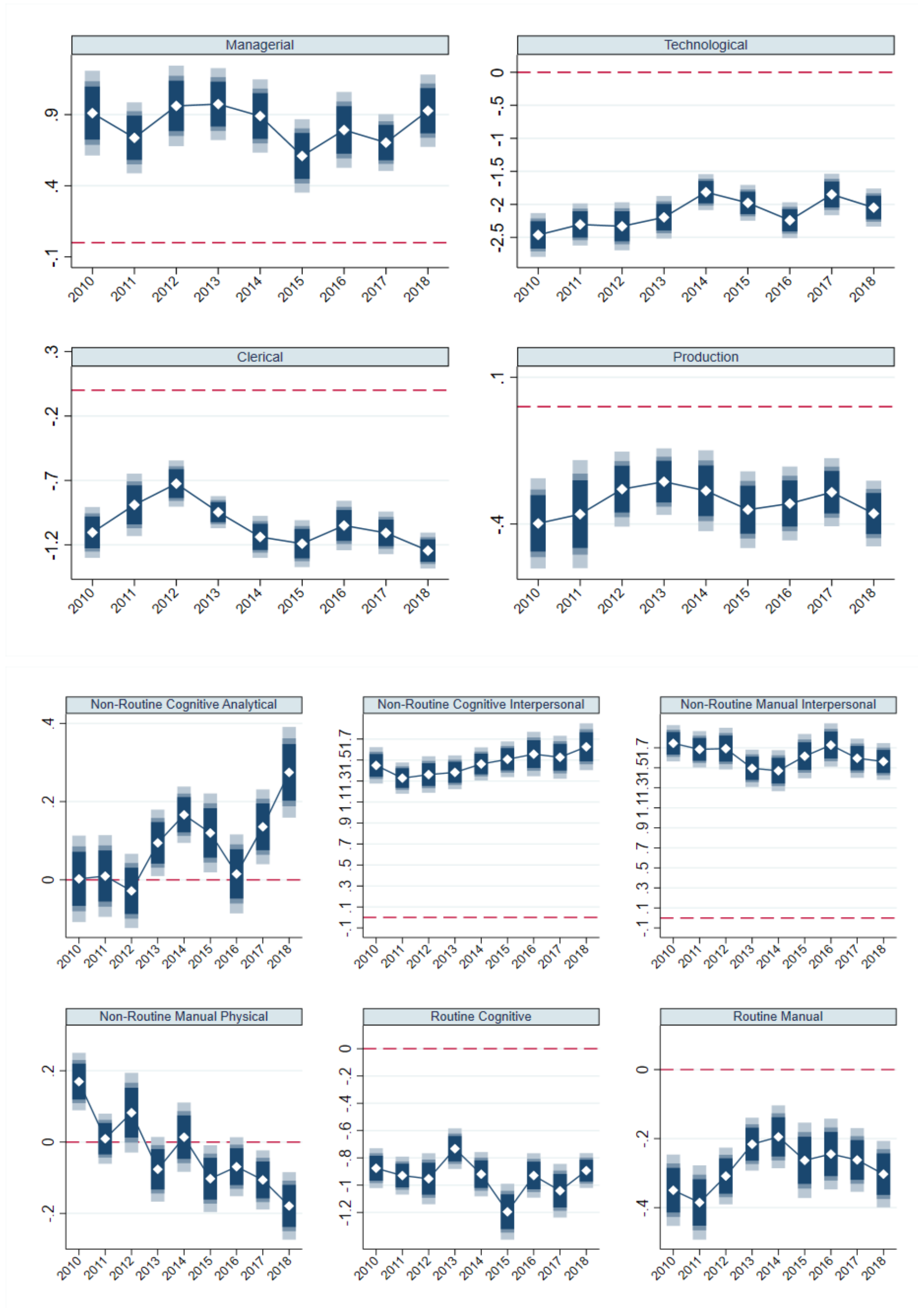

Figure C.10: Changes in New Work Shares: BGT Job Demands

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Compared to the baseline, the dependent variable is constructed using BGT data (2010-2018).

C.6 Validation Exercises

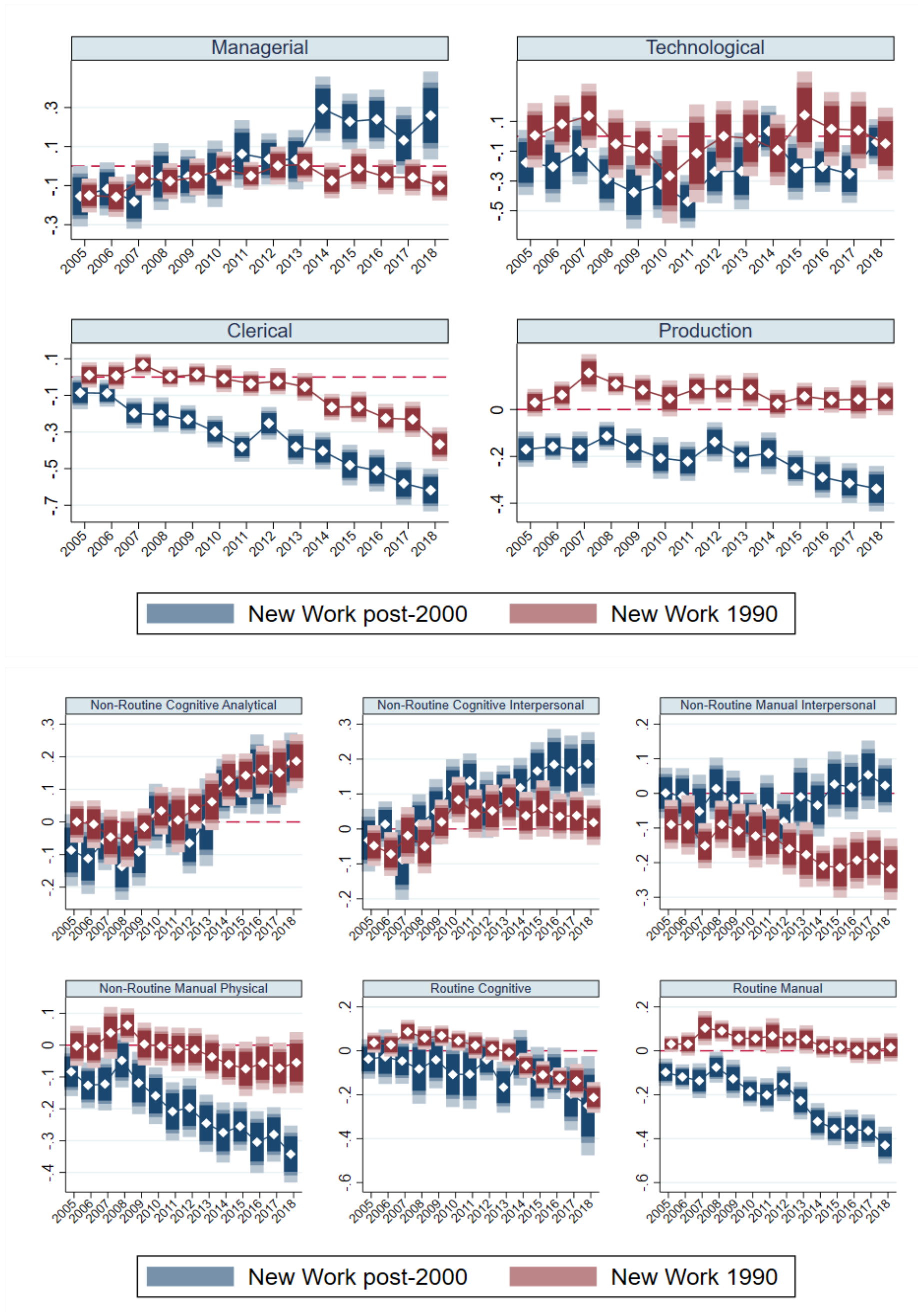

Figure C.11: Changes in New Work Shares: cp. New Work Emerged in 1990

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Baseline results are reported in blue; results using new work that emerged in 1990 are reported in red.

	Δ (2000-2015)	Δ (1980-2000)	Δ (1990-2000)	Δ (1980-2000)	Δ (1990-2000)
Total Effects by Occupation					
Managerial	0.320***	-1.419***	-1.257***	-0.958***	-0.949***
	(0.0698)	(0.0914)	(0.0625)	(0.0532)	(0.0628)
Clerical	-0.389***	0.0687*	0.229***	0.0112	0.106*
	(0.0492)	(0.0364)	(0.0444)	(0.0600)	(0.0556)
Technological	-0.121	0.410***	0.950***	0.328***	0.622***
	(0.0912)	(0.0678)	(0.0813)	(0.0762)	(0.0750)
Production	-0.158***	0.602***	0.585***	0.427***	0.417***
	(0.0490)	(0.0350)	(0.0399)	(0.0587)	(0.0533)
Sample	All	All	All	Top Quartile	Top Quartile

Note: The table reports the estimated total effects ($\beta_{1t} + \beta_{2st}$) for occupation s in equation (4). The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Controls include initial characteristics of local labor markets. Census region fixed effects and time fixed effects are included. Robust standard errors are clustered on state (*** p<0.01, ** p<0.05, * p<0.1).

Table C.2: Falsification Exercise: Occupation Types

C.7 Results for Mechanisms

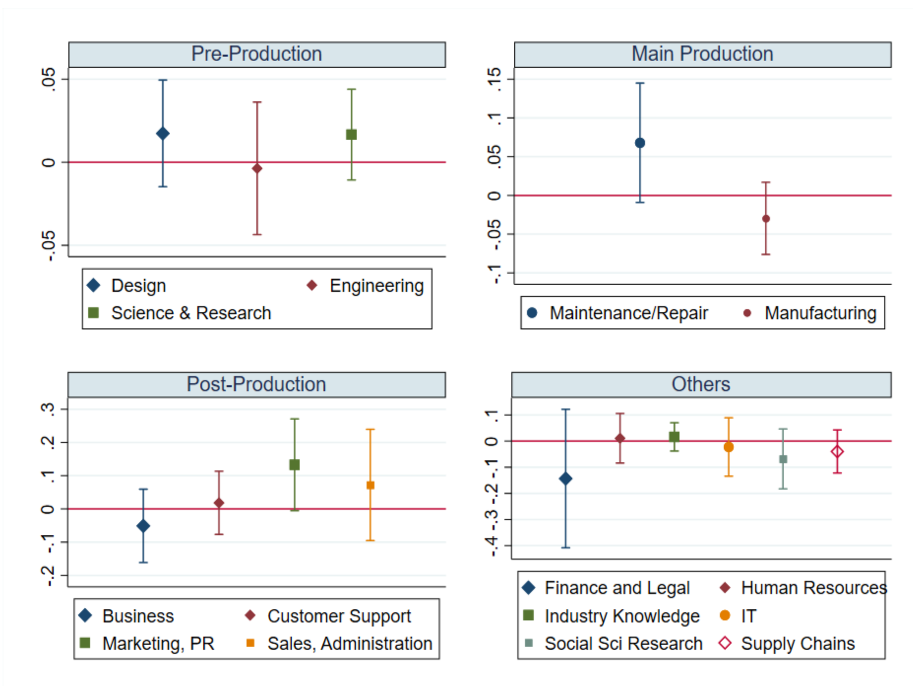

Figure C.12: Change in BGT skill Requirements in Managerial New Work

Note: Each graph plots the point estimates of β_1 in equation (3) examining overlapping differences (2010-2015, 2011-2016) with period-specific effects, and includes 95 percent confidence intervals. The dependent variable is constructed relative to skill intensities observed in 2010(2011). The regression is run for each knowledge category focusing on managerial new work. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year.

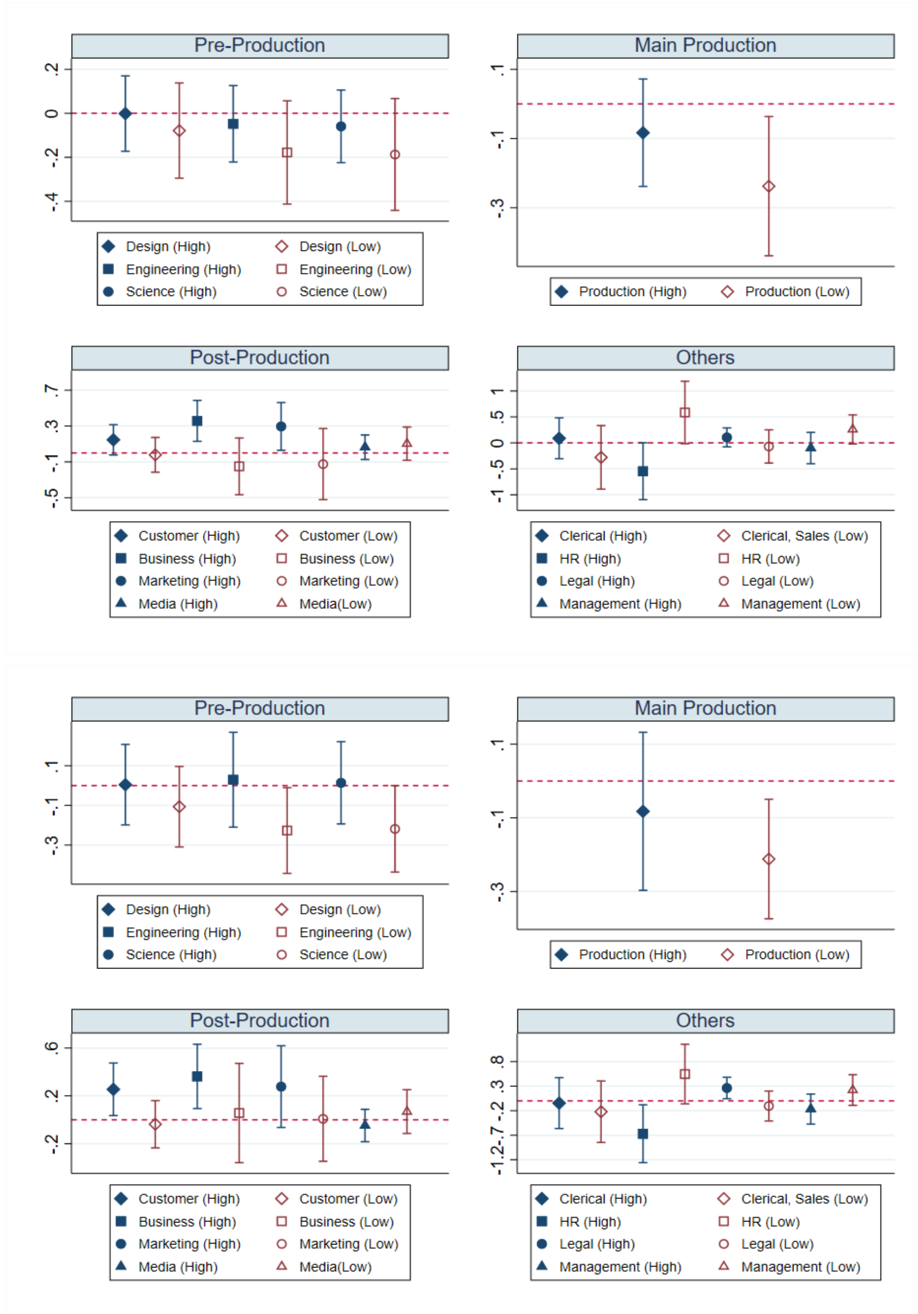

Figure C.13: Change in O*NET's Knowledge Requirements by Offshoring and Servitization

Note: Each graph plots the point estimates of β_1 in equation (3) pooling years (2015, 2016) and includes 95 percent confidence intervals. The regression is run for each knowledge category focusing on managerial new work. I separately examine high- and low-exposed regions. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Estimates with the filled symbols in blue are estimates for high-exposed regions; those with the corresponding hollow symbols in red are for low-exposed regions. The top panel focuses on exposures to offshoring; the bottom panel on servitization.

C.8 Results for Labor Market Inequality

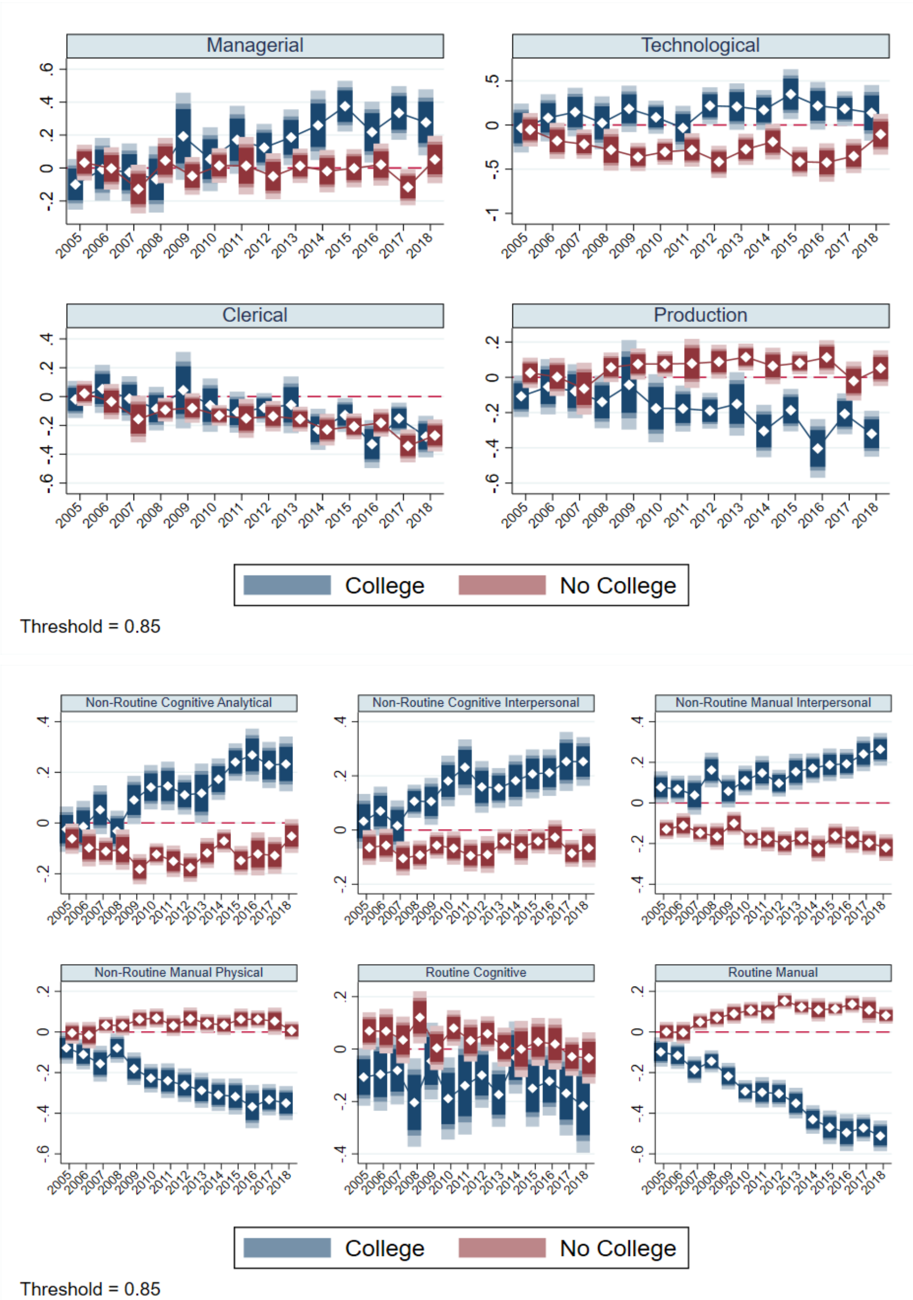

Figure C.14: Changes in New Work Shares: by College Education

Note: On the top panel, each graph plots the point estimates of the total effects ($\beta_{1t} + \beta_{2st}$) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4). Occupations are classified into five mutually exclusive categories. On the bottom panel, each graph plots the point estimates of the relative effects (β_{2st}) and 90, 95, and 99 percent confidence intervals for task s obtained through separate regressions using equation (4). Occupations are categorized using a binary indicator for each task type. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Compared to the baseline, the dependent variable is constructed separately for workers with college education and those without it.

	Δlog wage$_{\text{col-nocol}}$	Δlog wage$_{\text{col-no col}}$	Δlog wage$_{\text{new-ex}}$	Δlog wage$_{\text{new-ex}}$
NTR Gap × 2005	0.416	-0.0924	0.608	0.0978
	(0.496)	(0.396)	(0.429)	(0.340)
NTR Gap × 2006	0.276	-0.244	0.742	0.228
	(0.472)	(0.416)	(0.518)	(0.359)
NTR Gap × 2007	0.195	-0.288	0.167	-0.287
	(0.439)	(0.333)	(0.456)	(0.249)
NTR Gap × 2008	0.667	0.248	0.443	0.0339
	(0.521)	(0.533)	(0.631)	(0.255)
NTR Gap × 2009	-0.0737	0.387	0.368	0.828*
	(0.588)	(0.490)	(0.551)	(0.430)
NTR Gap × 2010	0.518	0.0569	0.393	-0.0663
	(0.454)	(0.578)	(0.550)	(0.380)
NTR Gap × 2011	0.355	-0.0835	0.799	0.364
	(0.314)	(0.490)	(0.487)	(0.330)
NTR Gap × 2012	0.0352	0.189	-0.0239	0.123
	(0.399)	(0.489)	(0.356)	(0.360)
NTR Gap × 2013	0.656	-0.128	0.709	-0.0686
	(0.410)	(0.388)	(0.513)	(0.267)
NTR Gap × 2014	1.094***	0.413	0.822**	0.148
	(0.367)	(0.422)	(0.355)	(0.268)
NTR Gap × 2015	0.735*	0.139	0.977*	0.384
	(0.398)	(0.461)	(0.581)	(0.292)
NTR Gap × 2016	0.897**	-0.0666	0.660	-0.296
	(0.368)	(0.442)	(0.510)	(0.337)
NTR Gap × 2017	1.251**	0.274	0.475	-0.497
	(0.551)	(0.426)	(0.466)	(0.304)
NTR Gap × 2018	0.901**	-0.0676	0.525	-0.438*
	(0.373)	(0.481)	(0.534)	(0.220)
Sample	New Work	Existing Work	College	No College
Dependent	(College-No College)	(College-No College)	(New-Existing)	(New-Existing)
Observations	222,376	222,376	222,376	222,376
R-squared	0.004	0.008	0.003	0.002
Joint Significance	2.143*	0.848	1.406	3.496***

Note: The table provides estimation results of β_{1t} in equation (3). The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Controls include initial characteristics of local labor markets. Census region fixed effects are included. Robust standard errors are clustered on state (*** p<0.01, ** p<0.05, * p<0.1).

Table C.3: Wage Differences by Group

	Δlog wage$_{\text{col-nocol}}$	Δlog wage$_{\text{col-no col}}$	Δlog wage$_{\text{new-ex}}$	Δlog wage$_{\text{new-ex}}$
NTR Gap	-0.0517	-0.875**	0.574	-0.252
	(0.403)	(0.422)	(0.536)	(0.383)
NTR Gap × Managerial	1.699***	-0.499	3.020***	0.823*
	(0.439)	(0.528)	(0.597)	(0.455)
NTR Gap × Clerical	0.356	1.083***	0.418	1.147***
	(0.355)	(0.267)	(0.411)	(0.188)
NTR Gap × Technological	0.627	4.278***	0.371	4.023***
	(0.385)	(1.144)	(0.866)	(0.870)
NTR Gap × Production	-0.904	-0.259	-3.682***	-3.036***
	(0.890)	(0.279)	(0.957)	(0.446)
Sample	New Work	Existing Work	College	No College
Dependent	(College-No College)	(College-No College)	(New-Existing)	(New-Existing)
Observations	15,884	15,884	15,884	15,884
R-squared	0.007	0.023	0.020	0.035

Note: The table provides estimation results of β_1 and β_2 in equation (4) for year 2015. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year. Controls include initial characteristics of local labor markets. Census region fixed effects are included. Robust standard errors are clustered on state (*** p<0.01, ** p<0.05, * p<0.1).

Table C.4: Wage Differences across Occupation Types by Group

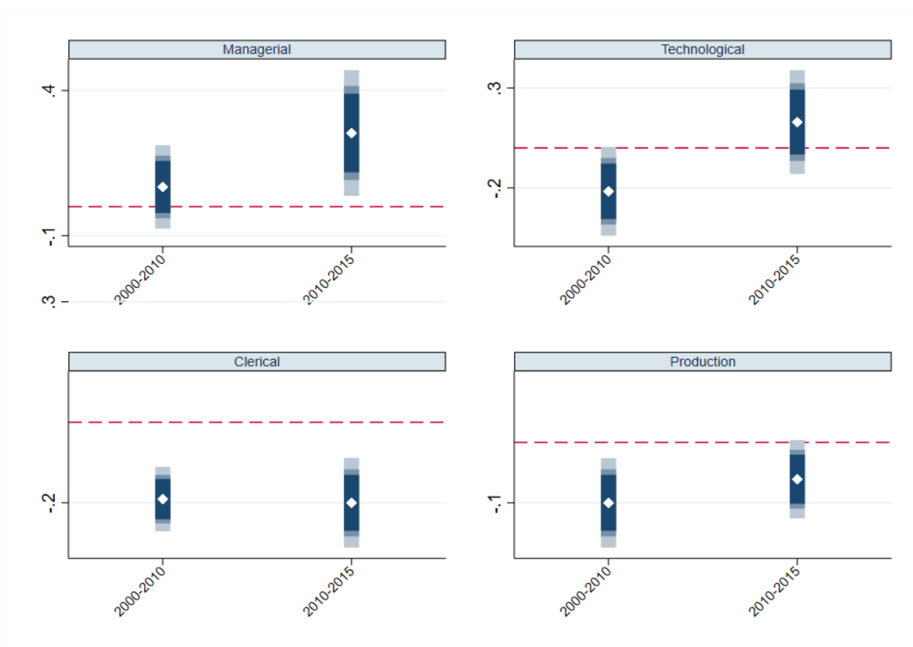

Figure C.15: Regional Estimates Comparing Pre and Post 2010

Note: Each graph plots the point estimates of the total effects (β_{1t}+β_{2st}) and 90, 95, and 99 percent confidence intervals for occupation s using equation (4) separately examined for changes 2000-2010 and 2010-2015. Occupations are classified into five mutually exclusive categories. The unit of analysis is a triplet of CZ-occupation(2-digit SOC)-year.

C.9 Tables Corresponding to Figures in the Main Text

	New Work Shares
NTR Gap × 2005	0.0195
	(0.0437)
NTR Gap × 2006	0.0423
	(0.0415)
NTR Gap × 2007	-0.0470
	(0.0577)
NTR Gap × 2008	-0.0374
	(0.0534)
NTR Gap × 2009	0.112
	(0.0879)
NTR Gap × 2010	0.0173
	(0.0695)
NTR Gap × 2011	0.0264
	(0.0460)
NTR Gap × 2012	-0.0211
	(0.0482)
NTR Gap × 2013	0.0876*
	(0.0493)
NTR Gap × 2014	-0.0724
	(0.0523)
NTR Gap × 2015	0.0794*
	(0.0428)
NTR Gap × 2016	-0.0733*
	(0.0426)
NTR Gap × 2017	-0.0145
	(0.0382)
NTR Gap × 2018	-0.0000
	(0.0394)
Observations	222,376
R-squared	0.004
Joint Significance	1.622

Table C.5: Regression Results: Figure 4

Managerial		Clerical		Technological		Production			
NTR Gap × 2005 × occ	-0.154**	NTR Gap × 2005 × occ	-0.0857**	NTR Gap × 2005 × occ	-0.176**	NTR Gap × 2005 × occ	-0.170***	NTR Gap × 2005	0.0875*
	(0.0578)		(0.0334)		(0.0814)		(0.0279)		(0.0443)
NTR Gap × 2006 × occ	-0.117**	NTR Gap × 2006 × occ	-0.0885***	NTR Gap × 2006 × occ	-0.204**	NTR Gap × 2006 × occ	-0.158***	NTR Gap × 2006	0.106**
	(0.0505)		(0.0273)		(0.0888)		(0.0211)		(0.0442)
NTR Gap × 2007 × occ	-0.181***	NTR Gap × 2007 × occ	-0.198***	NTR Gap × 2007 × occ	-0.0982	NTR Gap × 2007 × occ	-0.171***	NTR Gap × 2007	0.0280
	(0.0518)		(0.0307)		(0.0835)		(0.0286)		(0.0587)
NTR Gap × 2008 × occ	-0.0536	NTR Gap × 2008 × occ	-0.206***	NTR Gap × 2008 × occ	-0.287***	NTR Gap × 2008 × occ	-0.113***	NTR Gap × 2008	0.0301
	(0.0637)		(0.0352)		(0.0791)		(0.0224)		(0.0541)
NTR Gap × 2009 × occ	-0.0526	NTR Gap × 2009 × occ	-0.232***	NTR Gap × 2009 × occ	-0.376***	NTR Gap × 2009 × occ	-0.165***	NTR Gap × 2009	0.197**
	(0.0507)		(0.0290)		(0.0911)		(0.0311)		(0.0909)
NTR Gap × 2010 × occ	-0.0392	NTR Gap × 2010 × occ	-0.298***	NTR Gap × 2010 × occ	-0.323***	NTR Gap × 2010 × occ	-0.207***	NTR Gap × 2010	0.107
	(0.0634)		(0.0320)		(0.0838)		(0.0331)		(0.0809)
NTR Gap × 2011 × occ	0.0626	NTR Gap × 2011 × occ	-0.382***	NTR Gap × 2011 × occ	-0.438***	NTR Gap × 2011 × occ	-0.221***	NTR Gap × 2011	0.123**
	(0.0645)		(0.0299)		(0.0661)		(0.0309)		(0.0485)
NTR Gap × 2012 × occ	0.0368	NTR Gap × 2012 × occ	-0.252***	NTR Gap × 2012 × occ	-0.236***	NTR Gap × 2012 × occ	-0.138***	NTR Gap × 2012	0.0371
	(0.0488)		(0.0331)		(0.0796)		(0.0310)		(0.0469)
NTR Gap × 2013 × occ	0.0329	NTR Gap × 2013 × occ	-0.381***	NTR Gap × 2013 × occ	-0.234**	NTR Gap × 2013 × occ	-0.203***	NTR Gap × 2013	0.167***
	(0.0566)		(0.0352)		(0.0958)		(0.0249)		(0.0547)
NTR Gap × 2014 × occ	0.294***	NTR Gap × 2014 × occ	-0.403***	NTR Gap × 2014 × occ	0.0344	NTR Gap × 2014 × occ	-0.187***	NTR Gap × 2014	-0.0534
	(0.0613)		(0.0372)		(0.0636)		(0.0331)		(0.0526)
NTR Gap × 2015 × occ	0.229***	NTR Gap × 2015 × occ	-0.481***	NTR Gap × 2015 × occ	-0.212**	NTR Gap × 2015 × occ	-0.250***	NTR Gap × 2015	0.145***
	(0.0530)		(0.0413)		(0.0797)		(0.0278)		(0.0461)
NTR Gap × 2016 × occ	0.240***	NTR Gap × 2016 × occ	-0.511***	NTR Gap × 2016 × occ	-0.205***	NTR Gap × 2016 × occ	-0.289***	NTR Gap × 2016	-0.00164
	(0.0565)		(0.0424)		(0.0624)		(0.0328)		(0.0457)
NTR Gap × 2017 × occ	0.132**	NTR Gap × 2017 × occ	-0.580***	NTR Gap × 2017 × occ	-0.253***	NTR Gap × 2017 × occ	-0.314***	NTR Gap × 2017	0.0860*
	(0.0640)		(0.0435)		(0.0722)		(0.0316)		(0.0478)
NTR Gap × 2018 × occ	0.259***	NTR Gap × 2018 × occ	-0.617***	NTR Gap × 2018 × occ	-0.0367	NTR Gap × 2018 × occ	-0.338***	NTR Gap × 2018	0.0696*
	(0.0839)		(0.0433)		(0.0565)		(0.0362)		(0.0382)
								Observations	222,376
								R-squared	0.015

Table C.6: Regression Results: Figure 5

NR Cog Analytical	
NTR Gap × 2005 × task	-0.0863**
	(0.0410)
NTR Gap × 2006 × task	-0.112***
	(0.0405)
NTR Gap × 2007 × task	-0.0595*
	(0.0328)
NTR Gap × 2008 × task	-0.137***
	(0.0379)
NTR Gap × 2009 × task	-0.0917**
	(0.0388)
NTR Gap × 2010 × task	0.0177
	(0.0369)
NTR Gap × 2011 × task	-0.00476
	(0.0361)
NTR Gap × 2012 × task	-0.0648*
	(0.0346)
NTR Gap × 2013 × task	-0.000771
	(0.0501)
NTR Gap × 2014 × task	0.102***
	(0.0342)
NTR Gap × 2015 × task	0.0926***
	(0.0246)
NTR Gap × 2016 × task	0.146***
	(0.0455)
NTR Gap × 2017 × task	0.101***
	(0.0280)
NTR Gap × 2018 × task	0.181***
	(0.0345)
Observations	222,376
R-squared	0.005

NR Cog Interpersonal	
NTR Gap × 2005 × task	-0.0322
	(0.0334)
NTR Gap × 2006 × task	0.0135
	(0.0243)
NTR Gap × 2007 × task	-0.0886**
	(0.0425)
NTR Gap × 2008 × task	0.0141
	(0.0316)
NTR Gap × 2009 × task	0.0493
	(0.0349)
NTR Gap × 2010 × task	0.114***
	(0.0319)
NTR Gap × 2011 × task	0.137***
	(0.0293)
NTR Gap × 2012 × task	0.0689*
	(0.0353)
NTR Gap × 2013 × task	0.113***
	(0.0254)
NTR Gap × 2014 × task	0.118***
	(0.0318)
NTR Gap × 2015 × task	0.166***
	(0.0308)
NTR Gap × 2016 × task	0.185***
	(0.0377)
NTR Gap × 2017 × task	0.167***
	(0.0373)
NTR Gap × 2018 × task	0.186***
	(0.0339)
Observations	222,376
R-squared	0.005

NR Manual Interpersonal	
NTR Gap × 2005 × task	0.118***
	(0.0282)
NTR Gap × 2006 × task	0.169***
	(0.0357)
NTR Gap × 2007 × task	0.105***
	(0.0386)
NTR Gap × 2008 × task	0.221***
	(0.0320)
NTR Gap × 2009 × task	0.223***
	(0.0323)
NTR Gap × 2010 × task	0.219***
	(0.0313)
NTR Gap × 2011 × task	0.281***
	(0.0330)
NTR Gap × 2012 × task	0.218***
	(0.0307)
NTR Gap × 2013 × task	0.295***
	(0.0410)
NTR Gap × 2014 × task	0.271***
	(0.0318)
NTR Gap × 2015 × task	0.353***
	(0.0394)
NTR Gap × 2016 × task	0.344***
	(0.0386)
NTR Gap × 2017 × task	0.384***
	(0.0429)
NTR Gap × 2018 × task	0.386***
	(0.0334)
Observations	222,376
R-squared	0.014

NR Manual Physical	
NTR Gap × 2005 × task	-0.0834***
	(0.0285)
NTR Gap × 2006 × task	-0.126***
	(0.0268)
NTR Gap × 2007 × task	-0.122***
	(0.0310)
NTR Gap × 2008 × task	-0.0479
	(0.0317)
NTR Gap × 2009 × task	-0.119***
	(0.0365)
NTR Gap × 2010 × task	-0.159***
	(0.0332)
NTR Gap × 2011 × task	-0.208***
	(0.0340)
NTR Gap × 2012 × task	-0.196***
	(0.0344)
NTR Gap × 2013 × task	-0.245***
	(0.0335)
NTR Gap × 2014 × task	-0.274***
	(0.0352)
NTR Gap × 2015 × task	-0.255***
	(0.0284)
NTR Gap × 2016 × task	-0.305***
	(0.0362)
NTR Gap × 2017 × task	-0.280***
	(0.0319)
NTR Gap × 2018 × task	-0.342***
	(0.0333)
Observations	222,376
R-squared	0.009

R Cognitive	
NTR Gap × 2005 × task	-0.0375
	(0.0335)
NTR Gap × 2006 × task	-0.0273
	(0.0462)
NTR Gap × 2007 × task	-0.0463
	(0.0386)
NTR Gap × 2008 × task	-0.0826
	(0.0590)
NTR Gap × 2009 × task	-0.0410
	(0.0484)
NTR Gap × 2010 × task	-0.108*
	(0.0552)
NTR Gap × 2011 × task	-0.106*
	(0.0589)
NTR Gap × 2012 × task	-0.0405
	(0.0352)
NTR Gap × 2013 × task	-0.166***
	(0.0432)
NTR Gap × 2014 × task	-0.0317
	(0.0470)
NTR Gap × 2015 × task	-0.122**
	(0.0520)
NTR Gap × 2016 × task	-0.103**
	(0.0437)
NTR Gap × 2017 × task	-0.197***
	(0.0615)
NTR Gap × 2018 × task	-0.250***
	(0.0841)
Observations	222,376
R-squared	0.005

R Manual	
NTR Gap × 2005 × task	-0.0977***
	(0.0231)
NTR Gap × 2006 × task	-0.119***
	(0.0212)
NTR Gap × 2007 × task	-0.136***
	(0.0296)
NTR Gap × 2008 × task	-0.0750***
	(0.0263)
NTR Gap × 2009 × task	-0.128***
	(0.0324)
NTR Gap × 2010 × task	-0.185***
	(0.0251)
NTR Gap × 2011 × task	-0.201***
	(0.0283)
NTR Gap × 2012 × task	-0.151***
	(0.0293)
NTR Gap × 2013 × task	-0.227***
	(0.0317)
NTR Gap × 2014 × task	-0.322***
	(0.0311)
NTR Gap × 2015 × task	-0.355***
	(0.0282)
NTR Gap × 2016 × task	-0.358***
	(0.0332)
NTR Gap × 2017 × task	-0.364***
	(0.0274)
NTR Gap × 2018 × task	-0.430***
	(0.0313)
Observations	222,376
R-squared	0.011

Table C.7: Regression Results: Figure 6

Appendix D Establishment and Firm Analysis

The final sample includes 1,128 firms, 33,759 establishments posting 307,490 and 582,069 job ads in 2010 and 2016 respectively. Compared to firms in Compustat that are not matched to BGT, firms in the sample are larger in terms of firm size, sales, and capital expenditure. As for the distribution of job ads across occupations, a significant share is concentrated in managerial and high-skill professional occupations.

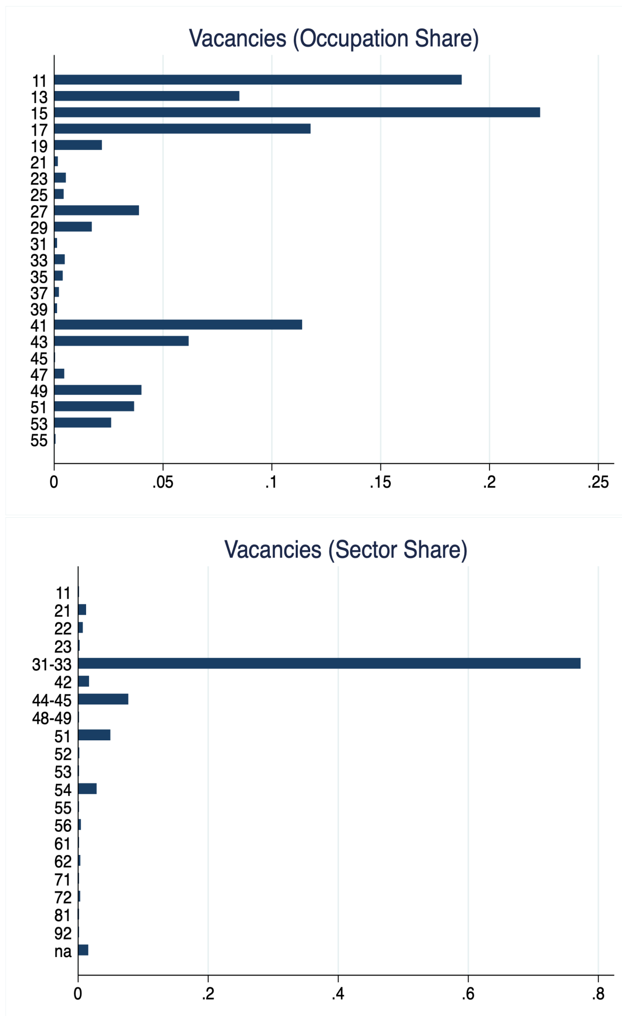

Figure D.1: Occupation and Sector Distribution

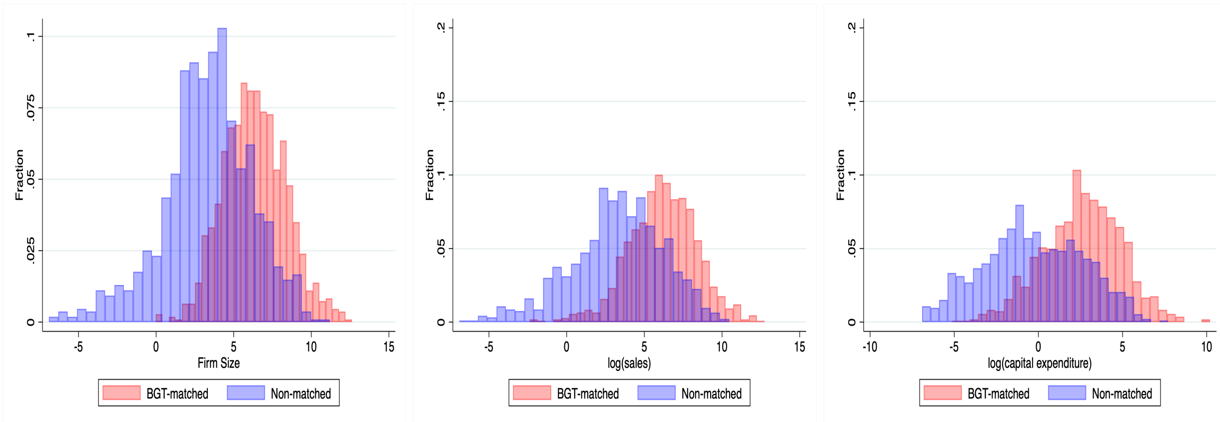

Figure D.2: Compustat firms: Matched to BGT vs. Unmatched

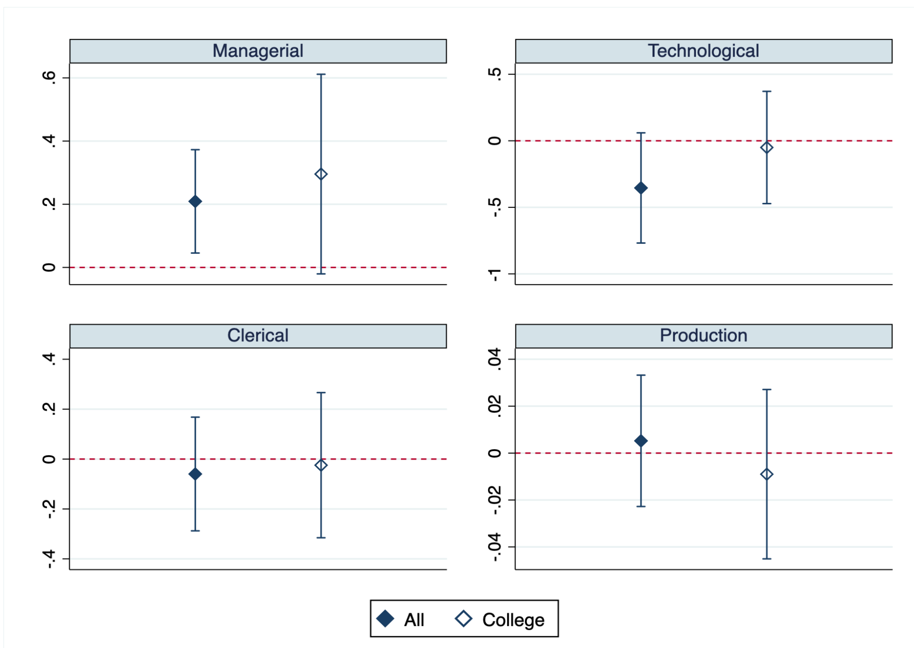

Figure D.3: College Demands in New Work

Note: Each graph plots the point estimates of β_1's in equation (5) for year 2015 and includes 95 percent confidence intervals. The regression is run for each occupation type. The unit of analysis is a triplet of firm-occupation (2-digit SOC)-year. Controls include initial characteristics of firms. Industry fixed effects (2-digit SIC) are included. Robust standard errors are clustered on 4-digit SIC industries. The blue filled symbols show estimates examining all firms. The blue hollow ones show estimates examining job ads that require college education.

	ΔSTEM-related	ΔSTEM-related	ΔBusiness-related	ΔBusiness-related
NTR Gap	0.0106	0.0161	0.170**	0.167**
	(0.0619)	(0.0608)	(0.0766)	(0.0767)
CIP	6-digit	4-digit	6-digit	4-digit
Observations	13,645	13,645	13,645	13,645
R-squared	0.021	0.019	0.020	0.020

Note: The table provides estimation results of β_1's in equation (5) for year 2015. The unit of analysis is a firm-year pair. Controls include initial characteristics of firms. Industry fixed effects (2-digit SIC) are included. Robust standard errors are clustered on 4-digit SIC industries (*** p<0.01, ** p<0.05, * p<0.1).

Table D.1: College Major Demands in New Work

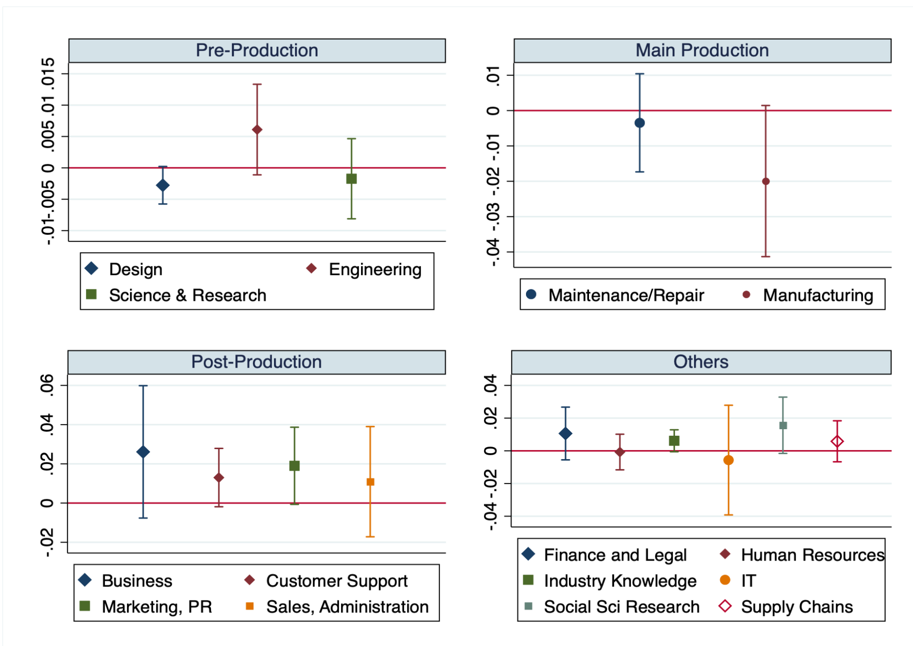

Figure D.4: Skill Requirements in Managerial New Work

Note: Each graph plots the point estimates of β_1's in equation (5) for year 2015 and includes 95 percent confidence intervals. The unit of analysis is a triplet of firm-occupation (2-digit SOC)-year. Controls include initial characteristics of firms. Industry fixed effects (2-digit SIC) are included. Robust standard errors are clustered on 4-digit SIC industries.

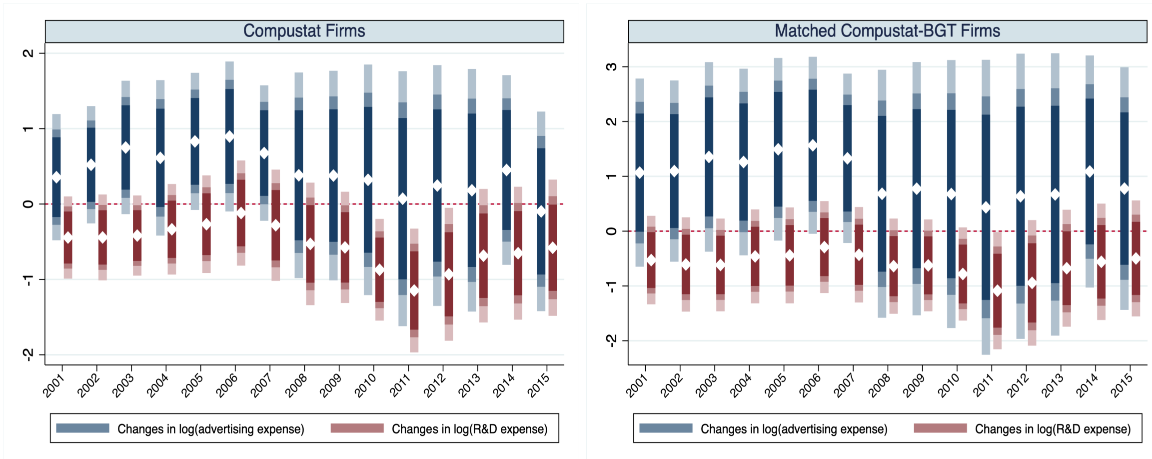

Figure D.5: Changes in Advertising and R&D Expenses

Note: Each bar graph plots the point estimates of β_1's in a dynamic version of equation (5) and includes the 90, 95, and 99 percent confidence intervals. The unit of analysis is a triplet of firm-occupation (2-digit SOC)-year. The dependent variable is constructed using the base year 2000. Controls include initial characteristics of firms. Industry fixed effects (2-digit SIC) are included. Robust standard errors are clustered on 4-digit SIC industries. On the left, the sample includes all the Compustat firms; on the right, Compustat firms matched to BGT.

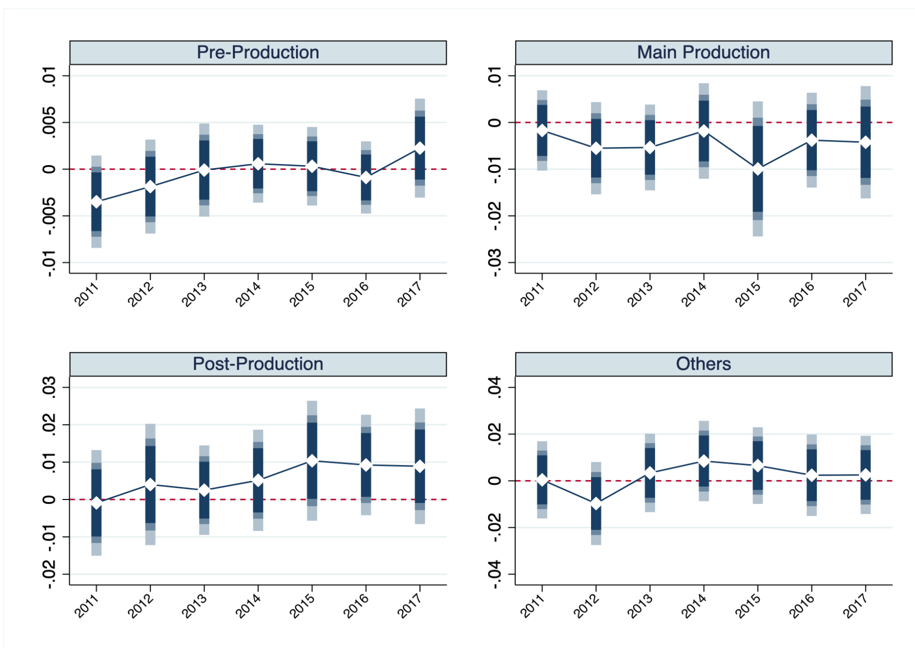

Figure D.6: Changes in Skill Requirements in Managerial New work

Note: Each bar graph plots the point estimates of β_1's in a dynamic version of equation (5) and includes the 90, 95, and 99 percent confidence intervals. The unit of analysis is a triplet of firm-occupation (2-digit SOC)-year. Controls include initial characteristics of firms. Industry fixed effects (2-digit SIC) are included. Robust standard errors are clustered on 4-digit SIC industries.

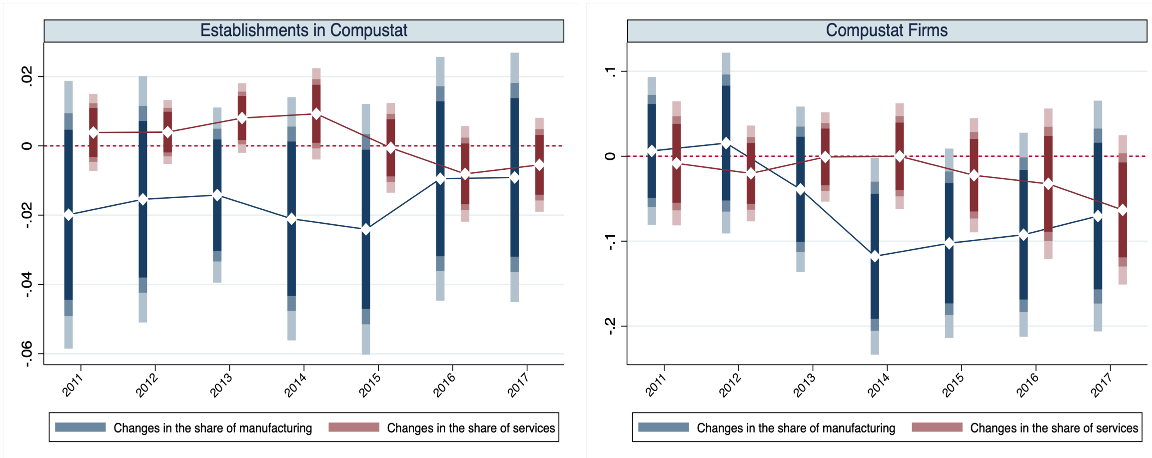

Figure D.7: Changes in the Share of Job Ads

Note: Each bar graph plots the point estimates of the coefficient of β_1's in a dynamic version of equation (5). I include the 90, 95, and 99 percent confidence intervals for each year in the sample period. Controls include initial characteristics of firms. Industry fixed effects (2-digit SIC) are included. Robust standard errors are clustered on 4-digit SIC industries. On the left, the unit of analysis is a triplet of establishment-year; on the right, a triplet of firm-year.

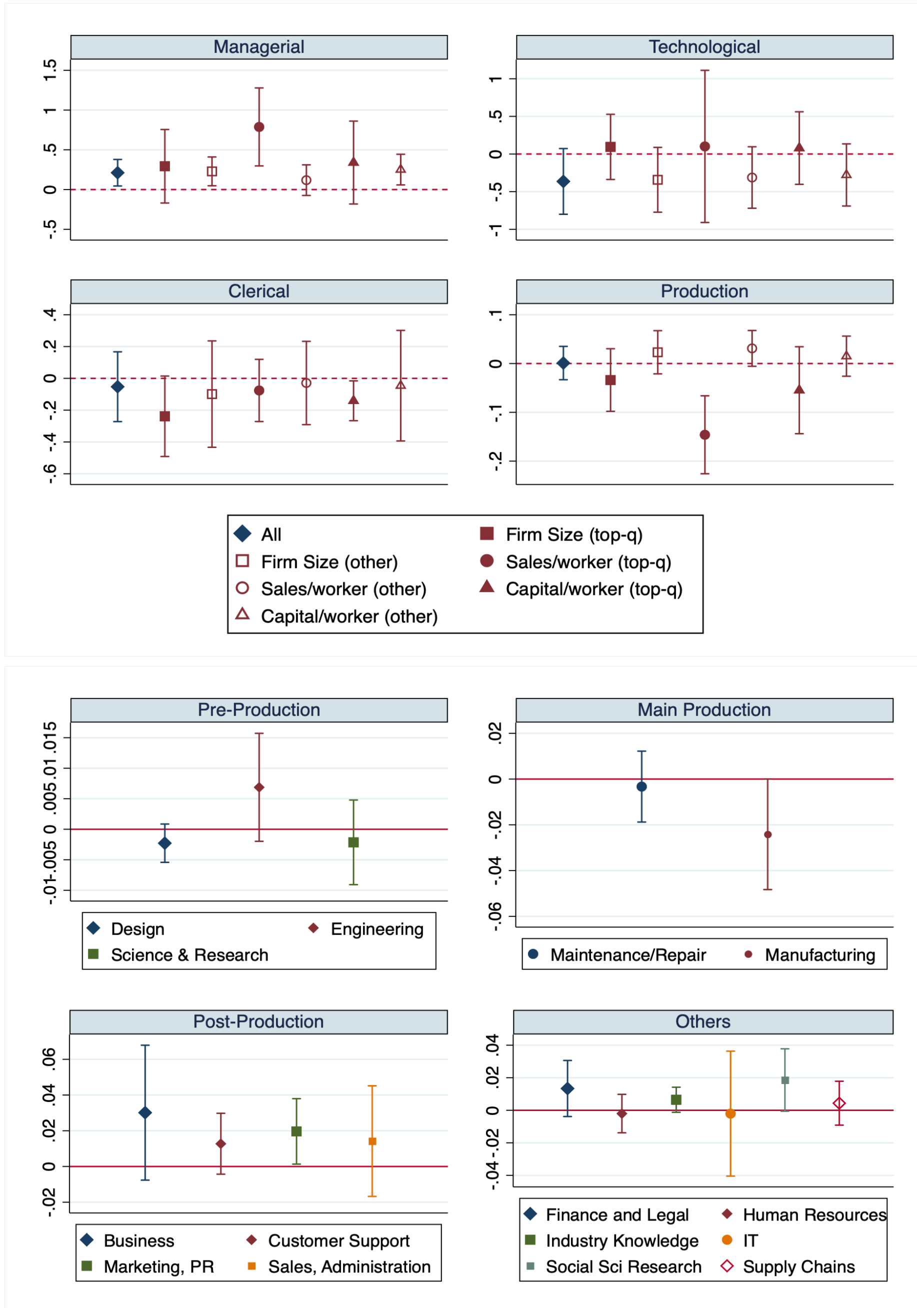

Figure D.8: Compustat Firms (Not Switching out of Manufacturing)

Note: Each graph plots the point estimates of β_1's in equation (5) for year 2015 and includes 95 percent confidence intervals. The regression is run for each occupation type. The unit of analysis is a triplet of firm-occupation (2-digit SOC)-year. On the top panel, the blue filled symbols show estimates examining all firms. The red filled ones show firms in the top quartile group and the red hollow ones, the rest of the firms. Controls include initial characteristics of firms. Industry fixed effects (2-digit SIC) are included. Robust standard errors are clustered on 4-digit SIC industries.

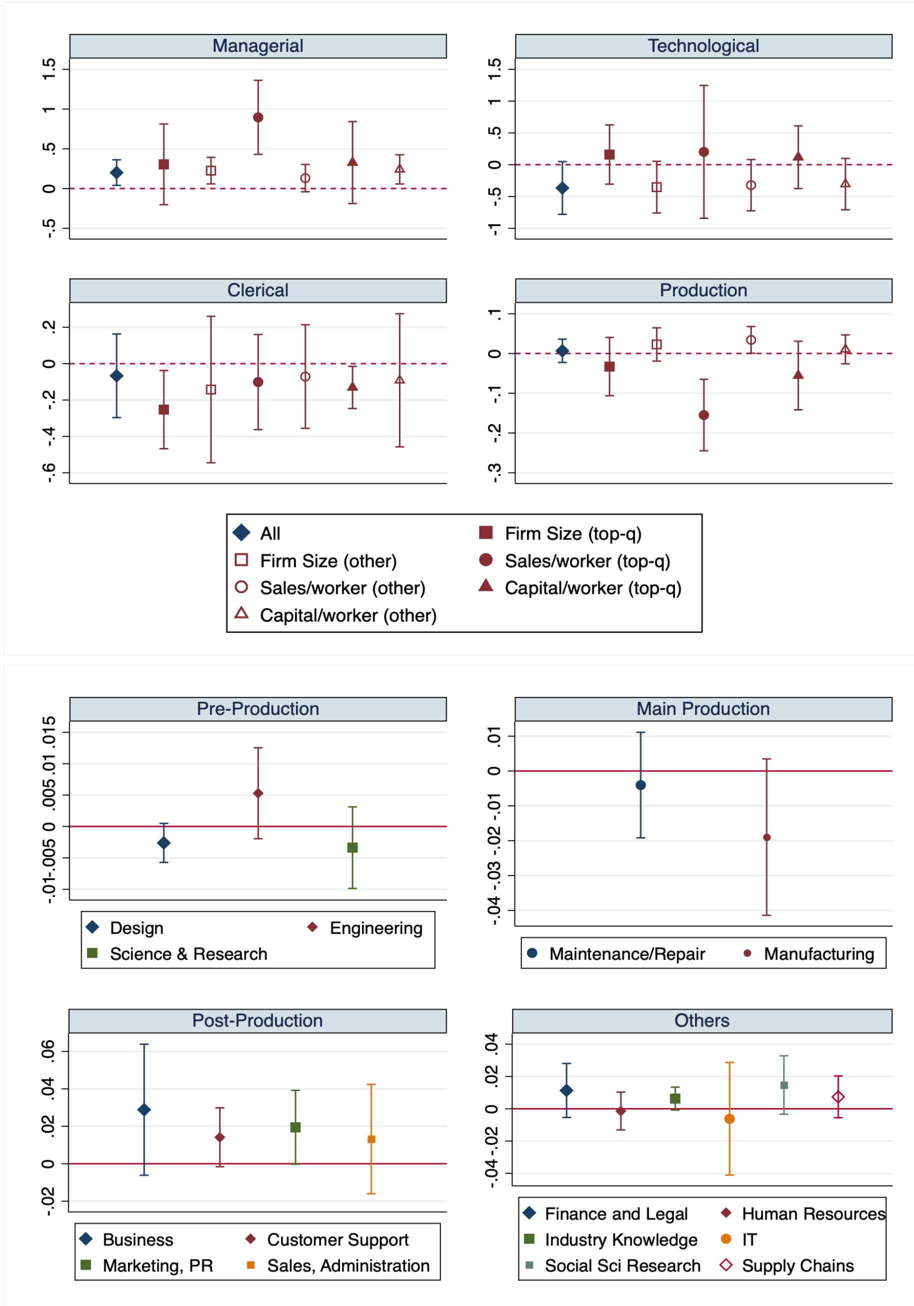

Figure D.9: Compustat Firms (Not Switching to Services)

Note: Each graph plots the point estimates of β_1's in equation (5) for year 2015 and includes 95 percent confidence intervals. The regression is run for each occupation type. The unit of analysis is a triplet of firm-occupation (2-digit SOC)-year. On the top panel, the blue filled symbols show estimates examining all firms. The red filled ones show firms in the top quartile group and the red hollow ones, the rest of the firms. Controls include initial characteristics of firms. Industry fixed effects (2-digit SIC) are included. Robust standard errors are clustered on 4-digit SIC industries.