Trade-Induced Restructuring and New Work*

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Abstract

I examine the impact of the trade-induced restructuring process on firms' incentives to innovate using the firm's demand for jobs that employ new knowledge, skills, and technologies, which I define as *new work*. To construct new work measures, I use the emergence of new job titles identified employing word embedding models. I find that local labor markets with greater import exposures show a persistent increase in managerial new work over time yet a decrease in technological new work. Exploring online job vacancies data, I find that managerial new work requires skills related to post-production firm activities. I provide a model where firms in import-competing industries optimally choose to increase new tasks in the post-production stage to expand consumer demand as competition intensifies.

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1 Introduction

One of the critical discussions on the labor market consequences of trade shocks has centered around the magnitude of employment declines caused by the contraction of import-competing sectors due to rising foreign competitions (Acemoglu et al., 2016). While some jobs are destroyed through firm deaths, a significant share of job losses are also caused by surviving firms as they restructure and continue to operate (Bloom et al., 2019). Firm-level adjustments embody altering the set of tasks performed in-house as they face greater incentives to focus on the core competencies (Bernard and Fort, 2015) and even shifting their industry orientation toward professional services (Breinlich et al., 2018; Ding et al., 2020). To what extent does the trade-induced restructuring process affect firm's incentives to innovate? Which types of innovative investments do firms focus on as their strategies to escape competition?

I address these questions using a job-based measure of innovation, *new work*, which I define as the firm's demand for jobs that employ new knowledge, skills, and technologies. Unlike conventional measures of innovation such as patents and R&D expenditure, new work enables a comprehensive analysis of the effects of trade on innovation, ranging from developing patents on inventions, upgrading production methods, to implementing novel business strategies. The analysis delivers important implications on how firm-level adjustments to import shocks through various innovation efforts reshape comparative advantages and pave future economic growth paths. The job-based measure further sheds light on labor market inequality induced by post-shock restructuring strategies, as transitions to implement new work shift the skill demand towards specific tasks potentially generates distributional consequences across worker groups.[1]

In the first part of the paper, I construct new work measures and document important skill complementarities of new work. In the second part of paper, I use these measures to perform a series of analyses that relate import competition to new work adoptions at both regional and firm level. In the regional approach, I find that regions with high import exposures show a persistent increase in the demand for managerial new work over time yet a decrease in technological new work. I conduct two complementary analyses using detailed information on skill demands provided in Burning Glass Technologies (henceforth BGT) online job ads. First, I use publicly listed firms in Compustat and examine the skill requirements in new work demanded by firms that face industry-level import shocks. Second, I focus on establishments certified through Trade Adjustment Assistance

[1] Autor et al. (2014) studies the distributional consequences of the China shock and reports substantial heterogeneity in worker adjustment patterns. Low-wage individuals relocate within manufacturing and even continue to stay in industries that face increasing import competitions from China, contrary to the high-wage individuals who manage to move out of the trade-exposed sector quickly.

(henceforth TAA) and closely follow the dynamic adjustment process using firm-level incidents of import shocks that accompany layoffs and potential restructuring. I find that firms show a significant increase in managerial new work and that these jobs demand more skills related to post-production activities. Finally, I provide a model to help interpret the empirical results related to new work adoption as firms adjust to import shocks.

Building on Lin (2011), I identify new work using the emergence of new job titles.[2] I employ word embedding models to measure the pairwise distance between job titles based on the context of their appearances in large texts. The methodology brings advantages in measurement that reduces misclassifications and in the applicability to job titles data retrieved from various sources. I then use the distance measures to construct new work intensity scores for each job title, aggregated to detailed occupations to merge with other data sources.[3] I classify new work in different occupation types (managerial, technological, clerical, and production) to guide analysis on studying various innovation investments.[4] Examining the characteristics of new work that emerged after 2000, I find that new work is concentrated in jobs with greater requirements in cognitive, social, and computer skills. New work is also intensive in skills that complement recent developments in technology and globalization, which substantially replaced routine-intensive tasks. Consistent with skill intensities, there is a significant wage premium related to the new work intensity.

In regional analysis, I examine the effects of import shocks on new work demand constructed using the share of employment in occupations with high new work intensity. I follow Pierce and Schott (2016, 2020) and use regional variations in the exposure to changes in trade-policy uncertainty 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, regions with heavy reliance on industries that faced large tariff gaps between the Normal Trade Relations (NTR) rates and the non-NTR rates were more exposed to import shocks. 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. I find statistically significant and positive effects for managerial new work. In all other occupation groups, the estimated effects are negative. The validity of the results is supported by a series of robustness tests on pre-existing trends and alternative measures of new work and import shocks.[5]

[2]I use job titles data from three sources: Dictionary of Occupation Titles (1980, 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)

[3]I focus on workers in occupations with high new work intensity (top quartile) to obtain new work employment.

[4]I construct the categories using 2-digit SOC occupation codes: managerial (11, 13, 23), technological (15, 17), clerical (41, 43), and production (49, 51, 53)

[5]For new work measures, I iterate the exercise using new work intensity measures based on O*NET's

The results for 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), though new work in these jobs potentially corresponds to a broader notion of innovation.[6] The effects on new work in clerical and production occupations support evidence of decreased investments in process innovation as firms increasingly replace routine-intensive jobs (Kueng et al., 2016; Bena and Simintzi, 2015). The results for managerial new work provides empirical support for studies examining how import competition leads firms to improve management (Bloom and Van Reenen, 2007, 2010; Bloom et al., 2013, 2016b), reduce managerial slack (Leibenstein, 1978; 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). More recent evidence on manufacturing firms focusing on their core competencies (Bernard and Fort, 2015) and moving into the service sector (e.g. Breinlich et al., 2018; Ding et al., 2020; Bloom et al., 2019) potentially reinforces these investments. Not to mention, reorganizing production or industry switching accompanies considerable restructuring of the firm hierarchies (Caliendo et al., 2020a,b) where managerial new work gains importance.

While regional analysis provides clean identification, there are limitations in exploring the mechanisms through which new work demands arise. I, therefore, perform two supplementary analyses linking firm-level data matched to data on skill demands from BGT online job postings. I classify the detailed skills data into 15 mutually exclusive categories and construct skill intensities of each job ad using the share of each skill category in the number of skill mentions. I first work with a merged sample of Compustat firms and use changes in industry-level variations in U.S. imports from China to examine the effects on changes in firm-level skill requirement intensities in new work. Combining both new and existing work across all occupation types, there is an increased demand for skills related to the main production (maintenance, repair, and installation) and post-production (business, marketing, PR, sales, and customer support, social science research) stage, but not in pre-production activities (science and research). Separately examining new work, the positive effects remain primarily for the post-production activities and relevent skills in managing supply chains. Similar results hold examining different occupation types. This suggests that firms continue to perform some part of the production-related tasks in-house, but their

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.

[6] It would be more narrow compared to using the number of scientists and engineers or R&D expenditure. Aghion et al. (2005) shows that incentives to innovate depend on the distribution of technological advancements across firms. That is, firms that are in neck-in-neck competition increase innovation activities to escape competition, but technological laggards decrease investments as increased competition already reduces profits.

innovation efforts are concentrated in enhancing post-production activities.[7]

To further investigate the dynamic adjustment process in skill demands for managerial new work, I turn to TAA-certified establishments (henceforth TAA-firms) merged with BGT. Using detailed information on establishment-level layoff events caused by trade shocks, I estimate event study models that compare the evolution of job postings made by TAA-firms to those of a matched control group from 4 quarters prior to 8 quarters following the layoff event.[8] After undergoing layoffs, TAA-firms tend to post fewer jobs; however, there is a notable increase in the demand for managerial new work. I also confirm that these jobs tend to require skills that were not previously sought in-house. Similar to the Compustat based analysis, I find greater demands for skills related to marketing, public relations, and sales. The growth in demand subsides, which may be partly due to the cyclicality in hiring. Nonetheless, the demand for skills related to post-production activities in TAA-firms remains significantly higher than the controls even after two years past the import shock. No such pattern is observed for other skill categories.

Finally, I provide an illustrative model to explain the reduced-form findings and discuss mechanisms, which extends Kim and Lee (2021). In that paper, we build a model to explain an increase in marketing and a decrease in innovation facing increased import competition. While it is difficult to generate increasing innovation or marketing when the overall profitability falls, since returns from marketing effort is reaped in the short run unlike R&D, the price stickiness helps to explain an increase in marketing and a decrease in innovation. To introduce the notion of new work, I differentiate the "new" marketing from the traditional means of marketing by imposing less convex costs on the former. The assumption reflects how consumers today are satiated or do not respond sensitively to the traditional means while new strategies such as web-based market analysis and marketing tools are increasingly more effective (e.g., Greenwood et al., 2021). The additional elements deliver an equilibrium where firms increase new tasks in the post-production stage disproportionately more than the existing ones as competition rises.

This paper contributes to three strands of literature. 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) identifies new work (1940-2000) using the distribution of job title appearances in newspaper adver-

[7] Again, the results indicate that import competition led to a prominent increase in managerial new work. The effects are largest for firms that are larger in firm size, more capital-intensive, and more profitable. And I find statistically signifiant effects on post-production investments separately examining managerial new work.

[8] I focus on layoffs due to the rise of import competition driven by exogenous forces outside the company and use (i) the impacted date to identify the timing; and (ii) the estimated number of affected workers to proxy for the magnitude of the shock.

tisements. Using Word2Vec models to process job titles and identify new components, I build a comparable measure where the methodological advantage lies in the applicability to job titles data retrieved from various sources.[9] Examining the importance of trade in explaining the adoption of new work complements other studies that mainly focus on the role of agglomeration Lin (2011) and foreign high-skill labor supply (Hanson, 2021).

It is also related to studies examining the impact of import competition on innovation, which has been studied extensively using data from various countries: the U.S. (Autor et al., 2020; Hombert and Matray, 2018; Xu and Gong, 2017), Europe (Bloom et al., 2016a), China (Brandt et al., 2017; Bombardini et al., 2018), South Korea (Ahn et al., 2018).[10] Much of the focus has been on product innovation employing conventional measures such as R&D expenditure and patents (Cohen, 2010; Kogan et al., 2017; Hall et al., 2005; Moser, 2016, etc.). Using new work in different occupation types enables analyzing various innovation activities, which provides a more comprehensive view on firm's incentives to innovate and reshape comparative advantages as import competition rises.

Lastly, this paper complements 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 that generate greater degrees of service orientation of firms (Bernard et al., 2017; Breinlich et al., 2018; Ding et al., 2020). Assessing the skill demands involved in the restructuring process using online job vacancies provides a complementary perspective on how firms make adjustments in labor inputs as transition occurs. The analysis further sheds light on the important shifts in the skill demand involved in restructuring which potentially generates distributional effects across worker groups.

The rest of the paper is organized as follows. In section 2, I discuss how new work measures are constructed and present descriptive analysis on new work. Section 3 presents estimates from the regional analysis of the impact of trade shocks on new work adoption. Section 4 presents the results from the firm-level analysis. In section 5, I provide a model to explain mechanisms. In section 6, I conclude.

[9] In a very recent study, Autor et al. (2021) identifies new work (1900-2020) and constructs new work intensity by linking texts of patents and consumer demand surveys to job titles.

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

2 Data and Construction of New Work Measures

2.1 Data

To construct measures of new work that serve as dependent variables of my analysis, I begin with data on job titles from three sources: Dictionary of Occupation Titles (1980, 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).[11] After classifying jobs as new, I aggregate to detailed occupation codes to merge with other data sources, which record employment and job demands at detailed occupations, not job titles.[12] For regional analysis, I combine the new work measures with the Decennial Censuses 1980, 1990, 2000 5 percent sample and American Community Surveys (ACS) 2005-2018 (Ruggles et al., 2020).[13] For firm analysis, I begin by combining the measures with BGT, which provides the near-universe of online job ads (2010-2020) collected from around 40,000 job boards.[14] Then, I use employer names listed in BGT job ads to merge with two separate data: publicly traded firms in Compustat and establishments certified through TAA petitions.

In each exercise, I use different import shocks. For regional analysis, I construct regional exposures to the China shock using the historical tariff rates of U.S. trading partner countries (Pierce and Schott, 2016). I exploit China's unprecedented emergence in the world economy in the early 2000's using industry-level variations in gaps in the Normal Trade Relations (NTR) rates and the non-NTR rates. Then, initial local industry compositions constructed using the County Business Patterns Data (1980, 1990, 2000) are used as weights to apportion industry-level shocks to local labor markets. The firm analysis requires a different import shock as BGT data is available after 2010. For Compustat firms, I use industry-level imports of U.S. and high-wage countries from UN Comtrade. For TAA-certified establishments, I leverage information on the impacted establishment and trade shocks (impacted date, estimated number of impacted workers, reasons for layoffs, etc.) in the TAA petitions.

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

[12] BGT reports job titles included in each job ad; I do not utilize titles information from BGT in this project.

[13] I also combine supplementary data (Occupation Employment Surveys (1997-2018); Quarterly Census of Employment and Wages (1990-2018);) to perform various robustness checks in the later sections.

[14] Each posting in BGT contains detailed information on the job characteristics (employer name, occupation, geography, skill and education requirements, wage and non-wage benefits, etc.). Occupations and industries requiring greater skill are overrepresented in the data (e.g., Hershbein and Kahn, 2018; Deming and Kahn, 2018, etc.). See Appendix A.1 for comparisons in the occupation and industry distributions with OES and JOLTS. While the aggregate number of job ads demonstrates an increasing trend, the occupation and industry distributions remain stable over time.

2.2 Identification Strategy

Building on Lin (2011), I identify new work through the emergence of new job titles.[15] While previous work uses official documents on conversion tables and string matching methods to identify new job titles, I construct newness measured as distances from previous job titles based on the context of their appearances in large texts.[16] More precisely, I employ the Continuous Bag of Words (henceforth CBOW) model 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.[17] Thus, the methodology avoids misclassifications due to relabeling of job titles over time. As the CBOW model assigns similar vectors to words that are close in meaning, job titles reflecting similar tasks demonstrate high similarity numerically.[18]

For each job title (x), I compute the pairwise distance with all existing ones in the past period ($\forall y \in Y$) using cosine similarity scores and construct a continuous new work intensity measure, which can be interpreted as the probability that job title x is not observed in the previous period, and therefore, is new.

$$\text{New Work Intensity (x)} = 1 - \max\left[\frac{x \cdot y}{||x||\,||y||}\right], \quad \forall y \in Y, \tag{1}$$

Due to the model's sensitivity to small differences in word combinations observed in some job titles which translate into positive distances, a small portion of existing work show non-zero values in the intensity measures. To correct this issue, I manually inspect titles and draw a threshold below which I assign zero's to the intensity measure. In the empirical analysis of the paper, I use a binary indicator which identifies occupations in the top quartile of new work intensity scores as new and the rest as existing work.

Comparing the current measure for years 1990 and 2000 to new job titles identified by Lin (2011), which constructs a binary measure for new job titles by effectively combining information from census revision documents and applying direct string matching methods,

[15]Using changes in occupation classifications can be problematic since merging and splitting of occupation codes may arise due to growing supply of workers in particular jobs or revisions to improve the classifications.

[16]Lin (2011) uses U.S. Department of Labor and U.S. Employment Service (1979), and U.S. Department of Labor, U.S. Employment Service, & North Carolina Analysis Field Center (1991) as references.

[17]The CBOW model is one of the Word2Vec algorithms which provide numerical representations of words. 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. In Skip-gram, the target word is used to predict the surrounding words.

[18]Before employing the CBOW model, I clean the job titles by removing stop words, specific words used solely for survey purposes, (e.g., "all other", "not specified", etc.), punctuation marks.

I find that the two methods mostly agree on identifying job titles that are present in the past. Around 95 percent of new job titles identified in the previous work are assigned a non-zero new work intensity score in the current measure. For the remaining 5 percent, the CBOW model is able to find matching job titles from the past. Through manual inspection, I find that direct string matching methods can be sensitive to the ordering of words, punctuations, conjunctions, and abbreviations, etc. The correlation coefficient between the two measures are close to 0.75. Further experimenting with new work intensity scores obtained using alternative word embedding models (Glove and Fasttext), I find correlation coefficients that range between 0.72 and0.74, which are similar to those obtained using the CBOW model.[19]

To test the robustness of my results, I also construct an alternative measure of new work using "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."[20] Because matched data sets identify occupations at 3-digit census occupation codes, I create an indicator for new work that is equal to one if the census occupation code includes any of the 8-digit O*NET SOC codes listed as N&E.

2.3 Descriptive Analysis

Examining example job titles that the CBOW algorithm assigns high values of new work intensity within each of four broad occupation types, I find substantial heterogeneity in reflecting various channels through which the demand for new work arises (Table A.4). For example, the adoption of Artificial Intelligence or green technology can induce the demand for production workers and technicians whose skills complement the newly adopted machinery and mid-level managers that oversee the new production unit. Increased market access to foreign countries or global supply chains may give rise to the introduction of teams performing specialized tasks related to global operations within the organization. Figure 1 provides a visual summary of the distributions of new work intensity by 2-digit SOC occupation codes, which are weighted by national employment at 6-digit SOC occupation codes using the Occupation Employment Survey in 2010.[21] White-collar occupations tend to show higher average new work intensity than the blue-collar group. Nevertheless, there is significant variation in new work intensity within occupation groups. Using a simple variance decomposition exercise to examine the variation explained by within versus

[19]See Appendix A.3 for details on the measure comparisons discussed in this paragraph.

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

[21]Examining across detailed occupation categories, I find that job titles with high new work intensity tend to be associated with occupation codes with the "all other" category. See Appendix A.4 for more details.

between occupations, I find that about 60 percent of the aggregate variation is due to within-occupation variance.[22]

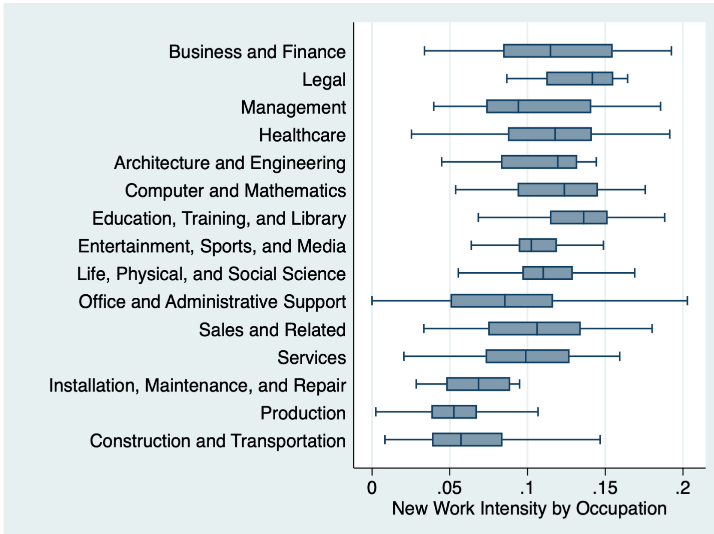

Figure 1: New work intensity by Occupations

Note: New work intensity scores are aggregated at the SOC 2-digit occupation-level, weighted by occupation-specific national employment using the Occupation Employment Survey in 2010. For each SOC 2-digit occupation category, the box plot includes the minimum, maximum, median, top and bottom quartile values of the new work intensity scores.

2.3.1 Skill Content of New Work

First, I follow Deming and Kahn (2018) and search for keywords and phrases in BGT job ads to classify skill requirements in the following dimensions: 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 (2010) as the unit of analysis. The dependent variable is the share of job ads with the corresponding skill requirement; and the explanatory variable is a binary indicator for being in the top quartile of the new work intensity score measured using CBOW. As shown in Figure 2 (left), occupations classified as new work show greater demand in different areas of analytical and interpersonal skills; the differences are insignificant for skills related to customer services.

[22]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 detailed occupation (census occupation codes 2010), and $\overline{x}$ is the aggregate average. See Appendix A.6 for a graphical illustration of the results.

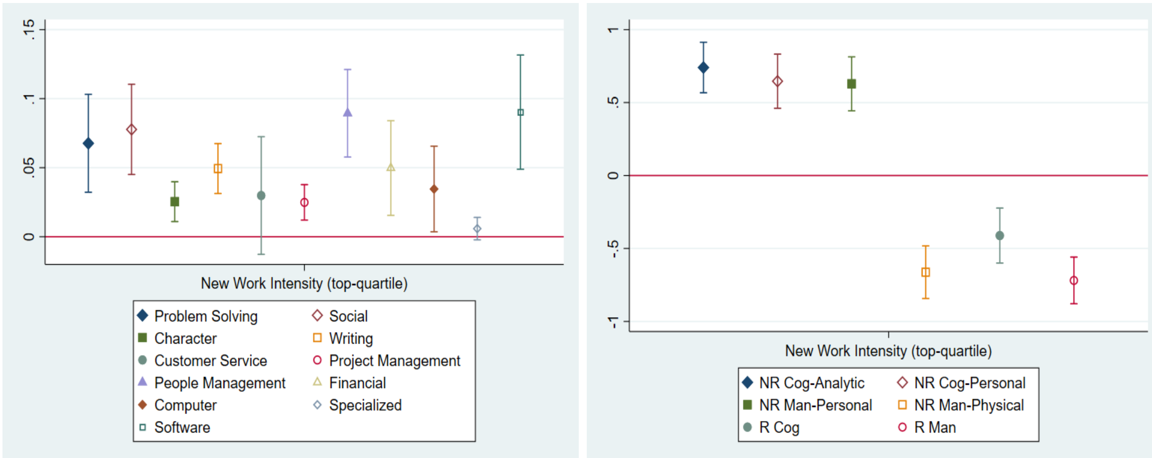

Figure 2: Skill Characteristics of New work post-2000

Note: Using various skill requirements scraped from BGT job ads in 2010, I construct the share of job ads with the corresponding skill requirement for each occupation-skill pair (left). Using O*NET skill descriptors, I construct the average task intensity score for each occupation-task pair (right). For both graphs, the estimated coefficients are obtained using a naive regression of the skill/task intensities on new work intensity.

As an alternative approach to quantifying the skill content of new work, I examine whether new work features intensity in skills that are complementary to recent developments in technology and globalization, which substantially replaced routine-intensive tasks (e.g., Goos et al., 2014; Acemoglu and Restrepo, 2018, etc.). Following Acemoglu and Autor (2011), I repeat the regression exercise for six mutually exclusive categories of skill: non-routine cognitive, non-routine analytical, non-routine manual, non-routine interpersonal, routine cognitive, and routine manual. The dependent variables are the average scores in each skill category. As shown in Figure 2 (right), new work that emerged post-2000 show greater intensity in tasks that are non-routine cognitive, analytical, and interpersonal compared to existing work, and these jobs are relatively less intensive in routine or manual tasks.[23] Figures A.7.1 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.

[23]In Appendix A.7.1, I repeat the exercises employing measures of new work identified using N&E occupations, which delivers quantitatively similar results. Finally, I also show results separately obtained for different occupation groups where a notable significant difference between new and existing work in non-routine analytical skills is demonstrated across all occupation groups.

2.3.2 Wage Premium of New Work

The content of new work examined so far implies important complementarities with individual's ability to perform tasks requiring greater skill, particularly those 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. The share of workers with a college education and beyond in new work employment has increased since 2000 and exceeds 50 percent in 2015 (Appendix A.7.2).[24] Figure 3 (left) plots 3-digit detailed census occupation-level new work intensity scores against the occupational wage percentile in 2015. The implications remain consistent. Moreover, there is a positive and significant correlation between occupational wage growth between 2000 and 2015 and the occupational new work intensity (Figure 3, right).[25]

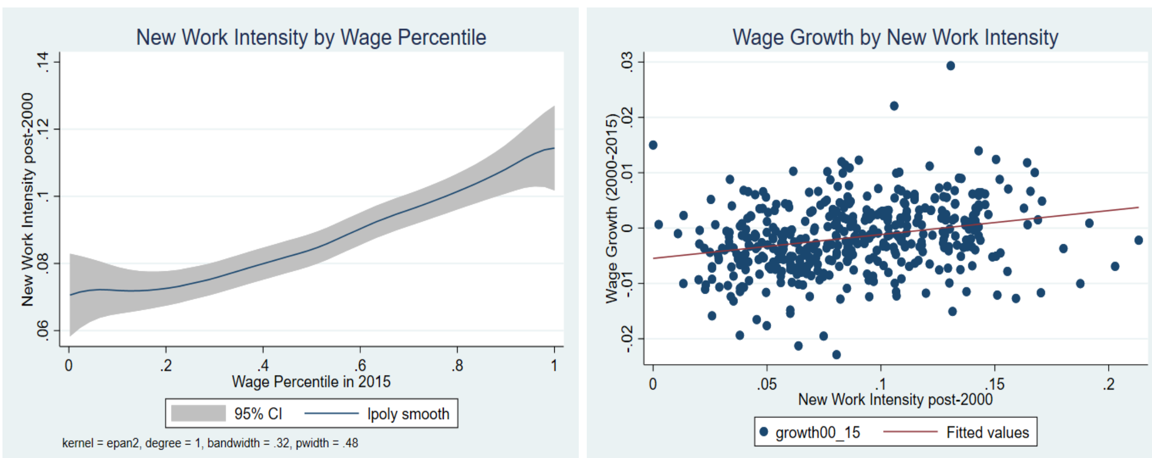

Figure 3: New Work and Skill Percentile (left), Wage Growth (right)

Note: I use microdata from IPUMS-USA 2000 and 2015 and construct average wage for detailed census occupation codes (2010). I report the kernel-weighted local polynomial regression of occupational new work intensity on log wages (left); and the percentage change in log wage between 2000 and 2015 and the fitted line (right).

To further examine the extent to which new work intensity explains variations in wages, I regress individual log(wages) on new work intensity scores. Table 1 reports coefficients on new work intensity from models that include no controls other than year fixed effects (odd columns) and from specifications that include both industry fixed effects and a set

[24] I also show the distribution of new work across different demographic groups. More women are employed in new work compared to men though I do not find any significant gender bias in terms of new work employment. The distribution across different race groups is proportional to the actual employment shares; however, it is worth noting the growth in the share of minority groups over time in new work employment.

[25] Wages are CPI-adjusted to the base year of 2000.

of controls (even columns).[26] For columns (1) and (2), I pool all years between 2005 and 2018, while in columns (3)-(6), I focus on a single year: for (3) and (4), I use data for year 2010; for (5) and (6), year 2015. Standard errors are clustered at the 3-digit census occupation-level. I find a positive and significant relationship between new work intensity scores and individual wages across all specifications. The coefficient estimate of 2.04 in column (2) implies that one standard deviation increase in new work intensity score (0.06) is associated with 12 percent increase in wages for otherwise observationally similar workers. As shown in columns (4) and (6), the estimated new work wage premium is larger in year 2015 compared to 2010: one standard deviation increase in new work intensity score is associated with 12.5 percent in 2010 and 0.9 percentage points higher in 2015.[27] The wage premium of new work highlights the potential consequences for inequality between those with comparative advantages in adapting to new tasks and those without increases.

	(1)	(2)	(3)	(4)	(5)	(6)
New Work	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	-	-	-	-
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: All specifications include commuting zone 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 1: Wage regressions for New Work post-2000's

[26] 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, beyond college), age (16-19, 20-29, 30-39, 40-49, 50-70).

[27] In Appendix A.7.3, I include results using the IPUMS-USA decennial census samples for 2000 and 1990 employing new work emerged between 1990 and 2000; and 1980 and 1990, respectively. I use new work intensity measures constructed using the CBOW model and compare similarity scores between job titles from the previous decade respectively. I obtain similar results using measures constructed by Lin (2011).

3 Regional Analysis

In this section, I take a local labor market approach using commuting zones (Tolbert and Sizer, 1996) and study the role of import competition in new work adoptions using regional variations in exposures to China's unprecedented emergence in the world economy in early 2000's known as the China shock. 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.[28] Upon China's accession to the WTO at the end of 2001, the U.S. granted the Permanent Normal Trade Relations (PNTR) to China, removing uncertainty associated with annual renewals of import tariff rates on Chinese goods, which were otherwise subject to higher rates initially set under the Smoot-Hawley Act of 1930.

Industries with a greater magnitude in the NTR gaps were expected to be more affected by China's entry to the world market. Consequently, local labor markets with heavy reliance on these hard hit industries being more exposed to the shock. Thus, regional import exposures are constructed 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 NTR $\text{Gap}_{j,1999}$, which is the difference between the non-NTR rate and the NTR rate for industry j in 1999, is weighted by the industry shares in the tradable sector in commuting zone i in year 2000.[29] Endogeneity concerns are mitigated as variations in the NTR gap are driven by the initial rates set in1930 (Pierce and Schott, 2016; Handley and Limao, 2017). To benchmark the patterns in my data against findings of others, I examine the magnitude of the China shock on the share of manufacturing employment and average wages over time. To obtain data on local labor markets for more pre-shock years, I use the Quarterly Census of Employment and Wages (1990-2019) and construct commuting zone level changes in manufacturing employment and wages in each year relative to those in year 2000.[30]

Figure 4 reports the estimated coefficients on the NTR Gap obtained separately for each year in a regression model that includes state fixed effects. Throughout the sample period since 2001, I find statistically significant and negative effects on local manufacturing employment and wages. And the lack of pre-existing trends ensures that there are no

[28]This is similar to the research design employed in the seminar China shock study of 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 with China.

[29]There are other existing work that constructs regional exposures using tariff rates to examine local labor market effects of trade shocks (e.g., Topalova, 2010; Kovak, 2013; Hakobyan and McLaren, 2016, etc.)

[30]ACS lacks commuting zone level data on employment and wages for years 1991-2004.

significant correlations between pre-existing differences in the manufacturing employment or average wages across commuting zones and local NTR Gaps. Autor et al. (2014) discusses how heterogeneous adjustments across worker groups constitute an important channel through which import shocks persist over the sample period. Dix-Carneiro and Kovak (2017) also shows how the effects of trade in Brazil have amplified in magnitude over decades after trade liberalization.

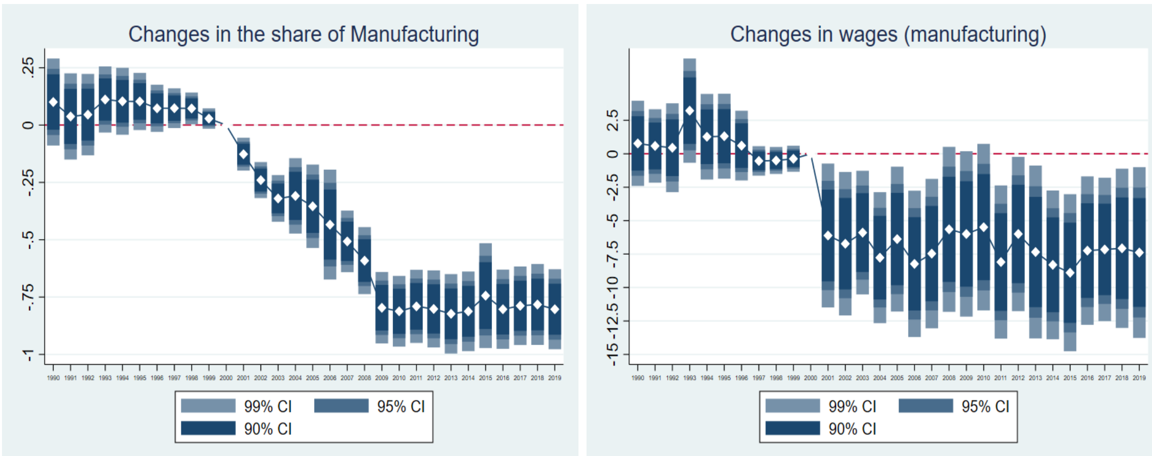

Figure 4: Changes in Manufacturing Employment (Data Source: QCEW 1990-2019)

Note: I use the Quarterly Census of Employment and Wages (1990-2019) and aggregate employment and wages at commuting zones. I run the following for each year: $\Delta y_{it,2000} = \beta_{0t} + \beta_{1t}\text{NTR Gap}_{i,1999} + \eta_{st} + e_{it}$ where the dependent variable $\Delta y_{it,2000}$ is the change in the share of manufacturing employment (or average log wages) in commuting zone i relative to that in year 2000; and η_{st} are the state fixed effects. Each bar in the graphs plots the point estimates of the coefficient of interest (β_{1t}) including 90 percent, 95 percent, and 99 percent confidence intervals. I report results for manufacturing employment (left) and average log wages (right).

3.1 Empirical Specification

To study whether regional exposures to Chinese imports have induced new work adoptions, I estimate the following:

$$\Delta y_{iot,2000} = \beta_0 + [\text{NTR Gap}_{i,1999} \times I^t]\beta_1 + I^t + \mathbf{X}'_{i,2000}\beta_2 + \eta_R + e_{iot} \tag{3}$$

The dependent variable Δy_{iot} is the change in the share of workers employed in new work in occupation o (2-digit SOC codes) observed in commuting zone i relative to that in year 2000; and the shares are constructed focusing on occupations in the top quartile of new work intensity. The coefficient of interest is a vector β_1 estimated for the sample period. I control for commuting zone specific characteristics related to education, gender, age, race, marital status, migration, and other economic indicators in 2000.[31] Robust standard errors

[31]Controls include education (the share of less than high-school, high-school graduates, some college,

are clustered on state. Note that the estimated results capture both the effects of import shocks on new work within surviving firms and any composition effects from firm entry and exit.[32] Since the impact of import competition on new work adoption likely varies across different occupation types, I investigate such heterogeneity using the following:

$$\begin{aligned}\Delta y_{iot,2000} =& \beta_0 + [\text{NTR Gap}_{i,1999} \times I^t]\beta_1 + [\text{NTR Gap}_{i,1999} \times I^t \times I^{occ}]\beta_2 \\ &+ I^t + \mathbf{X}'_{i,2000}\beta_3 + \eta_R + e_{iot},\end{aligned} \tag{4}$$

where I^{occ} is an indicator for occupation types defined at broad categories (2-digit SOC): managerial (11, 13, 23), technological (15, 17), clerical (41, 43), and manual production (49, 51, 53). I run regressions separately for each occupation type and obtain the coefficient of interest, a vector of β_2 that captures the effects on a particular occupation type relative to all other occupations.

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 managerial new work in the pre-China shock period is more prevalent in regions with an industry composition that is more 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 adding past changes in the new work share (1980-1990, 1990-2000) as controls and perform falsification exercises (section 3.3.2).

3.2 Main Results

Figure 5 summarizes the estimation results for equation (3). Each bar plots the point estimates of the coefficient of interest as well as the 90 percent, 95 percent, and 99 percent confidence intervals. The estimated effects of the China shock on local labor market adoption of new work are positive; however, the estimate lacks precision for many years.[33] Comparing commuting zones in the 90th percentile in terms of import exposures to those in the 10th percentile, I find that greater exposure is associated with an increase in the share of new work by 0.98 percentage points (ppt) in 2010, 1.60 ppt in 2015, and 2.03 ppt in 2018. The

college graduates, beyond college), gender, age (the share of younger than 20, between 21 and 29, 30 and 39, 40 and 49, older than 49), race (the share of white, black, hispanic, asian and others), marital status, migration, and economic indicators (the share of unemployed, average wage)

[32] I test whether the estimates provide suggestive evidence on the role of establishment turnovers by additionally controlling for changes in the number of establishments that exit. The analyses in section 4 focus on studying new work adoption in surviving firms.

[33] The estimated coefficients for β_1 lack precision at 95 confidence intervals for years 2006, 2008, 2009, 2010, 2012, 2016.

coefficient values remain relatively stable over time, and estimated changes in 2005 persist or slightly increase in subsequent years.

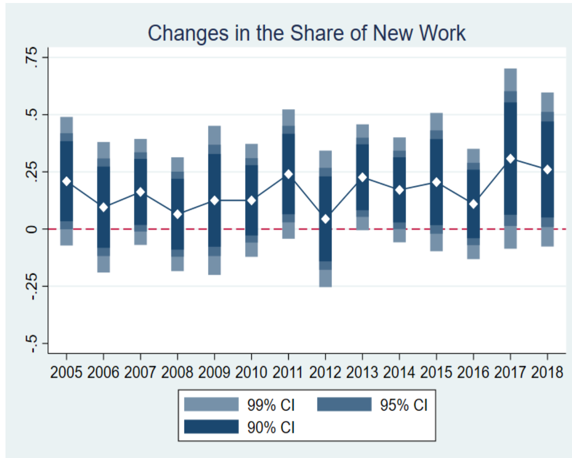

Figure 5: Changes in the share of new work

Note: Each bar plots the point estimates of the coefficient of interest (β_1) in equation (3) including 90 percent, 95 percent, and 99 percent confidence intervals. The unit of analysis is a triplet of commuting zone-occupation (2-digit SOC)-year. Controls include initial characteristics of local labor markets and changes in the number of operating establishments. Census region fixed effects and time fixed effects are included. Robust standard errors are clustered on state.

Beginning with new work in managerial roles, the coefficients (β_2) are near the value of zero and insignificant in 2005-2007; however, they become positive and significant in 2008, which persist and amplify in magnitude over time (Figure 6, left). One standard deviation increase in import exposure increase new work in managerial roles by 1.09 ppt in 2010, 2.23 ppt in 2015, and 2.17 ppt in 2018, relative to other occupations. Comparing commuting zones in the 90th and 10th percentiles in terms of exposed NTR gaps, the difference in the responsiveness of managerial new work relative to other occupations exceeds 5 ppt in 2018. This finding provides empirical support for studies examining how import competition leads firms to improve management (Bloom and Van Reenen, 2007, 2010; Bloom et al., 2013, 2016b), reduce managerial slack (Leibenstein, 1978; 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). More recent evidence on manufacturing firms focusing on their core competencies (Bernard and Fort, 2015) and moving into the service sector (e.g. Breinlich et al., 2018; Ding et al., 2020; Bloom et al., 2019) potentially reinforces these investments. Not to mention, reorganizing production or industry switching accompanies considerable restructuring of the firm hierarchies (Caliendo et al., 2020a,b) where managerial new work gains importance.

The results substantially differ for new work in technological jobs (Figure 6, right). The estimated effects are negative and statistically significant across all years and do not vary

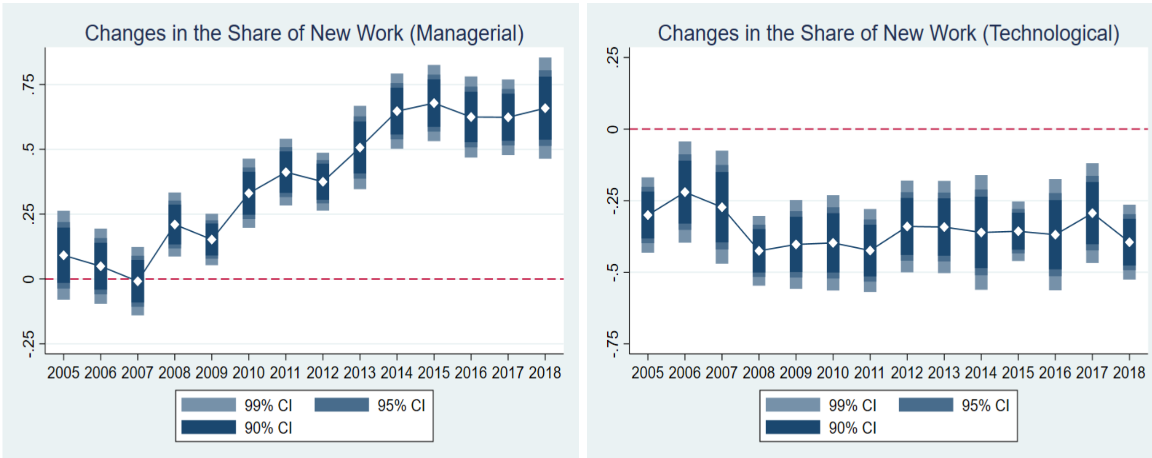

Figure 6: Changes in the share of managerial (left) and technological (right) new work

Note: Each bar plots the point estimates of the coefficient of interest (β_2) in equation (4) including 90 percent, 95 percent, and 99 percent confidence intervals. I^{occ} is an indicator for occupation types defined at broad categories (2-digit SOC): managerial (11, 13, 23), technological (15, 17), clerical (41, 43), and manual production (49, 51, 53). I run regressions separately for each occupation type. The unit of analysis is a triplet of commuting zone-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.

significantly over time. Import exposures reduce new work adoptions in this group by 1.31 ppt in 2010, 1.18 ppt in 2015, and 1.30 ppt in 2018, relative to other occupations. The results 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), though technological new work potentially corresponds to a broader notion of innovation.[34] Finally, I look into occupations in production and sales/administrative support. Similar to technological jobs, the estimated effects are negative and statistically significant; however, the magnitudes increase over time for both occupation groups. New work adoptions are discouraged by greater exposure of Chinese imports in both groups compared to the rest of the occupations: they decrease by 0.28 ppt in 2010, 0.74 ppt in 2015, and 1.14 ppt in 2018 for production occupations; and by 0.68 ppt in 2010, 1.06 ppt in 2015, and 1.18 ppt in 2018 for clerical jobs. The coefficient values are smaller in magnitude in the beginning few years compared to those obtained in the analysis with technological jobs; however, they reach similar levels closer to the end of the sample period. The negative effects support evidence of

[34]It would be more narrow compared to using the number of scientists and engineers or R&D expenditure. Note that empirical work using data from other countries find positive effects: Europe (Bloom et al., 2016a), China (Brandt et al., 2017; Bombardini et al., 2018), South Korea (Ahn et al., 2018). Autor et al. (2020) explains the opposite findings using the mechanisms discussed in Aghion et al. (2005) where innovation incentives depend on the distribution of technological advancements across firms. That is, firms that are in neck-in-neck competition increase innovation activities to escape competition, but technological laggards would decrease investments in innovation as increased competition already reduces profits.

decreased investments in process innovation as firms increasingly replace routine-intensive jobs (Kueng et al., 2016; Bena and Simintzi, 2015).[35]

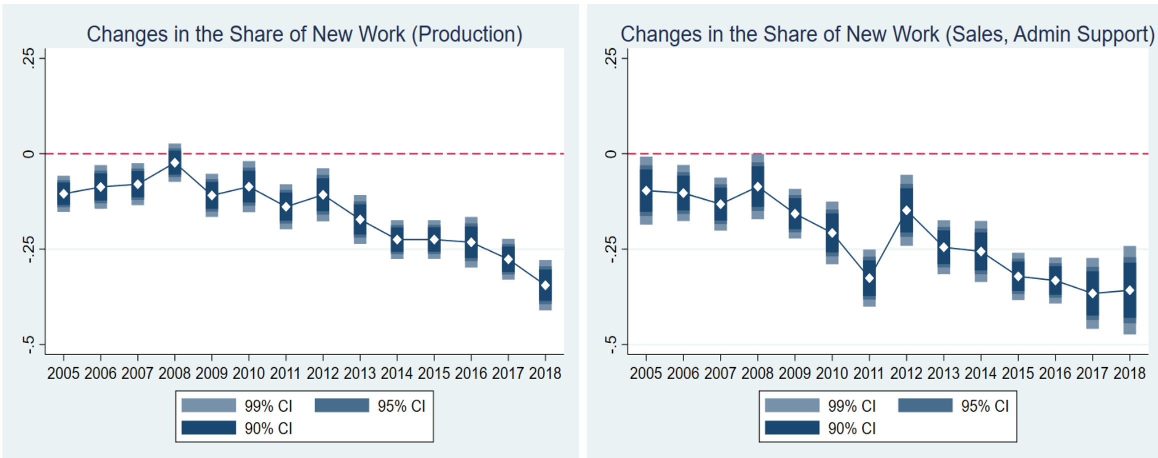

Figure 7: Changes in the share of new work: production (left), clerical (right)

Note: Each bar plots the point estimates of the coefficient of interest (β_2) in equation (4) including 90 percent, 95 percent, and 99 percent confidence intervals. I^{occ} is an indicator for occupation types defined at broad categories (2-digit SOC): managerial (11, 13, 23), technological (15, 17), clerical (41, 43), and manual production (49, 51, 53). I run regressions separately for each occupation type. The unit of analysis is a triplet of commuting zone-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.

3.3 Robustness Exercises

3.3.1 Alternative Measures

The validity of the presented results thus far is supported by a series of robustness tests described in detail in Appendix B.2. First, I show the conclusions are robust to alternative measures of new work. In Appendix B.2.2 I repeat the analysis using new work intensity measures based on O*NET's New and Emerging (N&E) Occupations.[36] 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 codes.[37] Appendix B.2.3 replaces the binary variable (indicator for exceeding the threshold in new work intensity with continuous measures.

[35]The results are consistent if I allow the coefficient values of control variables to change over time by running the specification separately for each year, which I report in Appendix B.2.6.

[36]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.

[37]New work measured using N&E occupations supports the validity of my constructed measure in various ways: new work intensive occupation titles, occupational and industry distribution.

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 commuting zone i for occupation group o. Both analyses produce results very similar to the baseline. Second, 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 using Chinese imports of other high-wage countries. The results in Appendix B.2.3 shows that the estimated effects remain consistent employing an alternative measure of import shocks though the magnitude of the coefficients are greater compared to the main result as the measure of import shocks differs in scale.

3.3.2 Validation Exercises

Finally, I perform two tests to verify that the estimated effects on changes in the new work share for each occupation category are not driven by pre-existing trends in the demand for new work. First, I focus on occupations identified as new work in the 1990's instead of post-2000's and compute the change in employment share in these jobs, which I use as the dependent variable in equation (4). Figure B.10 confirms that my results are not merely picking up long-run trends in the demand for particular jobs. Second, I conduct a falsification exercise by regressing changes in the employment share of new work between 1980 and 1990 on measures of future import shocks from China. Table B.3 suggests that the main findings capture period-specific effects of import shocks on new work adoptions.

4 Firm-level Analysis

Given the importance of managerial new work highlighted in the regional analysis, I further study the skill demands in these jobs using BGT online vacancies. First, I work with a merged sample of publicly listed firms in Compustat and examine the skill types firms demand in managerial new work induced by import exposure which vary across industries. Leveraging detailed firm characteristics provided in the data, I further examine the effects separately by firm type. Second, I focus on establishments that are TAA-certified and closely follow the skill demands before and after firms experience the import shocks. In addition to studying the types of activities performed in managerial new work using detailed skill requirements, the data structure further enables analyzing the dynamic adjustment process. Note that BGT data is only available for years after 2010, and therefore, I use updated measures of trade shocks, which I detail below. To avoid confounding factors due to the U.S.-China Trade War, I restrict the sample to years before 2017 for both exercises.

4.1 Publicly Traded Firms in Compustat

I focus on firms in the manufacturing sector and match to BGT using company name and geographic location. I work with a balanced sample of firms by restricting to those who post jobs in both 2010 and 2016. The final sample includes 828 firms, 18,283 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. While I mainly focus on manufacturing firms in Compustat, roughly 20 percent of job ads are posted outside of manufacturing.

4.1.1 Empirical Specification

The empirical strategy follows Autor et al. (2020) focusing on changes in firm-level skill demands in response to industry-level changes in Chinese imports between 2010 and 2016:

$$\Delta y_{ij} = \beta_0 + \beta_1 \Delta \mathrm{IP}_j^{US} + \eta_j + e_{ij}, \tag{5}$$

where $\Delta \mathrm{IP}_j^{US}$ is the change in imports for industry j normalized by the absorption value and η_j capture industry fixed effects at SIC 2-digits within manufacturing.[38] I use robust standard errors. Although the magnitude of the impact of U.S. imports from China post-2010 may not be as large compared to the first decade after China's emergence, the analysis will capture any continuous effort of firms in the import-competing sectors to make adjustments contemporaneously or with lags. Similar to equation (), endogeneity concerns are addressed following existing work using high-income countries' imports from China as instruments. See Appendix C.1.2 for the first-stage results. The main dependent variables are changes in (i) the share of new work and (ii) skill intensity measures for each skill type in different occupation categories. To provide details on the skill intensity measure construction: I classify detailed skills data into 15 broad categories,[39] and use the number of mentions in skill s normalized by the total number of skill mentions for each job ad, which I aggregate at the firm-level.

[38]Industry-level changes in import exposure are constructed using the following:

$$\Delta \mathrm{IP}_j^{US} = \frac{\Delta M_{j,2010-2016}}{Y_{j,2000} + M_{j,2000} - EX_{j,2000}}$$

[39]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, Supply Chain and Logistics.

4.1.2 Main Results

Throughout this section, I discuss results based on coefficients estimated using the instrument variable approach.[40] I begin by examining the effects on the adoption of new work in each occupation category. Consistent with the regional analysis, firms in high-exposed industries show a prominent increase in managerial new work. Examining across firm types by size, capital per worker, and profitability (ROI), the statistically significant and positive effects are mainly observed in firms that are larger, more capital-intensive, and more profitable. As for firms below the average values in each of these firm characteristics, I obtain negative coefficients which lack precision, except for capital per worker. I also add that investments in technological new work decrease in firms that face high import exposures and there are no differences observed across firm types with significant effects.

What about the changes in skill demands? Combining both new and existing work across all occupation types, there is an increased demand for skills related to the main production (maintenance, repair, and installation) and post-production (business, marketing, PR, sales, and customer support, social science research) stage, but not in pre-production activities (science and research). Separately examining new work, the positive effects remain primarily for the post-production activities and relevent skills in managing supply chains. The overall emphasis in post-production skills are also shown in existing work; however, there is also notable increase in the demand for skills related to the main production stage. The results suggest that firms continue to perform production-related tasks in-house, though it may not necessarily be the entire production process; however, their innovation efforts are mainly concentrated in improving post-production activities.

Next, I discuss the results for different occupation types. As for managerial new work, I find statistically signifiant effects on business activities related to analyzing markets, acquiring consumer demand through marketing and branding, improving customer service and support. Some examples of the commonly demanded skills include customer relationship management, market research, client base retention, online marketing (search engine optimization, search engine marketing), social media, web analytics, etc. Although there is no significant increase in the demand for new work in other occupation types (technological and clerical), I find a significant increase in skill investments in post-production activities for new work they seek in these occupations. In addition, none of the occupation types demonstrate a significant increase in pre-production activities (science and research). In other words, not only do firms show a decrease in their demand for technological new work, but also do not intensively require these skills even for the ones they intend to hire.[41]

[40] In the interest of space, see Appendix C.1.3 - C.1.8 for tables and graphs that I discuss but do not include in the main text.

[41] Of course, these skills may only capture a subset of what is needed in performing R&D. Nonetheless,

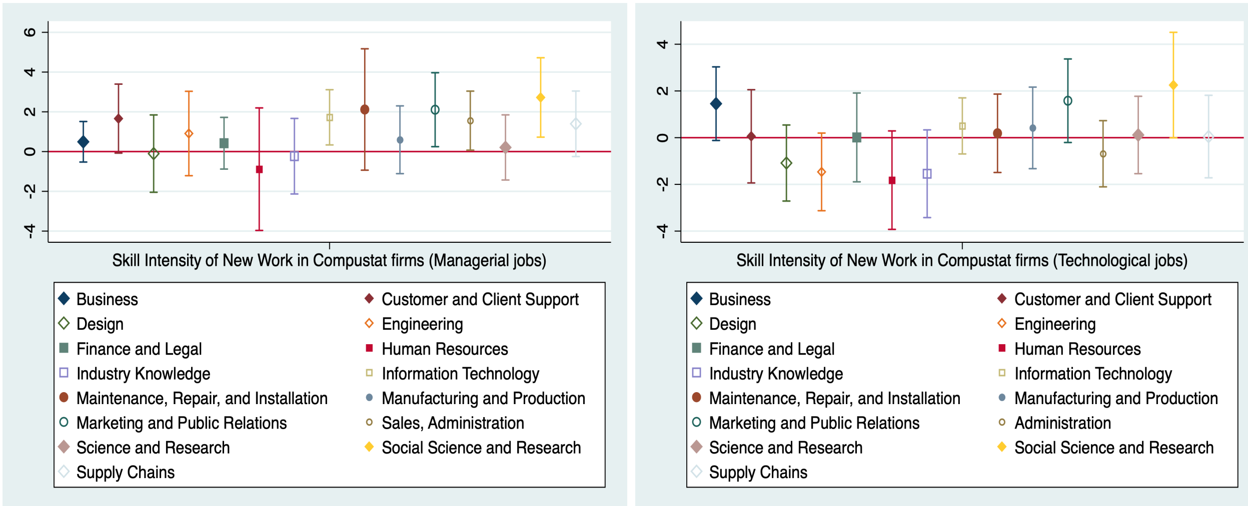

Figure 8: New Work in Compustat Firms: Managerial (left) vs. Technological (right)

Note: Each bar plots the point estimates of the coefficient of interest (β_1) in equation (4.1.1) including 95 percent confidence intervals. I run regressions separately for skill-occupation type pair. The unit of analysis is a firm. Industry fixed effects are included. Robust standard errors are employed.

Examining across different firm types, I do not find a significant increase in skill investments in post-production activities for firms that are below averages in the constructed sample in terms of firm-size, capital per worker and ROI. That is, larger, more capital-intensive, and profitable firms demand more new work in managerial and also increase investments in the post-production firm activities as foreign competition increases. Finally, I examine whether the concentrated investments in post-production are driven by firms moving out of manufacturing and switching into services. Using the industry codes firms include in job ads, I study changes in the share of jobs posted in manufacturing (NAICS 2 digits 31-33) and services (NAICS 2 digits 42, 54, 55) in response to import shocks. There is a decrease in the share of job ads posted in manufacturing, but not a significant increase in services to claim that the main findings are driven by firms becoming more service-oriented.

4.2 Trade-Induced Restructuring of TAA Firms

The analysis so far exploits industry variations in import shocks to examine any induced long-term changes in skills investments of firms. In this section, I combine BGT with the TAA petitions data to study firm-level responses of skill demands in greater frequency and closely study the dynamic adjustment process using firm-level incidents of import shocks

the discouraged response on the product innovation dimension in response to import shocks is consistent with findings in the previous sections as well as in the literature on the negative effects of import shocks on innovation in the U.S.

which accompany layoffs and potential restructuring.[42] Initiated under the Trade Act of 1974, the TAA program aims to provide financial assistance and various training programs to workers displaced due to trade-related layoffs. Petitions are made to the U.S. Department of Labor[43] by the impacted workers or any entity representing them; and certification requires that the reason of layoffs to be related to trade shocks.[44] I focus on layoffs due to the rise of import competition driven by exogenous forces outside the company and use (i) the impacted date to identify the timing; and (ii) the estimated number of affected workers to proxy for the magnitude of the shock.

I restrict the sample to TAA-certified establishments in the manufacturing sector with valid geographic (state and city) information. To allow for analysis of job demands before and after the import shock, I focus on certifications that occurred between 2012 and 2017. Roughly 74 percent of the petitions are certified, 22 percent of which are related to layoffs due to import competition.[45] Firm-level adjustments may occur through multiple certifications and reallocations within-firm across multiple establishments; in this paper, I limit the analysis to firms with a single certification in the sample period. The TAA sample is then matched to the BGT data using name and geographic location of establishments. This yields a merged sample of 153 establishments with 13,702 job ads. A major share of jobs are demanded in managerial and technological occupations as well as white-collar middle-skill occupations. Using the type of products or services that the impacted workers are engaged with and mapping them to four layers of the firm hierarchy (i.e., top management, senior staffs and managers, intermediary jobs, entry-level jobs) (Caliendo et al., 2020a,b),[46] I find that layoffs are concentrated in entry-level production/service jobs which correspond to the bottom layer of firm hierarchy.[47]

[42] I assume that firms that lay off workers and continue to hire by posting job ads undergo restructuring.

[43] TAA petitions data can be publicly downloaded from the U.S. Department of Labor's website.

[44] (i) company imports (the company replaced in-house tasks with imports); (ii) customer imports (buyers now purchase from foreign firms instead of this plant); (iii) production shift (the company replaced tasks with activities at own subsidiaries abroad); and (iv) increase in aggregate imports (an increase in imports of the plant's product at the aggregate level). See Monarch et al. (2017) for more details on TAA program and data.

[45] 74 percent of the certifications are related to offshoring and 4 percent of those with secondary effects through upstream or downstream production chains.

[46] I map the textual descriptions to a relevant occupation code to proxy for the impacted occupation group within the establishment. I use the Work Activities (average scores of 4A4B4, 4A4B2, 4A1A2, and 4AaC2) and Job Zones files in O*NET and assign information on layer for each detailed occupation codes; and map each occupation into a layer based on the level of required expertise and the supervisory role in the firm hierarchy.

[47] I also examine firm characteristics of TAA firms merged to Compustat data and find that firms with TAA events tend to be larger in firm size, total sales, and capital expenditure compared to non-TAA Compustat firms. Not all TAA establishments are matched to Compustat; given how Compustat firms are mostly large in size, those that are matched post more job ads than the unmatched establishments. See Appendix C.1.3.

4.2.1 Empirical Specification

The main specification is an event study where I examine the restructuring process of TAA-certified establishments (TAA-firms, henceforth) by comparing the quarterly job trends before and after the import shock relative to those of the matched control group.

$$y_{it} = \sum_{\tau=-4}^{8} \alpha_\tau \mathbb{1}(\text{event}_{it} = \tau) + \sum_{\tau=-4}^{8} \beta_\tau \mathbb{1}(\text{event}_{it} = \tau) \times \text{TAA}_i + \eta_i + \eta_t + e_{it} \tag{6}$$

I include indicator variables for 4 quarters before and 8 quarters after each firm experiences the import shock and interactions with an indicator for TAA certification (TAA_i). I add time fixed effects (η_t) for macroeconomic trends and establishment fixed effects (η_i) for time-invariant characteristics of establishments. Each firm in the matched control group is assigned an impacted timing (year-quarter) based on their matched TAA counterparts. I use the quarter before the shock as the reference period. The coefficient of interest β_τ captures the effect of the trade shock τ quarters away from the impacted time relative to the control group. Standard errors are clustered at NAICS 5-digit industries. The dependent variables are various forms of job demands which I transform using inverse hyperbolic sines.

To construct the matched control group, I use establishments observed in BGT that are not TAA-certified and look for the closest match based on industry, location, and job posting size in the pre-shock period. Using TAA as a proxy for trade-induced layoffs, the differences in the adoption of new work and skill demands between the two groups reveal information about what the restructuring process entails. TAA certification is potentially an imperfect proxy for restructuring as there may be firms that simply did not apply, which is possible as the program provides assistance to displaced workers, not to certified firms. Hence, including these firms in the control group would bias the results downwards.[48] One might be concerned about comparing inherently different firms if those in the control group were impacted by trade but did not lay off workers because they had better capacity to adjust. I mitigate this concern by matching on the the pre-shock job posting size. Using a naive regression, I check that TAA-certified firms, compared to the control group, are not likely to post more jobs or demand new work in the pre-shock period.[49]

4.2.2 Main Results

First, I examine the number of quarterly job ads to study post-TAA event job trends. I find that TAA firms post fewer job ads after undergoing layoffs where the change relative to

[48] I can address this concern by further imposing that the non-TAA firms do not reduce firm size over time; however, it is not feasible given the current data combination.

[49] See Appendix C.2.2 for results.

controls becomes significant after three quarters. Note that there are no significant differences between the two groups in terms of job demands in the pre-shock period. Running the specification separately by layer of the firm hierarchy (top management, senior staff, and managers; intermediate and entry-level jobs), I find that the overall decline is mainly driven by a fall in the demand for entry-level and intermediate-level jobs. Considering how the laid-off workers were mostly engaged in entry-level jobs, the result suggests that the in-house production mode no longer relies on their initially entry-level jobs. Then, do firms show any indication of switching out of manufacturing? Again, I look at changes in the share of quarterly job ads posted in manufacturing (NAICS 2 digits 31-33) and services (42, 54, 55). While TAA-firms are less likely to post jobs in manufacturing, there is not enough evidence to claim that these firms are more likely to seek jobs in services, and servitize.[50]

Next, I study the number of quarterly job ads in new work. There is an overall decrease in the demand for new work where the estimates lack precision for most periods but turn significant five quarters after the impacted time. Analyzing separately by occupation type, I find a notable difference in managerial new work demands relative to non-TAA firms in the quarter when the TAA event occurs, though the increase does not last in the subsequent quarters. For other occupation types, I do not find any significant effects.[51]

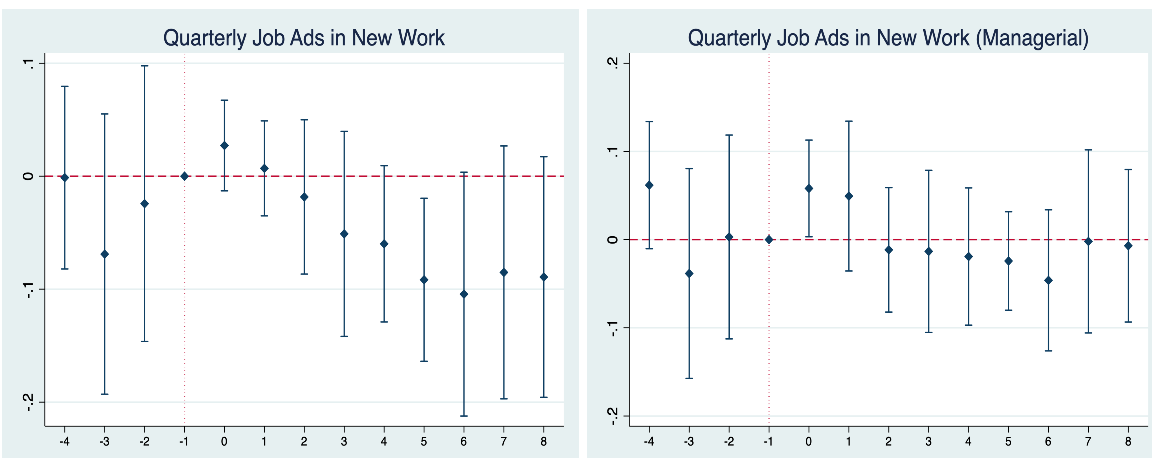

Figure 9: Job Demands in New Work (left) and Managerial New Work (right)

Note: Each bar plots the point estimates of the coefficient of interest (β_τ) in equation (6) including 95 percent confidence intervals. I run regressions separately for skill-occupation type pair. The unit of analysis is a establishment-year pair. Establishment fixed effects and time fixed effects are included. Standard errors are clustered at the 5-digit NAICS industries.

Are firms introducing de facto new tasks and knowledge in-house by hiring new work, or are they looking for jobs similar to their existing workforce but simply using different job labels? To answer this question, I compare the skill requirements of job ads of each firm

[50] See Appendix C.2.4 for results.

[51] See Appendix C.2.5 for results.

in the post-shock period to the pre-shock set of skills, which I construct by collecting the skills demanded by each firm for two years prior to the import shock.[52] Given the measure construction, I use the same empirical strategy but without the pre-shock years and firm fixed effects and effectively compare the average treatment effect on the treated for the post-shock period. I find that TAA firms are more likely to demand skills that were not previously sought in the pre-shock period for managerial new work where the difference is most salient in the first two quarters after the shock. The results suggest that the post-shock restructuring involves job demands that are not only new in occupational content, but also new in the set of skills sought in managerial work.[53]

To improve our understanding of the activity types involved in managerial new work in the restructuring process, I further examine various skill requirements in these job ads. Again, I work with the 15 skill categories in BGT and construct skill intensity measures using the total number of skill s mentions normalized by the total number of skill mentions for each firm-time pair. Using equation (6), I look for any significant changes in the skill-intensity of managerial new work as firms adjust to import shocks relative to the control group. For all managerial work, there is a notable increase in the demand for skills related to marketing, public relations, and sales. The results remain consistent if I separately look at managerial work with high new work intensity. The increase in the skill demand does not persist throughout the sample period, which may be partly affected by the cyclicality in hiring patterns. Nonetheless, the difference remains significant two years past the TAA event and no such pattern is observed for other skill categories examined. I add that skills related to the main production process increase in the first few quarters after the TAA event. It is possible that reorganizing production accompanies considerable restructuring of firm hierarchies where new strategies and knowledge in managerial work gains importance.[54]

5 Illustrative Model

In this section, I provide an illustrative model to explain the reduced-form findings and discuss mechanisms. I closely follow the framework of Kim and Lee (2021), which shows that when firms cannot easily adjust prices to compete with foreign firms, increasing investments to expand customer capital becomes optimal. Given the empirical findings, I mainly focus on post-production investments and extend the model to explain why new tasks in the post-production stage increase disproportionately more than the existing tasks

[52]In BGT, each job ad lists multiple skills with detailed information on the types of required skills, software and technologies, which can be obtained by studying the raw texts of job ads or the skills processed and categorized by BGT. Here, I work with the most detailed skill categories prepared by BGT.

[53]For other occupation categories, see Appendix C.2.6.

[54]See Appendix C.2.7 for results.

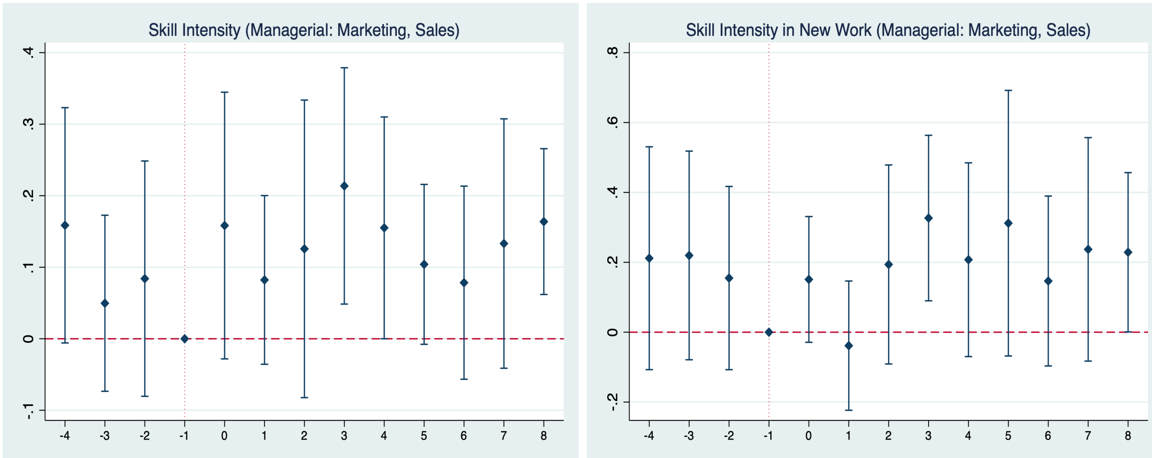

Figure 10: Skill Intensity in Marketing/Sales for Managerial Work: New (left) and All (right)

Note: Each bar plots the point estimates of the coefficient of interest (β_τ) in equation (6) including 95 percent confidence intervals. I run regressions separately for skill-occupation type pair. The unit of analysis is a establishment-year pair. Establishment fixed effects and time fixed effects are included. Standard errors are clustered at the 5-digit NAICS industries.

in-house for firms that are exposed to import shocks.

Consider an economy which consists of a continuum of industries that are aggregated with unit elasticity of substitution (i.e. Cobb-Douglas).[55] The level of import exposure differs across industries due to differential substitutability with foreign products: one can think of a set of industries producing standardized goods that are substitutable with foreign-produced ones; and others producing customized goods, and thus, less affected by foreign competition (Holmes and Stevens, 2014). In each industry, there is a continuum of firms with unit mass, each producing a single variety of good indexed by $i \in (0,1)$, and a mass of foreign firms that produce varieties indexed by $j \in (1, 1+z)$. The utility of the representative consumer is CES over all the available varieties subject to a standard budget constraint:

$$\mathbb{C} = \left(\int_0^1 (A_i c_i)^{\frac{\epsilon-1}{\epsilon}} di + \int_1^{1+z} (c_j)^{\frac{\epsilon-1}{\epsilon}} dj \right)^{\frac{\epsilon}{\epsilon-1}} \text{ s.t. } \int_0^1 p_i c_i di + \int_1^{1+z} p_j c_j dj = I,$$

where $\epsilon > 1$ and I denotes the total expenditure in an industry. While developing new products is an alternative strategy to acquire consumer demand, I assume that there is little room for product innovation in industries that produce standardized goods. Solving the consumer's problem, the demand for good c_i is,

$$c_i = \left(\frac{p_i}{A_i \mathbb{P}} \right)^{-\epsilon} \frac{I}{\mathbb{P}} \quad \text{where} \quad \mathbb{P} = \left(\int_0^1 \left(\frac{p_i}{A_i} \right)^{1-\epsilon} di + \int_1^{1+z} (p_j)^{1-\epsilon} \right)^{\frac{1}{1-\epsilon}}.$$

Each firm produces a unique variety employing labor, $y_i = L_i^\alpha$ ($\alpha \in (0,1]$) and optimally

[55]The current setup in a partial equilibrium approach allows me to focus on a single industry and proceed with the analysis, yet deliver cross-industry model predictions.

sets p_i that maximizes profits where the production technology is $y_i = L_i^{\alpha}$ with $\alpha \in (0,1]$:

$$\pi_i = p_i y_i - WL_i - c(A_i) = \left(\frac{p_i}{\mathbb{P}}\right)^{1-\epsilon} I - W\left(\frac{p_i}{\mathbb{P}}\right)^{-\frac{\epsilon}{\alpha}}\left(\frac{I}{\mathbb{P}}\right)^{\frac{1}{\alpha}} - c(A_i)$$

Acquiring consumer demand requires post-production investments using new (N) and existing (E) managerial tasks as inputs: $A_i = F(a_E^i, a_E^i) = (a_E^i)^{\epsilon} + (a_E^i)^{\epsilon}$. Note that A_i reflects the effect of post-production investments that raises the marginal utility from consuming good i. And the cost of hiring each input $k \in \{E, N\}$ is parameterized as,

$$c_k(a_k^{\epsilon}) = \frac{c_k}{(1+\gamma_k)}(a_k^{\epsilon})^{1+\gamma_k}.$$

with $\gamma_k > 0$, which satisfies $c_k'(a) > 0, c_k''(a) > 0$ for $a > 0$, and $c_k'(0) = 0$. I additionally assume $\gamma_N < \gamma_O$: new tasks in marketing and branding have less convex costs.[56] That is, new technology is more efficient in reaching consumers and establish brand loyalty compared to the existing one, not in the level but in terms of how quickly the marginal product diminishes. It is plausible that consumers today do not respond sensitively to the traditional means of marketing, while the web-based marketing tools through digital platforms have become the more effective (e.g. Greenwood et al., 2021).

The equilibrium is the vector $[p_i, \mathbb{P}, a_O, a_N]$ that satisfies the first order conditions with respect to p_i, a_O, a_N[57], and the condition for the equilibrium price index $\mathbb{P}$: $\mathbb{P}^{1-\epsilon} = (p_i/A_i)^{1-\epsilon} + \delta\mathbb{P}_0^{1-\epsilon}$. I assume that prices are set optimally at the pre-shock equilibrium with $\delta = 0$, but it cannot be adjusted immediately after the shock. Because there is no analytic solution, I proceed with log-linear approximation around the pre-shock equilibrium with $\delta = 0$, and consider the effect of a small perturbation ($\delta > 0$).[58] The solution to this system is,

$$\widehat{A_i} = \frac{1-\alpha-\frac{1}{\epsilon}}{\frac{1}{\epsilon}+\frac{\alpha\overline{\gamma}}{\epsilon-1}}\kappa\delta, \quad \widehat{a_E} = \frac{\overline{\gamma}}{\gamma_E}\widehat{A_i}, \quad \widehat{a_N} = \frac{\overline{\gamma}}{\gamma_N}\widehat{A_i}$$

where $\overline{\gamma} \equiv (\frac{s_E}{\gamma_E} + \frac{s_N}{\gamma_N})^{-1}$ is the harmonic mean of γ_E and γ_N; and $\kappa \equiv \frac{(\mathbb{P}_0)^{1-\epsilon}}{\epsilon-1}$. Assuming $\alpha < 1 - \frac{1}{\epsilon}$, $\widehat{A_i}$ is positive when $\delta > 0$, which means that firms optimally increase post-production investments when import exposure intensifies. When $\gamma_N < \gamma_E$, firms increase

[56]Note that convex costs in post-production investments along with the Inada condition guarantees a unique and positive interior solution for A_i.

[57]The first order condition with respect to p_i results in the optimal pricing rule, which reduces to the constant markup rule if $\alpha = 1$: $\frac{p_i}{W} = \frac{\epsilon}{\alpha(\epsilon-1)}\left(\frac{I}{\mathbb{P}}\right)^{\frac{1}{\alpha}-1}\left(\frac{p_i}{\mathbb{P}}\right)^{-\epsilon(\frac{1}{\alpha}-1)}$

[58]The list of log-linearized equations are

$$\widehat{\mathbb{P}} = \widehat{p_i} - \widehat{A_i} - \kappa\delta, \quad \widehat{p_i} = 0, \quad \widehat{A_i} = s_E\widehat{a_E} + s_N\widehat{a_N}$$

$$\frac{\alpha\gamma_E}{\epsilon-1}\widehat{a_E} = \frac{\alpha\gamma_N}{\epsilon-1}\widehat{a_N} = (1-\alpha)\left(\widehat{p_i} - \widehat{\mathbb{P}}\right) + \frac{1}{\epsilon}\mathbb{P} - (1-\alpha)\widehat{A_i}$$

where $s_k \equiv \frac{a_k}{A}$, and A, a_E, a_N are the pre-shock level of the variables.

the demand for new tasks more than existing ones (i.e. $\widehat{a}_N > \widehat{a}_E$) to acquire consumer demand in response to import competition.

6 Conclusion

In this paper, I use the firm's demand for jobs that employ new knowledge, skills, and technologies, which I define as new work, to measure various innovation activities firms pursue in response to import shocks. I build on Lin (2011) and use the emergence of new job titles to capture evidence of new work, assuming that job titles reflect the content of skills and tasks required in jobs. The measure obtained using CBOW is comparable to existing work with an important methodological advantage: applicability to job titles data retrieved from various sources. Furthermore, compared to conventional measures of innovation (Cohen, 2010; Kogan et al., 2017; Hall et al., 2005; Moser, 2016, etc.), using new work in different occupation types enables a more comprehensive analysis of incentives to innovate as firms re-optimize in response to import competition.

In the regional approach, I examine changes in the share of new work induced by the China shock and find that greater exposure to imports persistently increases managerial new work over time. Using BGT online vacancies combined with publicly listed firms in Compustat, I further study the types of activities performed in these jobs and find a significant increase in skill demands mainly concentrated in enhancing post-production activities. Examining the restructuring process of TAA-certified establishments, I again find greater skill demands in new work related to marketing, public relations, and sales. The findings on how firms adjust labor inputs as transitions occur complement existing studies analyzing job creation and destruction (Asquith et al., 2017; Bloom et al., 2019); and firm-level structural changes (Bernard et al., 2017; Breinlich et al., 2018; Ding et al., 2020) caused by trade shocks. Finally, I provide a model to explain the empirical results and discuss mechanisms extending Kim and Lee (2021).

The results of the paper shed light on several important questions that merit further research in future work. Do concentrated investments in marketing, branding, and sales generate different implications on economic growth compared to product innovation? Is this a permanent shift firms in import-competing industries make? If so, how does it reshape comparative advantages? What implications does it have on labor market inequality as firms transition the skill demand towards specific tasks and generate additional distributional effects in the post-shock outcomes across worker groups?

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Appendices

Appendix A Tables and Graphs: Data and Measurement

A.1 Distribution of Job Ads in BGT

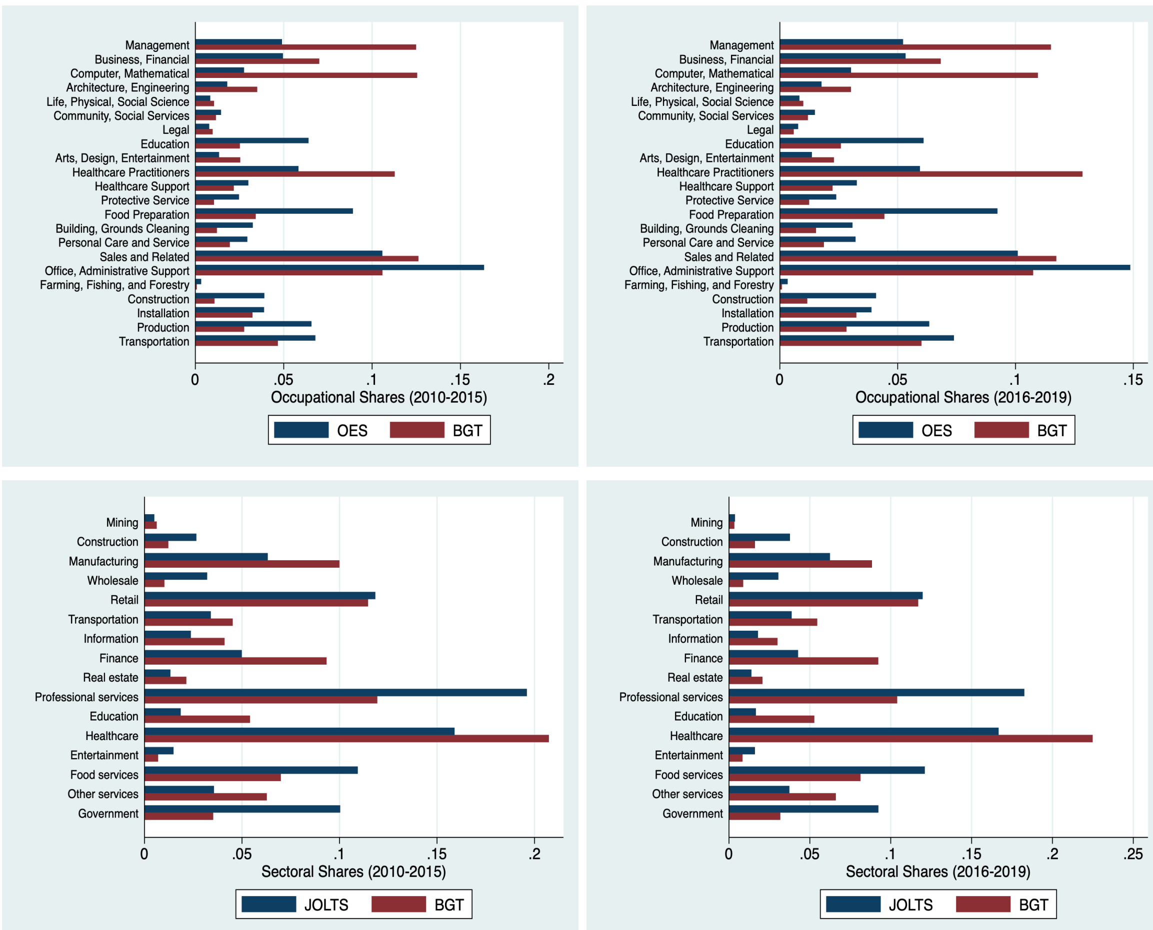

Figure A.1: Distribution of Occupations and Industries

A.2 Distribution of New Jobs

Data Source	Time Period	No. Titles	Mean	SD
Dictionary of Occupation Titles	1990	12,254	0.020	0.315
Classified Index of Industries and Occupations	2000	30,651	0.021	0.031
O*NET Alternative Job Titles	2016	59,958	0.105	0.061

**Mean and SD report the average and standard deviation of new work intensity scores.

Table A.1: Summary Statistics

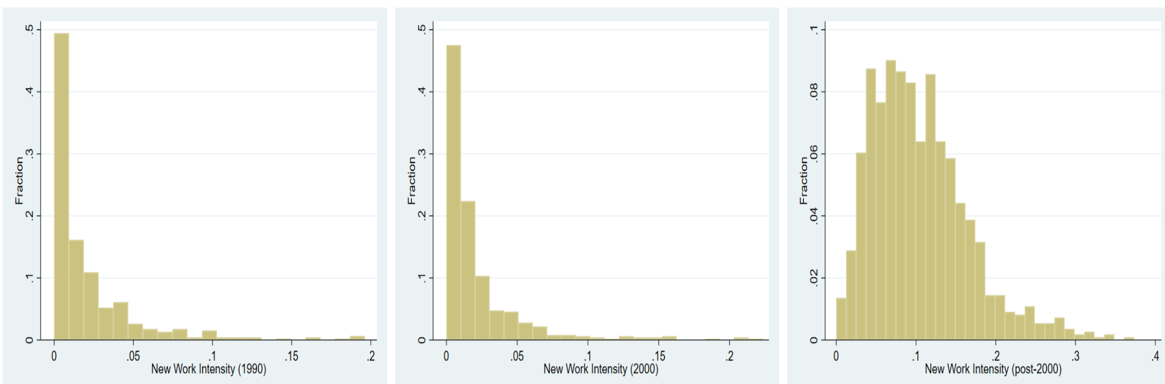

Figure A.2: Histogram of New Work Intensity over Time

A.3 Checking Measure Robustness

Employed Text Embedding Methods	1990	2000
CBOW	0.7540*	0.7483*
GloVe[a]	0.7434*	0.7294*
Fasttext[b]	0.7202*	0.7310*

Stars(*) indicate significance at the 1% level.

[a] Pre-trained word vectors obtained using GloVe, an "unsupervised learning algorithm for obtaining vector representations for words" (Pennington et al., 2014)
[b] Pre-trained word vectors obtained using https://fasttext.cc/

Table A.2: Correlations with new work measures of Lin (2011)

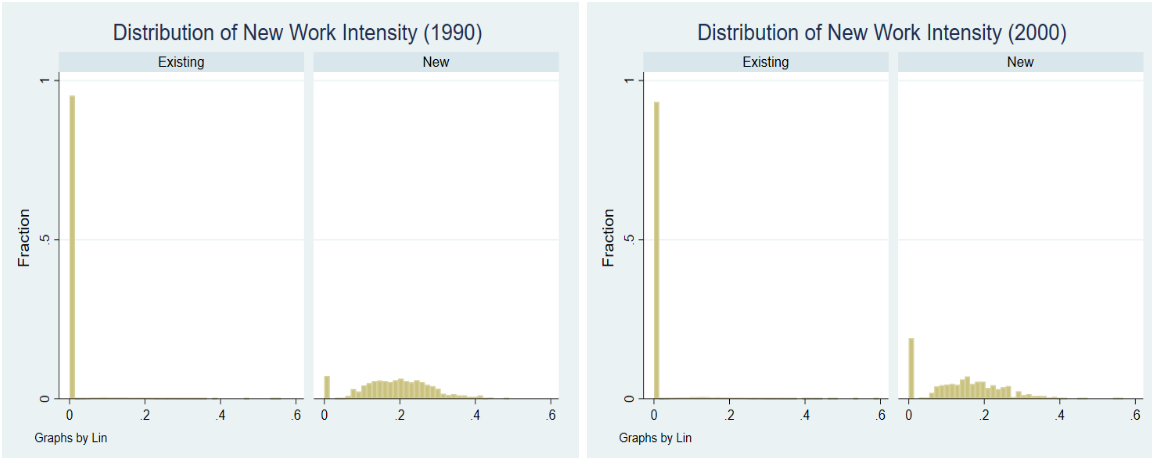

Figure A.3: Distribution of Job Titles by New Work Measures of Lin (2011)

A.4 Example Occupations Intensive in New Work

SOC	Occupation Titles	SOC	Occupation Titles
519199	Production Workers, All Other	291069	Physicians and Surgeons, All Other
151199	Computer Occupations, All Other	172199	Engineers, All Other
519061	Inspectors, Testers, Sorters, Samplers, and Weighers	119033	Education Administrators, Postsecondary
119199	Managers, All Other	251194	Vocational Education Teachers, Postsecondary
131199	Business Operations Specialists, All Other	173029	Engineering Technicians, Except Drafters, All Other

Table A.3: Occupation Codes (SOC) with the most job titles in new work

A.5 Example Job Titles in New Work

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

Table A.5: Example New and Emerging Job Titles

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 are grouped by 2 digit-SOC codes then further classified in to occupation types: managerial (2-digit SOC 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 A.4: Example Job Titles with High New Work Intensity Scores by Occupation Types

	Example New Job Titles	Corresponding Occupation Category
2000	Information systems security officer	Network and computer systems administrators
	Quality assurance specialist, applications	Computer software developers
	Dosimetrist	Radiation therapists
	Engineer, bio-mechanical	Biomedical engineers
post-2000	Configuration Manager	Computer software developers
	Online Facilitator	Managers in education and related fields
	Retinal Angiographer	Health technologists and technicians, n.e.c.
	Head of Import Coordination and Production	Material recording, scheduling, planning, expediting

Table A.6: Example New Job Titles in 2000 and post-2000

A.6 Within-Between Occupation Variation in New Work

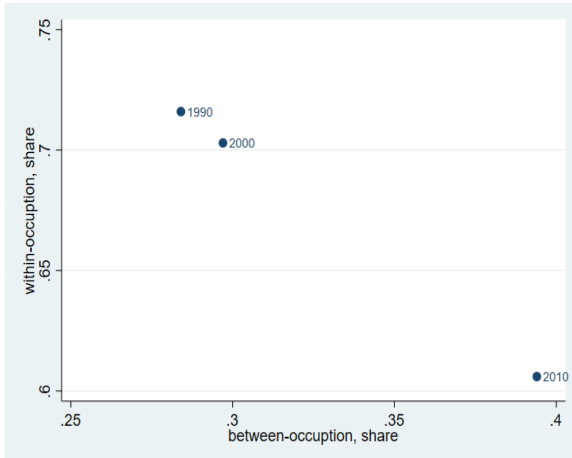

Figure A.4: Within-Between Occupation Variation in New Work

A.7 Content of New Work

A.7.1 Skill Characteristics

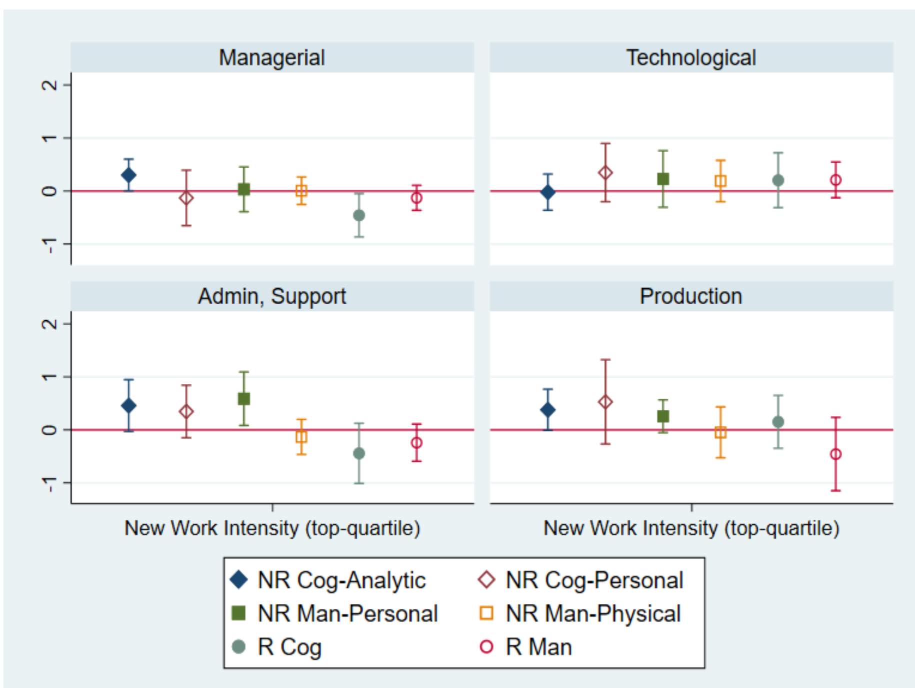

Figure A.5: Skill Characteristics of New Work by Occupations

Figure A.6: Skill Characteristics of New work (2000)

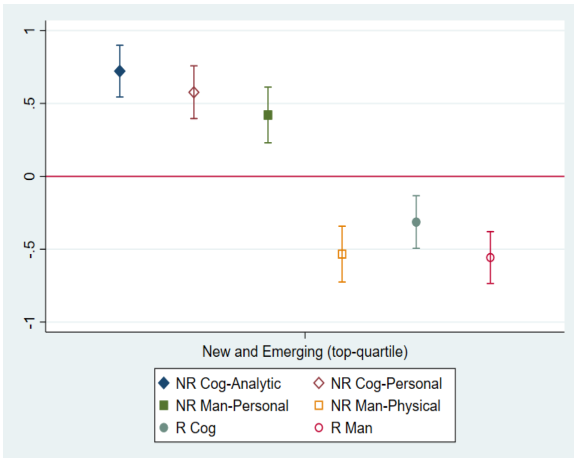

Figure A.7: Skill Characteristics of New Work (New and Emerging)

A.7.2 Demographic Distribution of New Work

Figure A.8: Employment shares of New (top quartile of new work intensity) and Existing Work

A.7.3 Skill Premium of New Work (2000, 1990)

I regress individual log(wages) on new work intensity scores using the IPUMS-USA decennial census samples for 2000 and 1990 employing new work emerged between 1990 and 2000; and 1980 and 1990, respectively. In columns (1)-(4), I report the coefficients for 2000; and in columns (5)-(8), for 1990. Columns (1)-(2) and (5)-(6) show results using new work intensity measures constructed using the CBOW model, comparing similarity scores between job titles from the previous decade; and columns (3)-(4) and (7)-(8) show results using measures constructed by Lin (2011). 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, beyond college), age (16-19, 20-29, 30-39, 40-49, 50-70). I show results separately for estimates with and without industry fixed effects. Standard errors are clustered at the 3-digit census occupation-level. Note that due to differences in the source of job titles data between the two decades, the coefficient magnitudes are not directly comparable.

Log hourly wages	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New Work	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
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

Robust clustered standard errors at detailed occupation-level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

[a] All specifications include commuting zone fixed effects. Controls include binary indicators for gender, marital status, nativity, migration status, race, education, age. Standard errors are clustered at the 3-digit census occupation-level.

Table A.7: Wage regressions for New Work (2000, 1990)

Appendix B Tables and Graphs: Regional Analysis

B.1 Summary Statistics and Regression Results

	Mean	SD	Min	Max
NTR Gap	.080	.029	.017	.202
year = 2005				
Δ New Work	.009	.123	-.977	1
Δ New Work Managerial	.007	.151	-.977	.589
Δ New Work Technological	-.012	.167	-.869	.599
Δ New Work Sales, Admin	.004	.054	-.203	.276
Δ New Work Production	-.002	.032	-.111	.228
year = 2010				
Δ New Work	.012	.130	-1	1
Δ New Work Managerial	.031	.150	-1	.690
Δ New Work Technological	-.018	.172	-1	.599
Δ New Work Sales, Admin	.002	.055	-.191	.236
Δ New Work Production	.003	.036	-.106	.197
year = 2015				
Δ New Work	.025	.137	-.924	.966
Δ New Work Managerial	.071	.151	-.788	.786
Δ New Work Technological	-.001	.149	-.780	.504
Δ New Work Sales, Admin	.001	.100	-.405	.925
Δ New Work Production	.010	.057	-.090	.966

Table B.1: Summary Statistics

	All Occupations	Managerial	Clerical	Technological	Production
NTR Gap× 2005	0.209*	0.196*	0.218**	0.236**	0.223**
	(0.104)	(0.104)	(0.104)	(0.103)	(0.104)
NTR Gap× 2006	0.0953	0.0886	0.105	0.115	0.107
	(0.105)	(0.105)	(0.105)	(0.106)	(0.106)
NTR Gap× 2007	0.162*	0.163*	0.174**	0.187**	0.173*
	(0.0856)	(0.0876)	(0.0854)	(0.0825)	(0.0856)
NTR Gap× 2008	0.0649	0.0362	0.0727	0.104	0.0681
	(0.0919)	(0.0905)	(0.0911)	(0.0911)	(0.0924)
NTR Gap× 2009	0.125	0.105	0.140	0.162	0.140
	(0.120)	(0.118)	(0.121)	(0.121)	(0.121)
NTR Gap× 2010	0.125	0.0803	0.144	0.162*	0.137
	(0.0911)	(0.0911)	(0.0908)	(0.0913)	(0.0909)
NTR Gap× 2011	0.240**	0.184*	0.270**	0.279**	0.259**
	(0.104)	(0.106)	(0.105)	(0.105)	(0.105)
NTR Gap× 2012	0.0444	-0.00675	0.0579	0.0753	0.0591
	(0.110)	(0.110)	(0.111)	(0.111)	(0.112)
NTR Gap× 2013	0.226**	0.157*	0.249***	0.257***	0.250***
	(0.0855)	(0.0888)	(0.0854)	(0.0860)	(0.0857)
NTR Gap× 2014	0.171*	0.0829	0.194**	0.204**	0.202**
	(0.0846)	(0.0851)	(0.0845)	(0.0836)	(0.0854)
NTR Gap× 2015	0.205*	0.113	0.234**	0.238**	0.236**
	(0.112)	(0.112)	(0.111)	(0.111)	(0.111)
NTR Gap× 2016	0.110	0.0245	0.140	0.143	0.141
	(0.0890)	(0.0890)	(0.0887)	(0.0886)	(0.0897)
NTR Gap× 2017	0.308**	0.223	0.341**	0.335**	0.346**
	(0.146)	(0.146)	(0.146)	(0.147)	(0.145)
NTR Gap× 2018	0.260**	0.170	0.293**	0.296**	0.307**
	(0.124)	(0.126)	(0.125)	(0.125)	(0.126)
NTR Gap× 2005 ×occ		0.0914	-0.0965***	-0.300***	-0.105***
		(0.0633)	(0.0329)	(0.0486)	(0.0175)
NTR Gap× 2006 ×occ		0.0492	-0.103***	-0.220***	-0.0870***
		(0.0536)	(0.0271)	(0.0653)	(0.0204)
NTR Gap× 2007 ×occ		-0.00863	-0.132***	-0.273***	-0.0797***
		(0.0487)	(0.0257)	(0.0729)	(0.0211)
NTR Gap× 2008 ×occ		0.210***	-0.0861***	-0.425***	-0.0233
		(0.0456)	(0.0316)	(0.0450)	(0.0186)
NTR Gap× 2009 ×occ		0.152***	-0.157***	-0.403***	-0.109***
		(0.0366)	(0.0241)	(0.0573)	(0.0209)
NTR Gap× 2010 ×occ		0.331***	-0.208***	-0.397***	-0.0862***
		(0.0492)	(0.0303)	(0.0615)	(0.0247)
NTR Gap× 2011 ×occ		0.412***	-0.326***	-0.424***	-0.139***
		(0.0475)	(0.0277)	(0.0536)	(0.0219)
NTR Gap× 2012 ×occ		0.375***	-0.148***	-0.340***	-0.107***
		(0.0413)	(0.0344)	(0.0591)	(0.0257)
NTR Gap× 2013 ×occ		0.507***	-0.245***	-0.342***	-0.172***
		(0.0594)	(0.0262)	(0.0595)	(0.0236)
NTR Gap× 2014 ×occ		0.647***	-0.256***	-0.361***	-0.225***
		(0.0536)	(0.0296)	(0.0740)	(0.0189)
NTR Gap× 2015 ×occ		0.678***	-0.321***	-0.357***	-0.225***
		(0.0543)	(0.0229)	(0.0383)	(0.0188)
NTR Gap× 2016 ×occ		0.625***	-0.332***	-0.369***	-0.232***
		(0.0578)	(0.0223)	(0.0718)	(0.0245)
NTR Gap× 2017 ×occ		0.624***	-0.366***	-0.294***	-0.277***
		(0.0538)	(0.0343)	(0.0644)	(0.0198)
NTR Gap× 2018 ×occ		0.659***	-0.358***	-0.395***	-0.345***
		(0.0721)	(0.0429)	(0.0483)	(0.0244)
Observations	30,800	30,800	30,800	30,800	30,800
R-squared	0.015	0.045	0.021	0.028	0.020

Table B.2: Regression Results

B.2 Robustness Results

B.2.1 Pre-existing trends: adding controls

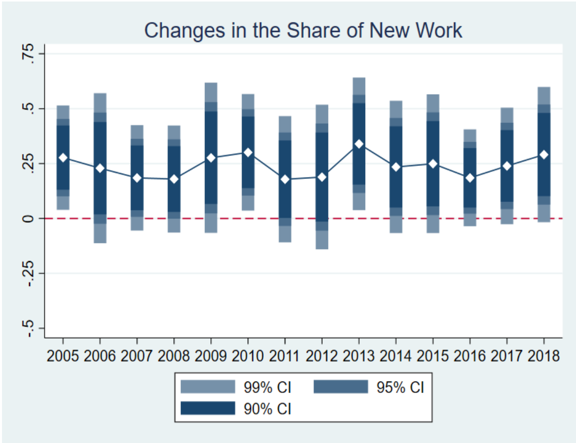

Figure B.1: Changes in the share of new work

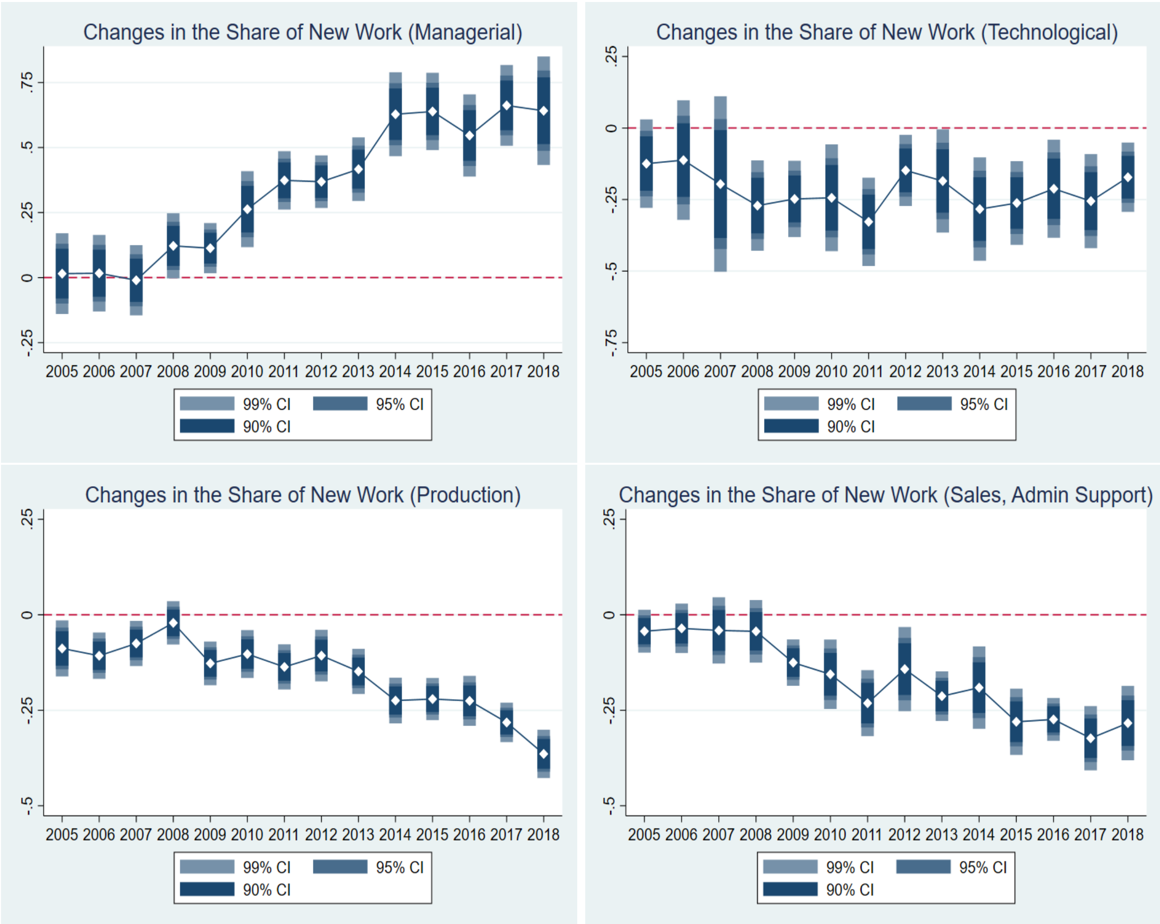

Figure B.2: Changes in the share of new work by occupational roles

B.2.2 Alternative Measures: N&E Occupations

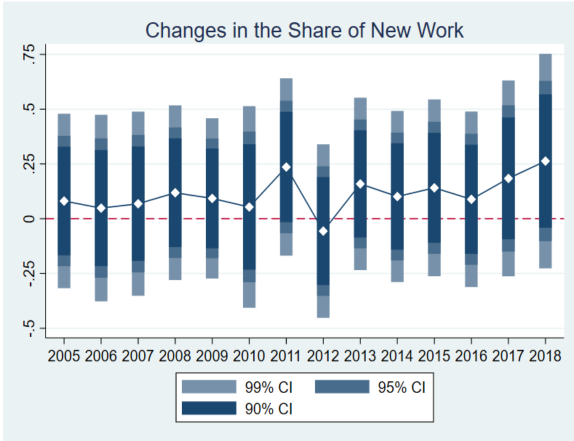

Figure B.3: Changes in the share of N&E

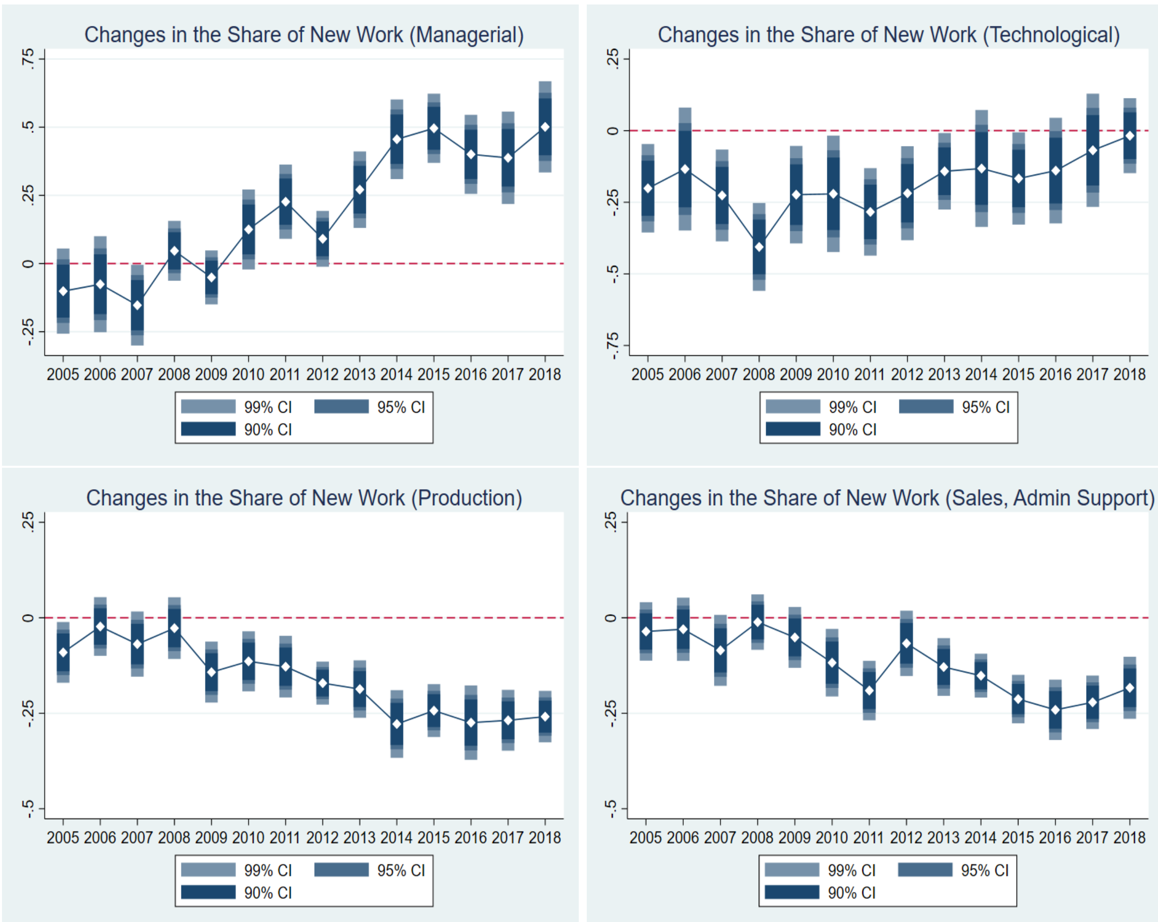

Figure B.4: Changes in the share of N&E

B.2.3 Alternative Measures: New Work (Continuous Measure)

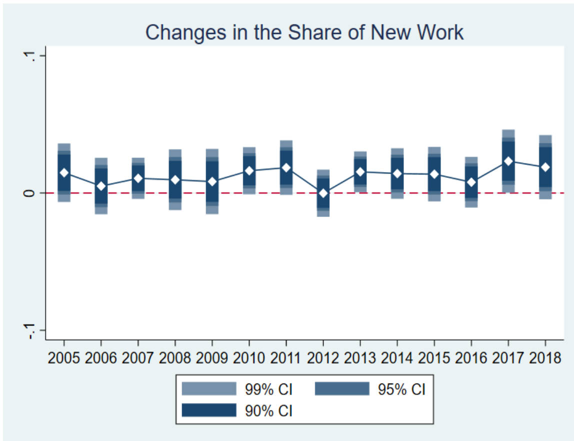

Figure B.5: Changes in the share of new work

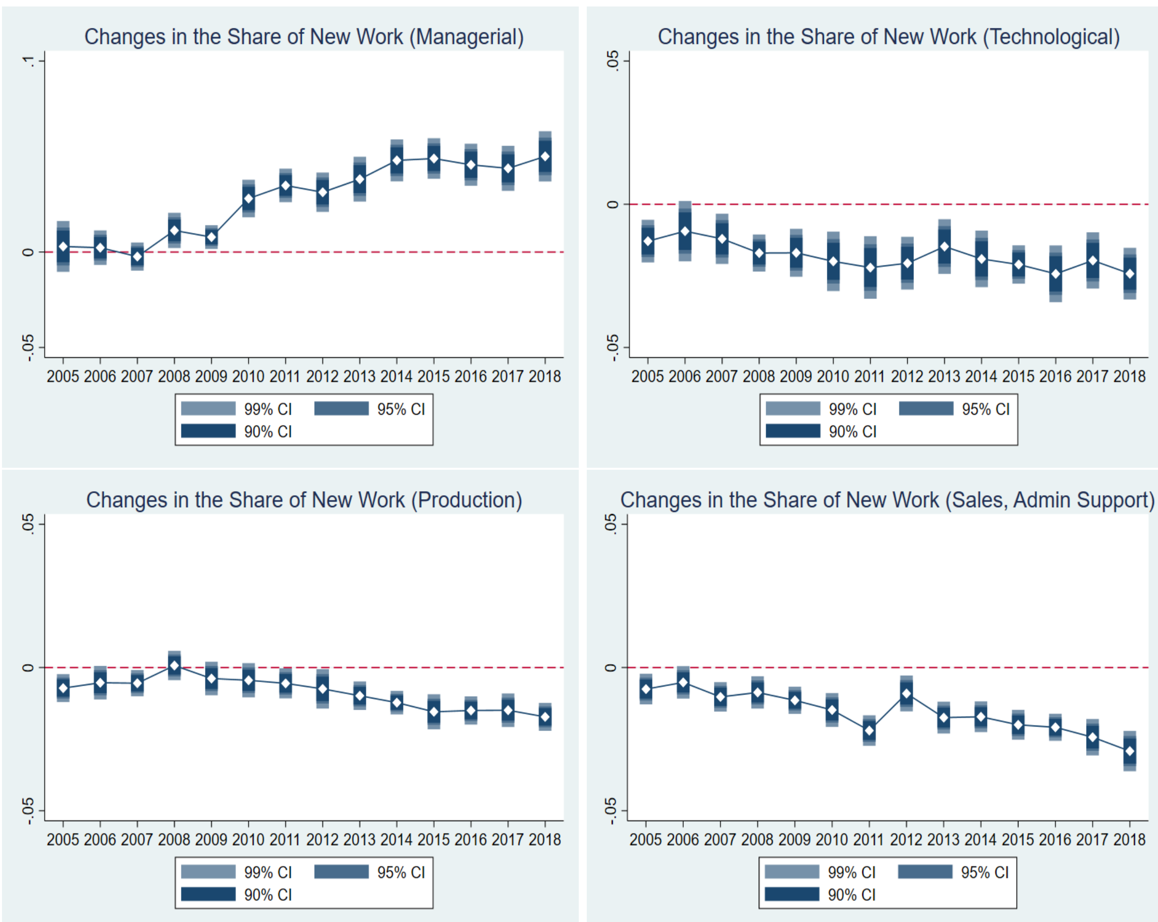

Figure B.6: Changes in the share of new work by occupational roles

B.2.4 Alternative Measures: Import Shocks

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 i.[59] Due to the unobserved shocks to U.S. product demand, which can be correlated with new work demands and U.S. imports, I also follow 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.[60]

$$\Delta \text{IPW}_{it} = \sum_j \frac{L_{ijt}}{L_{jt}} \frac{\Delta M^{US}_{j,2000-2007}}{L_{it}}, \quad \Delta \text{OPW}_{it} = \sum_j \frac{L_{ijt-1}}{L_{jt-1}} \frac{\Delta M^{OTH}_{j,2000-2007}}{L_{it-1}} \tag{7}$$

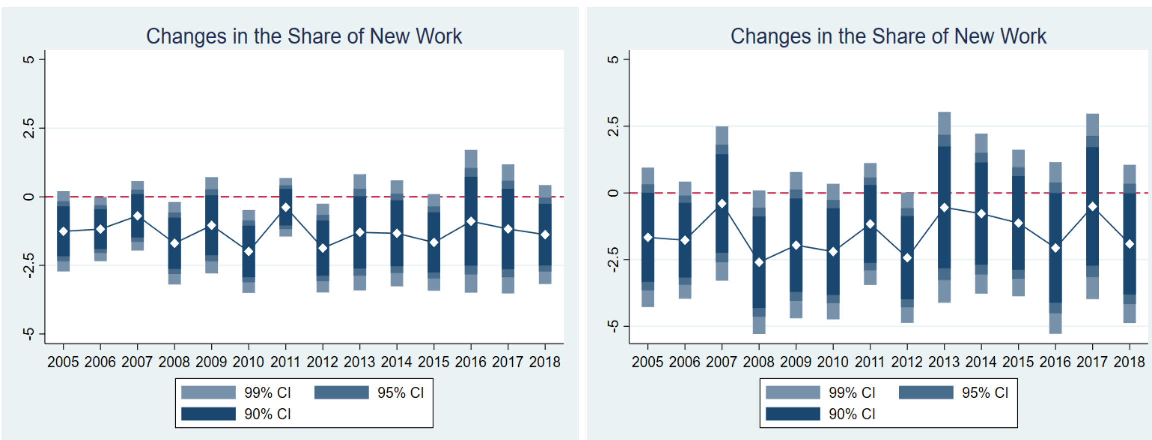

Figure B.7: Changes in the share of new work: OLS (left), IV (right)

[59] I obtain data on product-level (six-digits HS) bilateral trade flows from the UN Comtrade database and use the crosswalk provided in Pierce and Schott (2018) and Pierce and Schott (2012) to map HS product codes into 1987 SIC industry codes. I further use a crosswalk between SIC and the industry codes (IND) to merge trade data with the census labor market information.

[60] The list of countries includes Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

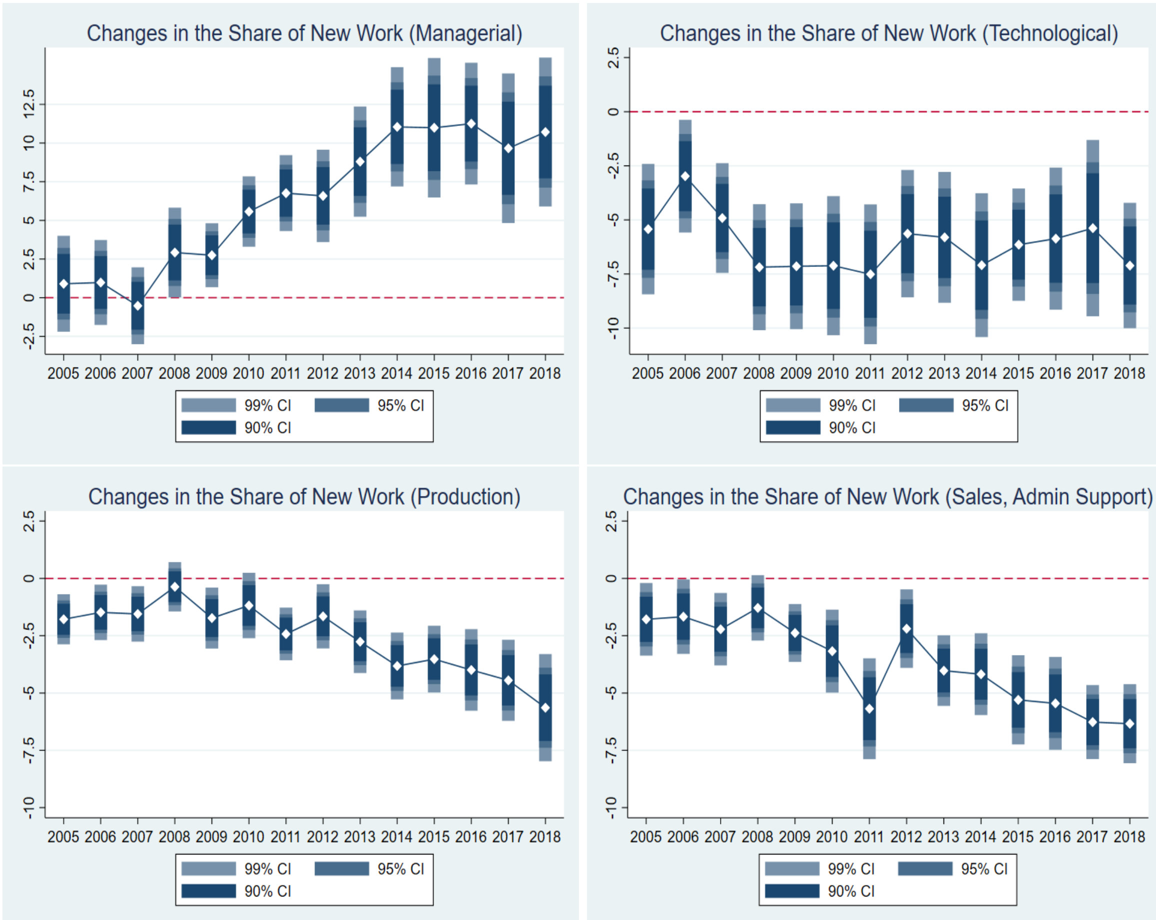

Figure B.8: Changes in the share of new work by occupational roles: OLS

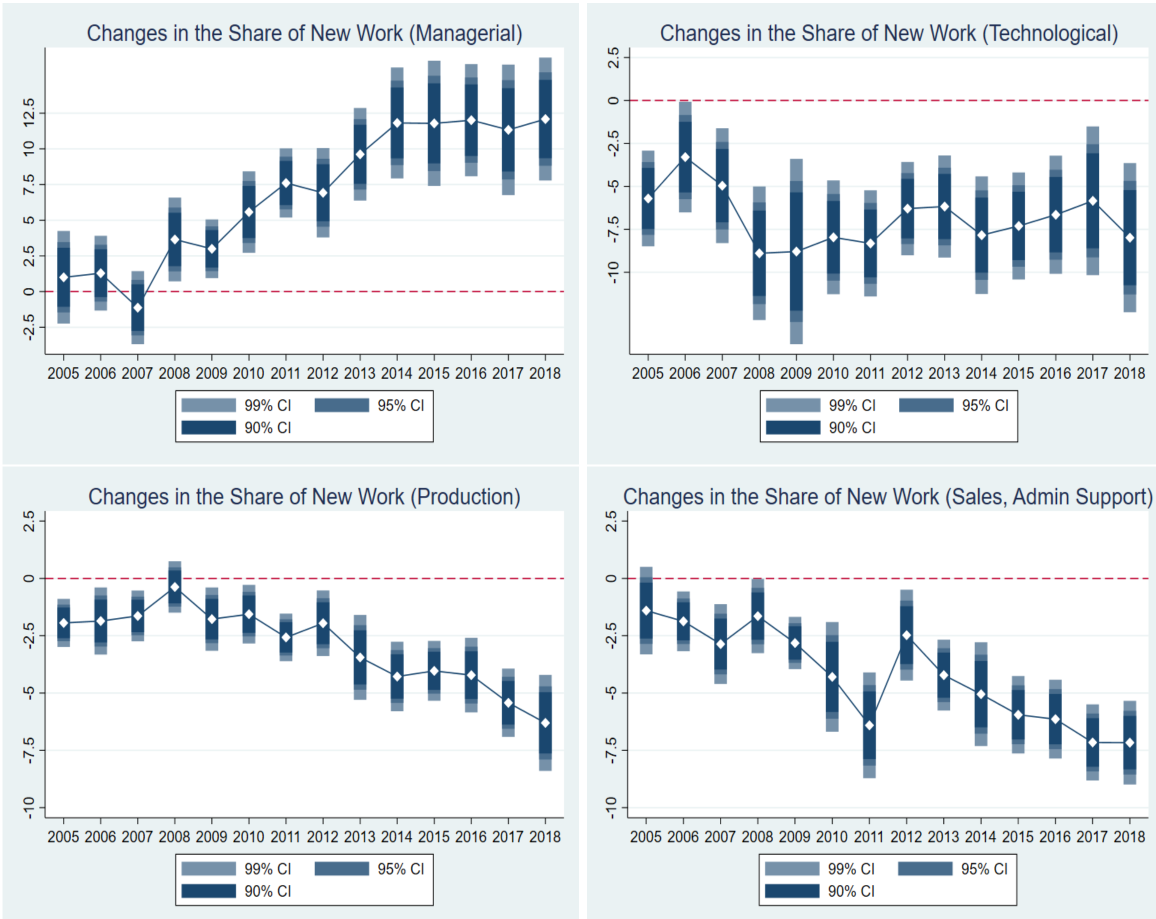

Figure B.9: Changes in the share of new work by occupational roles: IV

B.2.5 Validation Exercises

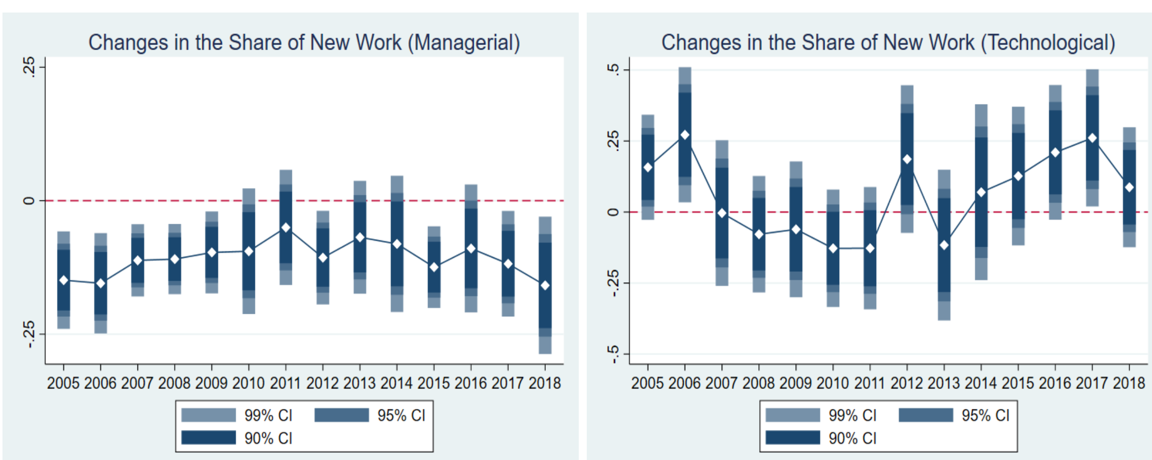

Figure B.10: Changes in the share of new work by occupational roles

Δ share of new work (1990-2000)	Managerial	Technological	Sales, Admin	Production
NTR Gap	0.172*	-0.222**	-0.247**	-0.265***
	(0.0961)	(0.0914)	(0.0912)	(0.0901)
NTR Gap × occ	-2.349***	0.812***	1.082***	0.856***
	(0.0945)	(0.0527)	(0.0456)	(0.0295)
Observations	1,540	1,540	1,540	1,540
R-squared	0.113	0.010	0.018	0.016

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B.3: Falsification Exercise

B.2.6 Alternative Specification: Estimation by Year

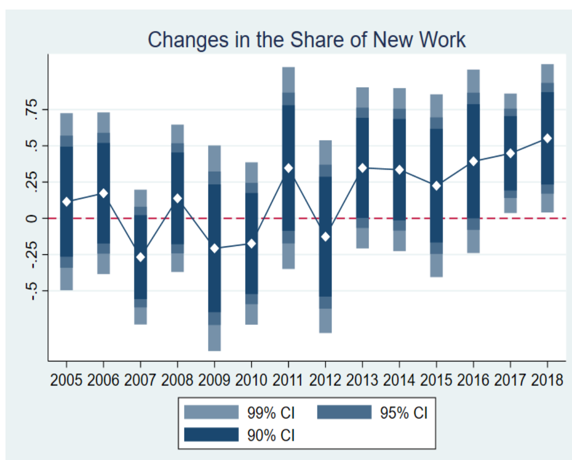

Figure B.11: Changes in the share of new work

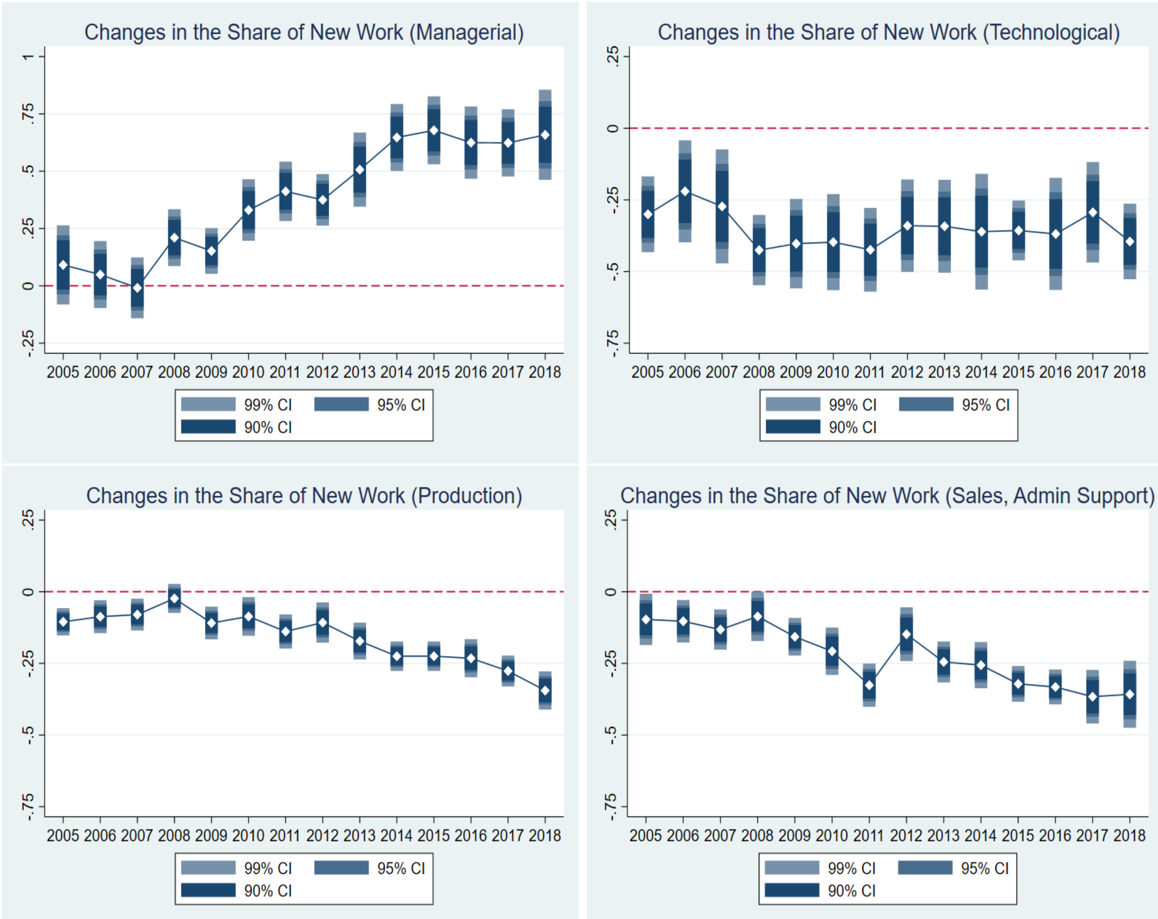

Figure B.12: Changes in the share of new work by occupational roles

Appendix C Tables and Graphs: Firm-level Analysis

C.1 Firm-level Analysis: Compustat

C.1.1 Sample Description

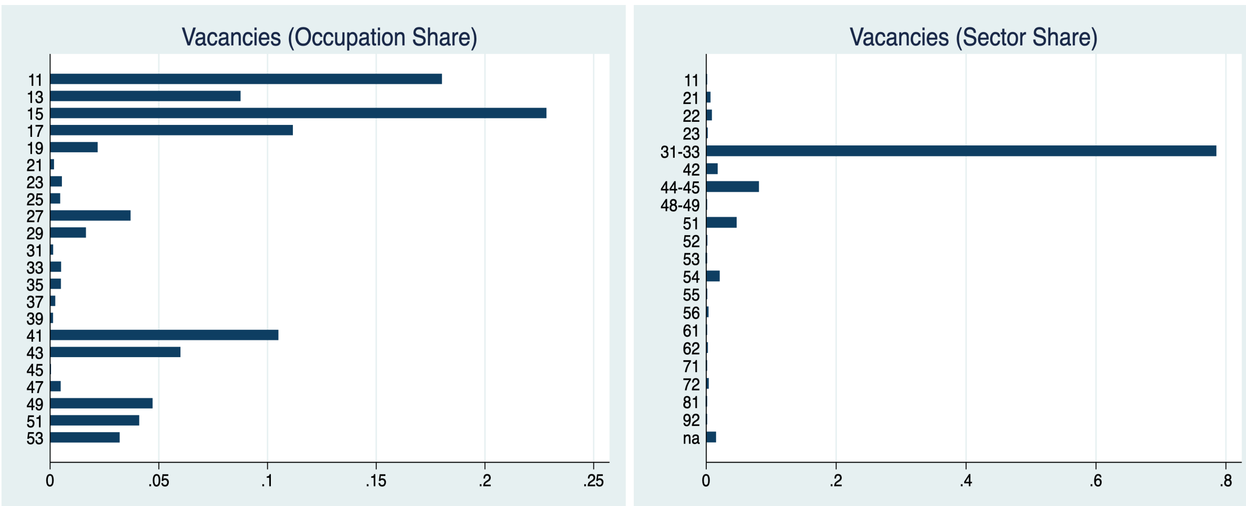

Figure C.1: Occupation and Sector Distribution

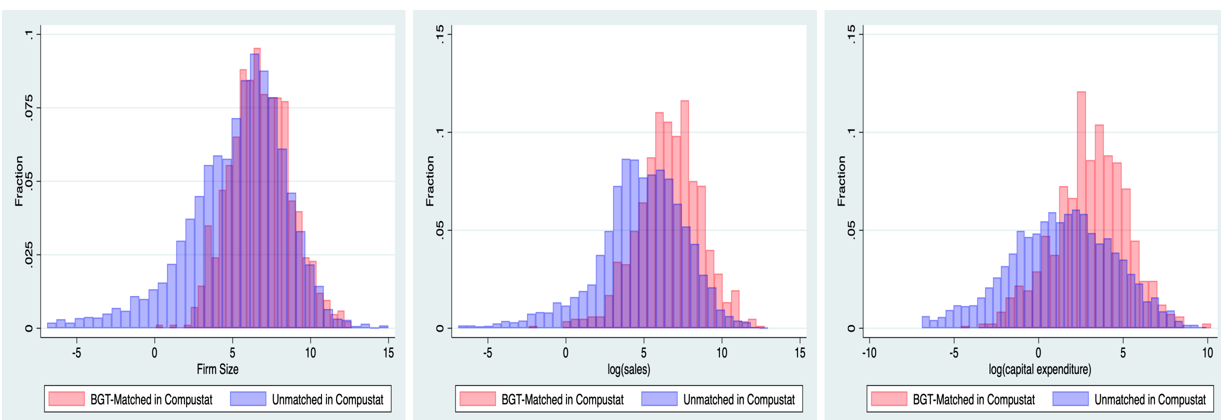

Figure C.2: Compustat firms: Matched to BGT vs. Unmatched

C.1.2 Import Shocks

The following reports the correlation between the import shocks and first-stage results:

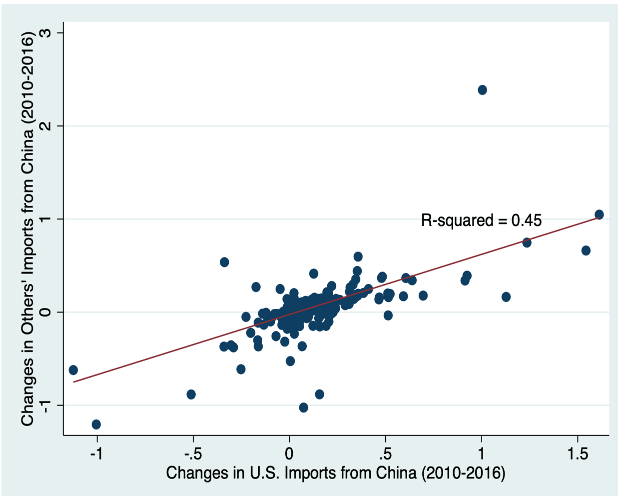

Table C.1: Comparing Measures

2SLS First-Stage	(1)
ΔIP^{OTH}	0.882***
	(0.0711)
Observations	18,283
R-squared	0.588

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.2: 2SLS First-Stage Estimates

C.1.3 Results: Sectoral Orientation

	Manufacturing (↓)	Services (↑)
ΔIP^{OTH}	0.360**	0.102
	(0.179)	(0.196)
Observations	18,283	18,283
R-squared	0.021	0.028

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.3: Sectoral Orientation

C.1.4 Results: New Work

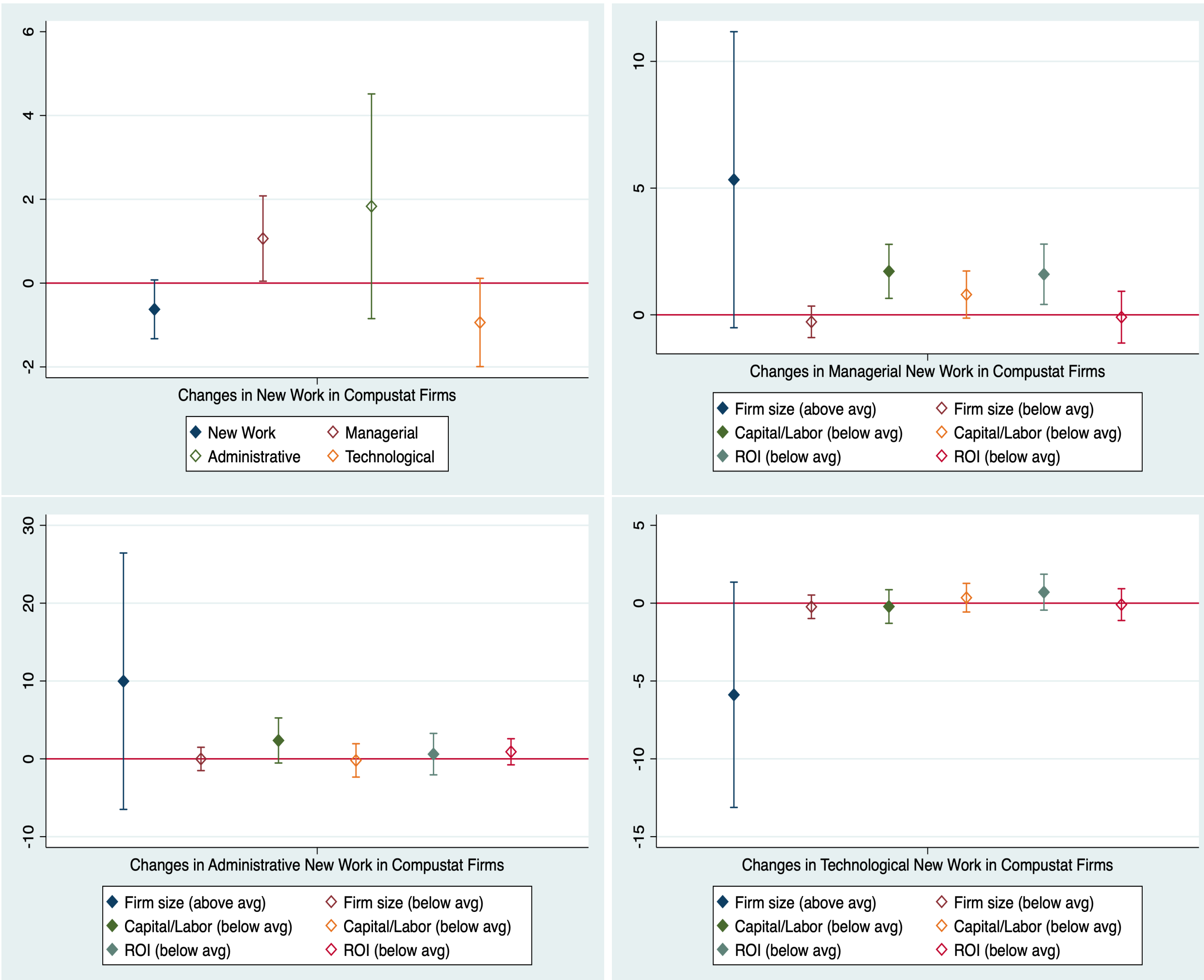

Figure C.3: Changes in New Work

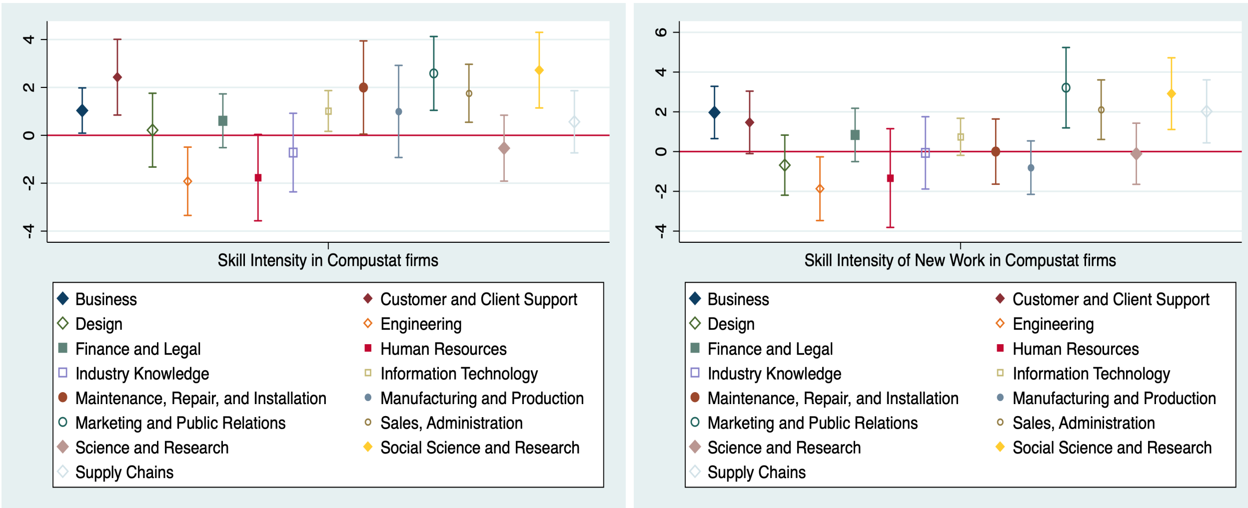

Figure C.4: Skill Demands in Compustat Firms: All (left) vs. New (right)

C.1.5 Results: Skills, All Firms

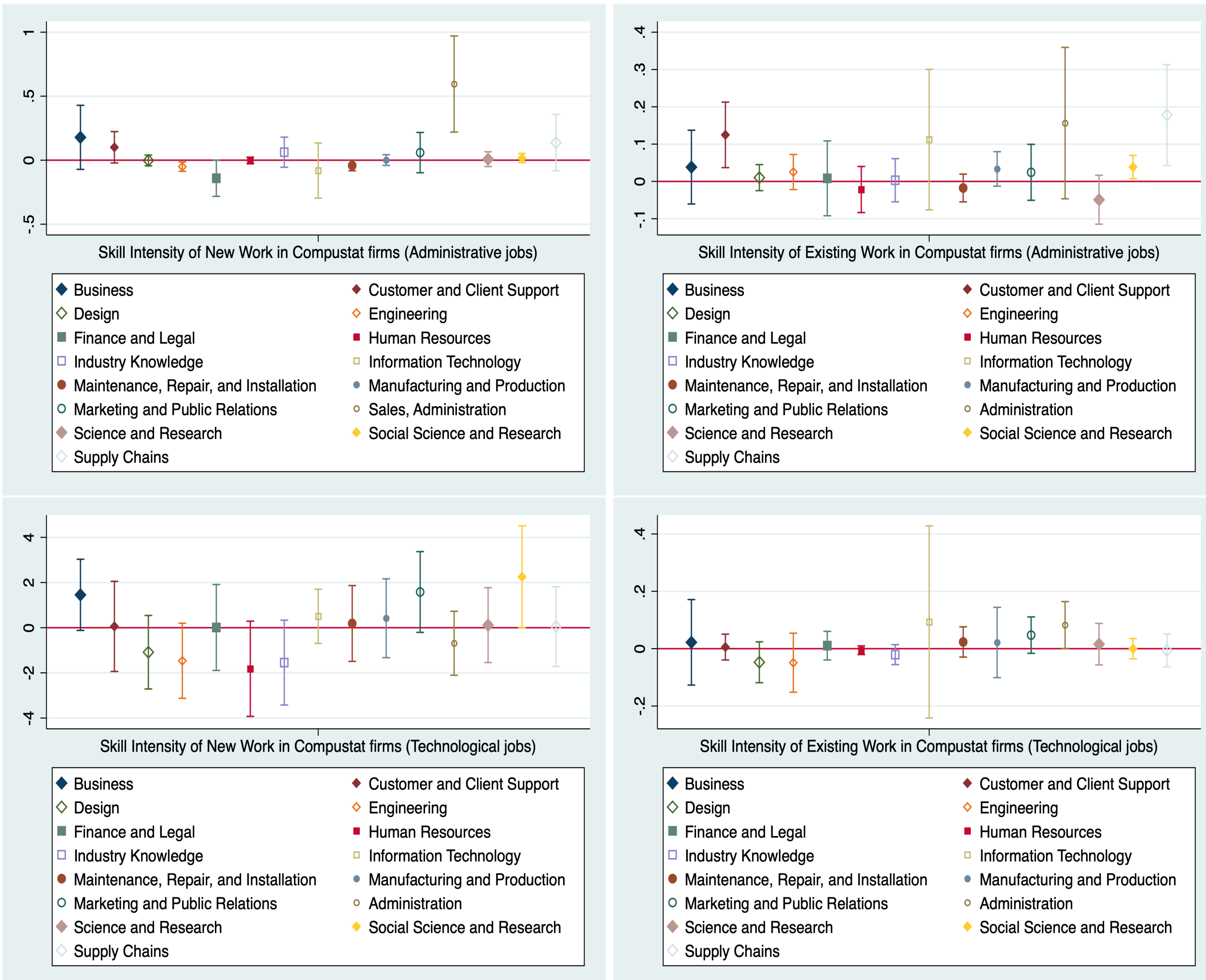

Figure C.5: Skill Demands in New Work by Occupation: New (left) vs. Existing (right)

C.1.6 Results: Skills, By Firm Characteristics (Firm Size)

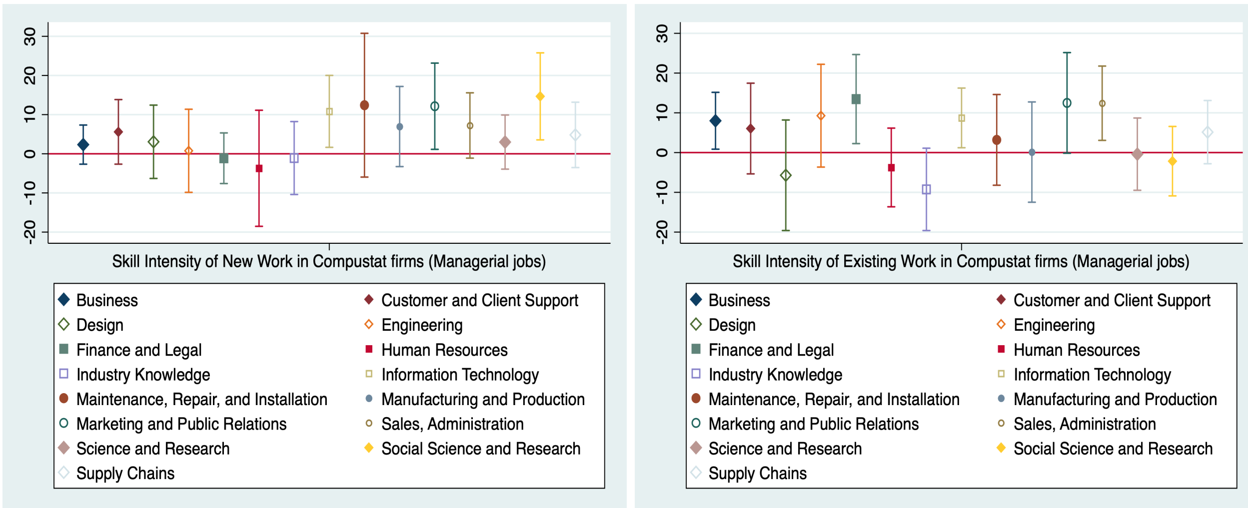

Figure C.6: Skill Demands in Managerial Work: Above (left) vs. Below Avg. (right)

C.1.7 Results: Skills, By Firm Characteristics (Capital per Worker, K/L)

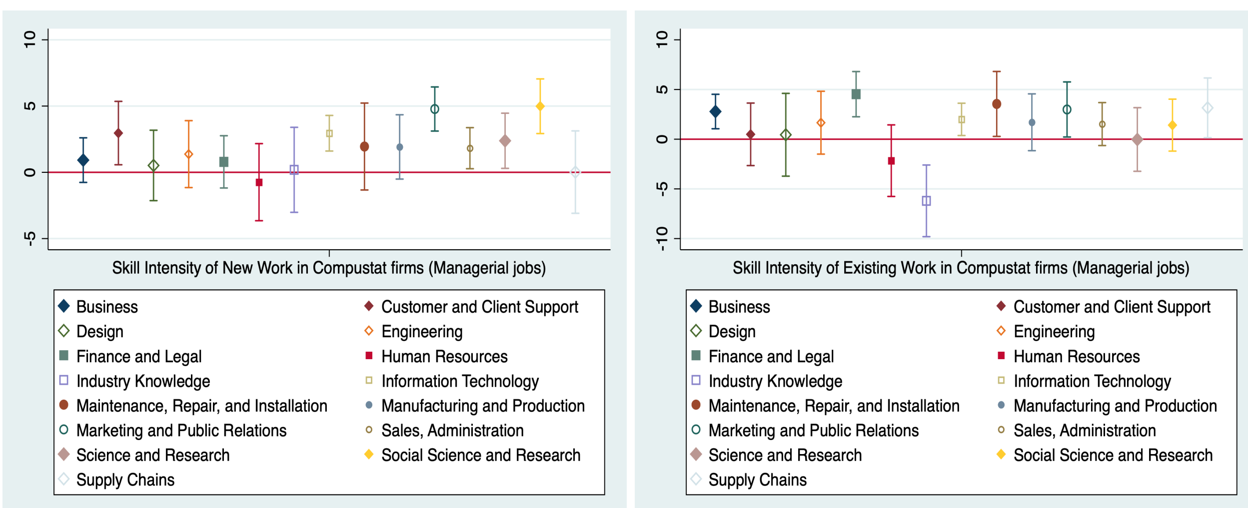

Figure C.7: Skill Demands in Managerial Work: Above (left) vs. Below Avg. (right)

C.1.8 Results: Skills, By Firm Characteristics (ROI)

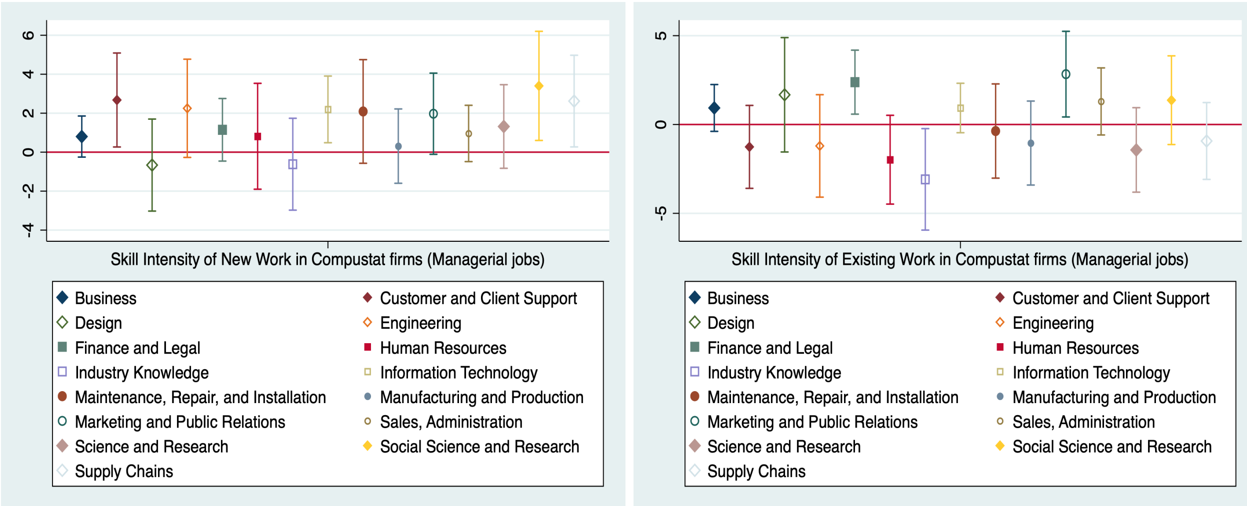

Figure C.8: Skill Demands in Managerial Work: Above (left) vs. Below Avg. (right)

C.2 Firm-level Analysis: TAA Firms

C.2.1 Sample Description

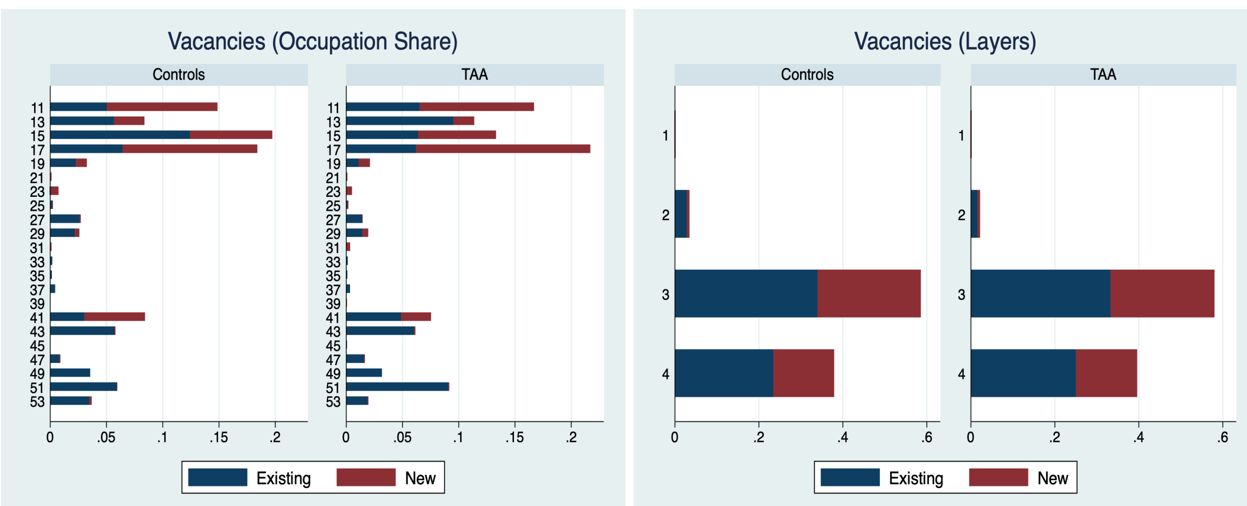

Figure C.9: Occupations and Layers by TAA status

C.2.2 Sample Description: Balance Check with Controls

	(1)	(2)
New Work	-0.00626	
	(0.0315)	
Average No. of Job Ads		-0.00237
		(0.00212)
Observations	693	693
R-squared	0.394	0.509

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.4: Comparing TAA Sample with Controls

C.2.3 Sample Description: cp. Compustat

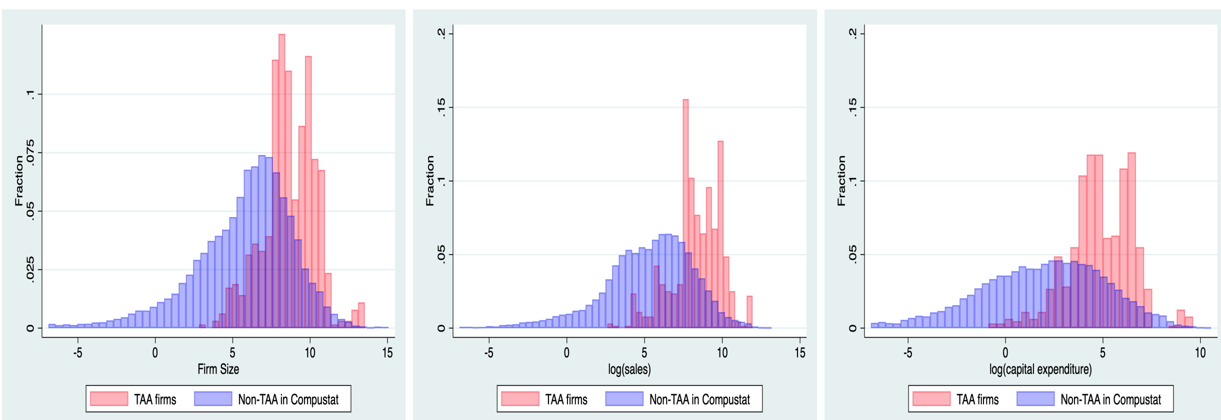

Figure C.10: TAA firms matched to Compustat firms

C.2.4 Job Demands

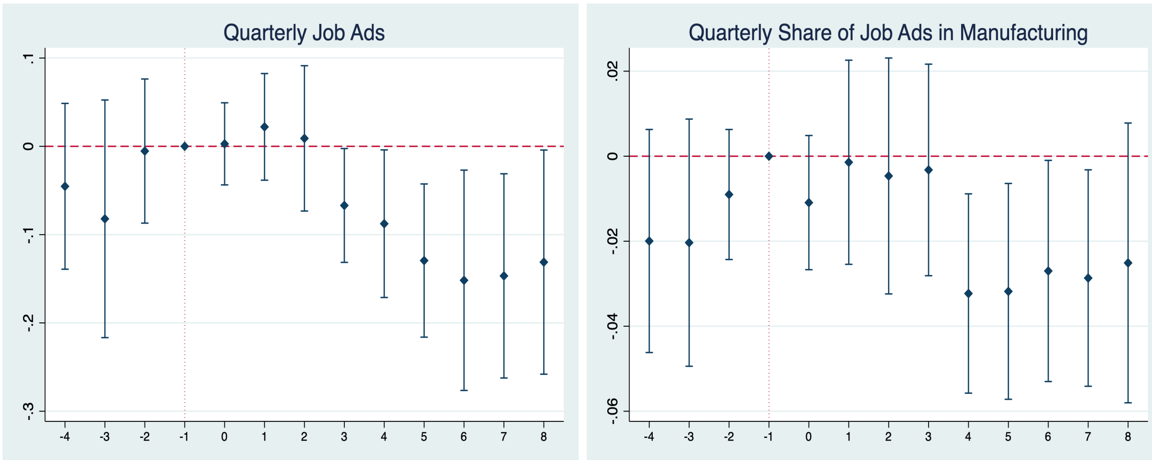

Figure C.11: Job Demands (left) and Share of Job Demands in Manufacturing (right)

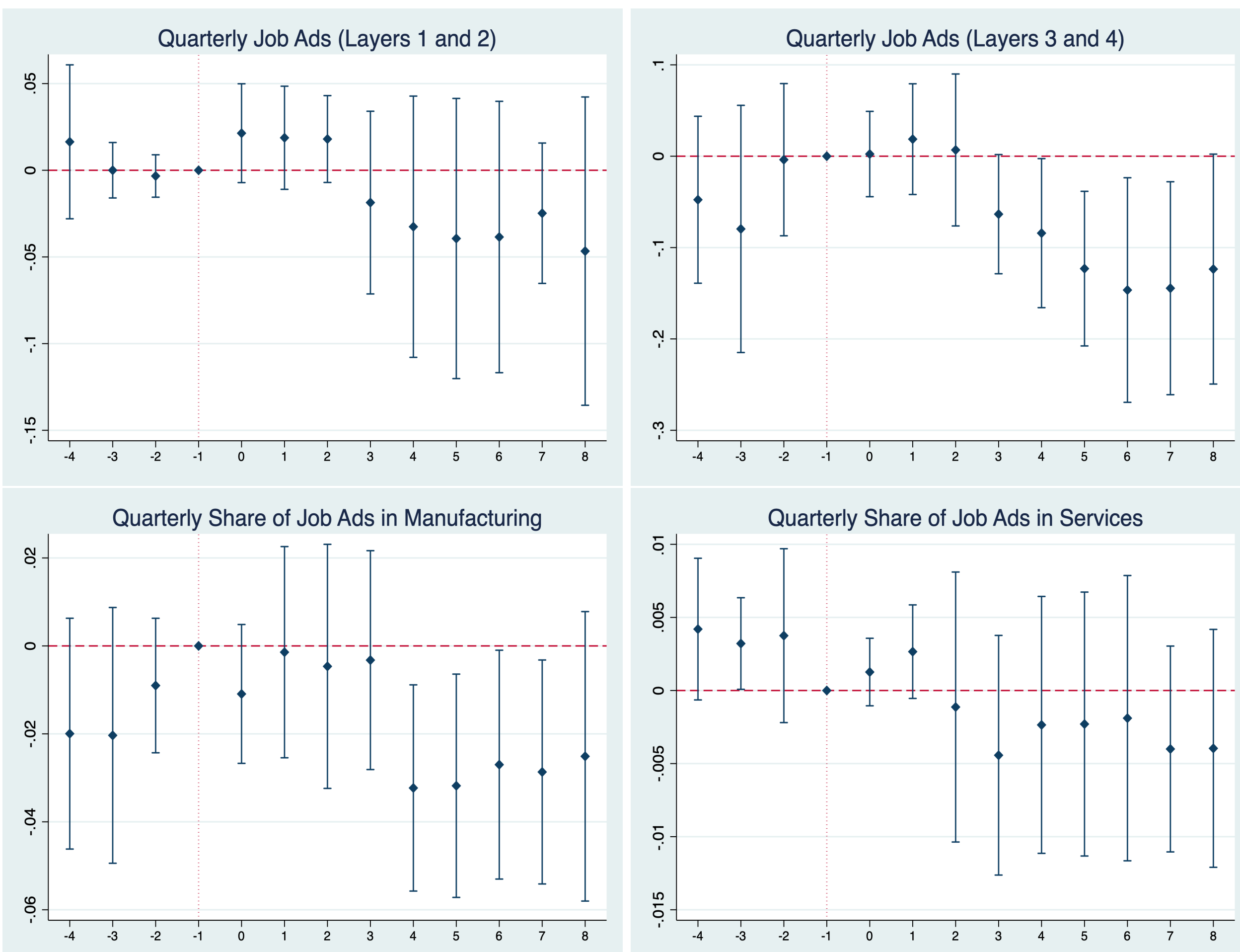

Figure C.12: Job Demands in Top (left) and Bottom (right) Layers

C.2.5 Job Demands in New Work by Occupation Type

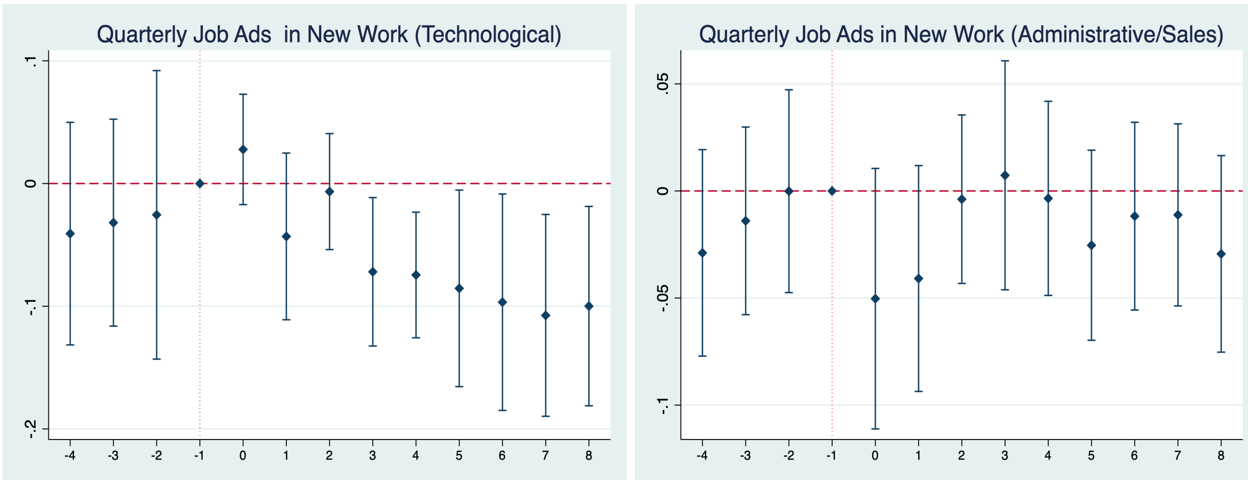

Figure C.13: Job Demands in New Work: Technological (left), Administrative (right)

C.2.6 Newly Observed Skill Demands in New Work by Occupation Type

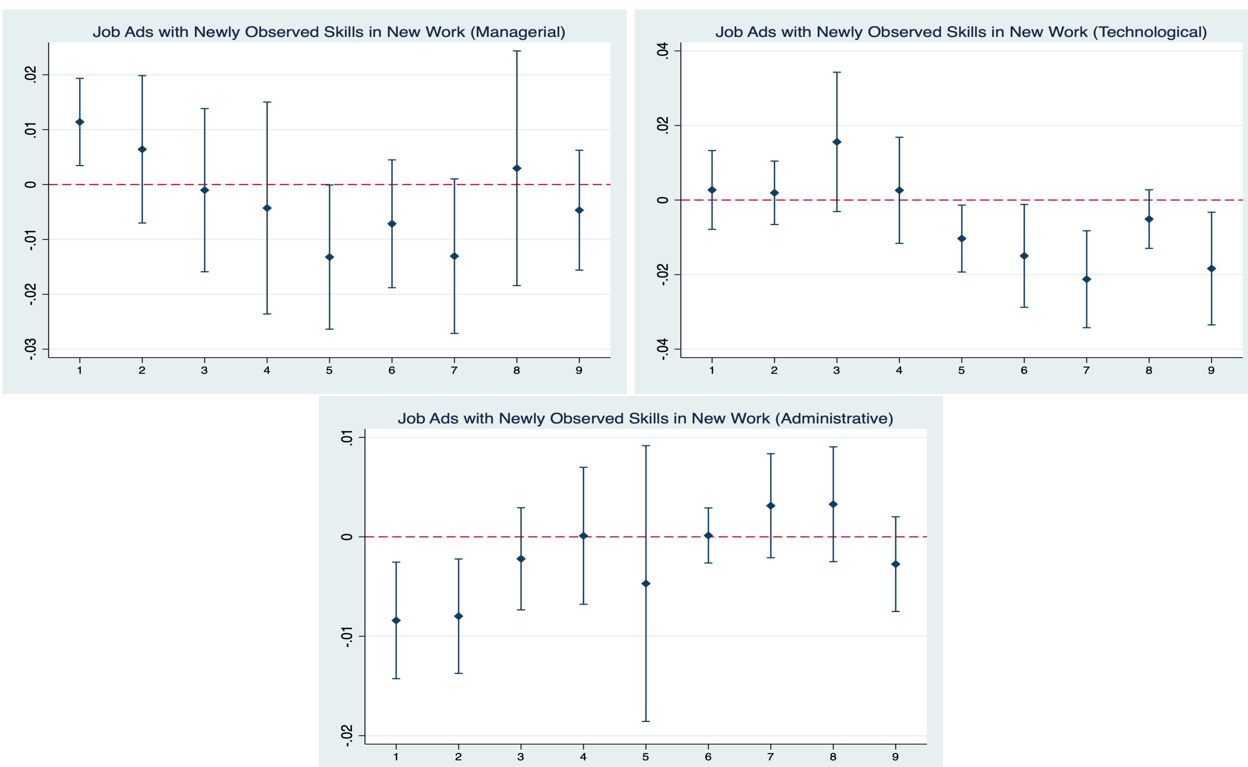

Figure C.14: Newly Observed Skill Demands in New Work

C.2.7 Skill Intensity of Managerial New Work in Manufacturing and Production

In the interest of space, I only include the results for those that show significant results.[61]

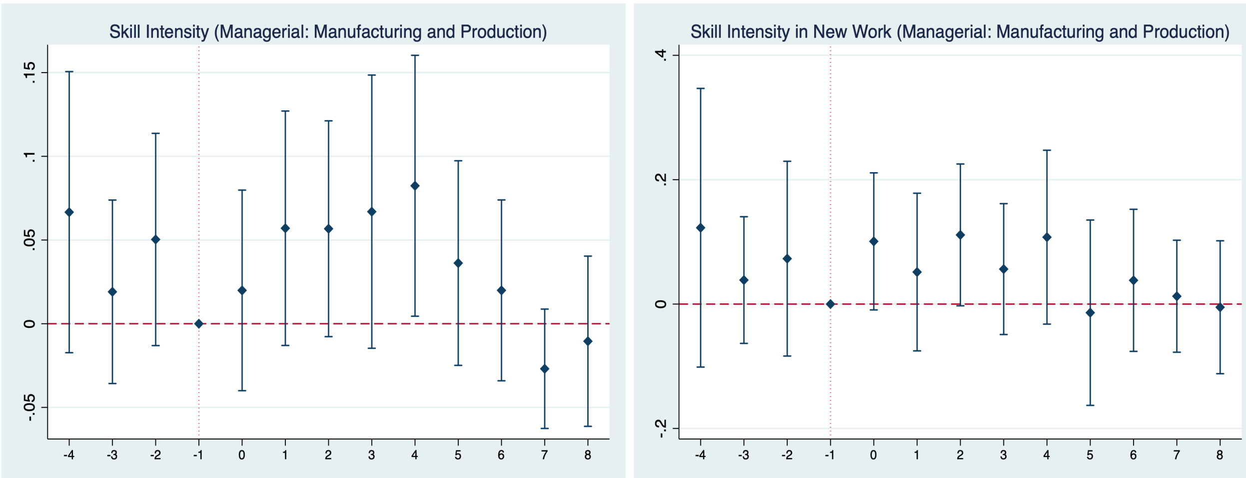

Figure C.15: Manufacturing and Production in Managerial: All (left), New (right)

[61] The rest of the results are available upon request.