

# Trade-Induced Creation of New Work

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## Abstract

This paper studies the effect of import competition on a previously unexplored dimension of U.S. local labor market adjustments: the emergence of new work. New work refers to jobs that involve tasks employing new knowledge, skills, and technologies. To identify new work, I exploit the emergence of new job titles in each decade (1990-2016) using word embedding models to capture those that reflect new tasks. New work in the post-2000's exhibits concentration in high-skill professionals and occupations in managerial roles; and shows intensity in non-routine tasks, excluding physical and manual work. I find that greater exposure to Chinese imports persistently increases managerial/organizational new work over time, yet deters technological new work in U.S. local labor markets.

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# 1 Introduction

A number of studies examining the labor market consequences of trade shocks have significantly improved our understanding of the role of globalization in the evolution of labor market inequality (e.g. [Feenstra, 2010](#); [Autor et al., 2013](#), etc.). More recently, further analyses on the labor market adjustment process have identified various factors<sup>1</sup> that explain why trade shocks are not easily arbitrated away, but in fact, persist and even amplify over time ([Mclaren, 2017](#)). Firm-level adjustments, in particular, to re-optimize production and organization are important channels through which import shocks significantly shift local labor market demands.

The restructuring process can result in shifts in the composition of tasks performed in-house. However, it can further induce firms to employ new knowledge, skills, and technologies, in other words, adapt new work on various aspects of firm operation: product development, business strategies, management and organizational practices, etc. Identifying and measuring new work can be an important step forward in understanding the tasks and skills newly demanded by firms in response to various shocks including import competition. In addition, as transitions to applying new work shift skill demand biased towards a specific set of skills, any possible complementarity between skill and the ability to perform new tasks potentially magnifies the disparity in post-shock labor market experiences and outcomes across worker groups.<sup>2</sup>

In this paper, I study the effect of import competition on a previously unexplored dimension of U.S. local labor market adjustments: the emergence of new work. To identify new work, I exploit the emergence of new job titles in each decade.<sup>3</sup> Building on [Lin \(2011\)](#), I hypothesize that job titles reflect the required content of skills and task. In terms of identification strategy, I employ word embedding models (Continuous Bag of Words) to (i) measure pairwise similarity (distance) between job titles based on the context of their appearances in large texts such as Google news, Wikipedia, etc. and (ii) identify the newly emerged job titles that significantly differ from all existing job titles in the past.

Next, I combine the constructed measure of new work with the census microdata in IPUMS-USA to examine various features of work that emerged after 2000. As job titles are not observed in the census microdata, I construct new work intensity scores at the level of

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<sup>1</sup>In addition to mobility cost, [Dix-Carneiro and Kovak \(2017\)](#) show how the short-run effects of trade greatly underestimate the long-run effects due to additional channels of agglomeration and slow capital adjustments.

<sup>2</sup>[Autor et al. \(2014\)](#) find that low-wage individuals relocate within manufacturing and even continue to stay in industries that face increasing import competitions from China. This is contrary to the high-wage individuals who manage to quickly move out of the trade exposed sector, minimizing loss in earnings.

<sup>3</sup>I use job titles data published in 1980, 1990 (Dictionary of Occupation Titles), 2000 (Census Bureau's Classified Index of Industries and Occupations), and 2016 (O\*NET database)

detailed occupation codes. First, I find that college-educated workers consist of a significant and increasing share of employment in new work. In fact, observationally similar workers hired in occupations with different new work intensities show a significant difference in wages, which also increases over time. Second, in terms of skill characteristics, I find that new work shows intensity in non-routine tasks, excluding physical and manual work; and employ more technologies compared to existing ones. A significant share of workers in new work are employed in professional occupations as well as managerial and technical, sales, administrative support work. Third, new work in post-2000's exhibit great concentration in professional services while finance and insurance, manufacturing industries also consist a nontrivial share.

Has increased market competition due to China's entry to the world economy post-2000's induced any adaptation of new work in local labor markets? If so, in what aspect of the firm operation do we see more innovation being adapted? To answer these questions, I use regional variations in the exposure to Chinese imports and examine changes in the share of new work relative to that of 2000. I follow [Pierce and Schott \(2016, 2020\)](#) to construct regional exposures to import shocks using the industry-level gaps in the Normal Trade Relations (NTR) rates and the non-NTR rates on Chinese imports before China's accession to WTO.<sup>4</sup> Industries with a greater magnitude in the NTR gaps were expected to be more affected by China's entry to the world market, and consequently, local labor markets with heavy reliance on these hard hit industries being more exposed to the shock.

I also examine whether Chinese imports have any heterogeneous effects across occupation groups in new work. In particular, I focus on new work in managerial occupations that closely reflect innovation in management practices and firm organization; and technological ones related to firm activities in R&D and developing patents or new product lines. This is a more informative exercise compared to analyzing the average effect of new work across all occupations, as the possible mechanisms through which intensified competition affects innovation can differ significantly depending on the type of innovation activities (product, process, management).

On the one hand, studies on X-efficiency ([Leibenstein, 1978](#); [Chen and Steinwender, 2017](#)) argue that intensified competition can incentivize firms to reduce managerial slack and exert more effort in improving managerial practices. There are also influential work focusing on management as a technology that affects firm productivity and demonstrate the positive relationship between competition and management practices ([Bloom and Van Reenen, 2007, 2010](#); [Bloom et al., 2013, 2016b](#)). On the other hand, theories on techno-

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<sup>4</sup>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 ([Pierce and Schott, 2016](#)).

logical innovations (Aghion et al., 2005) suggest how the impact is different depending on the distribution of technological advancements across firms. That is, while firms that are in neck-in-neck competition have greater incentives to innovate in order to escape competition, technological laggards with no hopes of catching up would decrease investments in innovation as increased competition already reduces profits.

My baseline results show a significantly positive and persistent effect of import shocks on the share of new work in managerial and organizational occupations relative to the reference group, which resonates with the theoretical implications in existing studies. On the other hand, I find a negative and persistent effect on the changes in new work in technological occupations. This is similar to what the previous empirical studies find using data in North America (Autor et al., 2020; Hombert and Matray, 2018; Kueng et al., 2016; Xu and Gong, 2017).<sup>5</sup> I do not find any statistically significant effect on changes in new work considering all occupations, which supports the importance of separate analyzing the effects by occupation group.

I also perform several robustness exercises through which I verify the main results. I begin by employing alternative measures of import shocks following Autor et al. (2013) using changes in Chinese import flows directly. In order to deal with endogeneity issues that may arise from unobserved shocks to U.S. product demand, I instrument Chinese imports to U.S. using Chinese imports to eight other high-wage countries. Next, in attempts to check the sensitivity of the results due to measurement error in new work, I iterate the exercise using an alternative new work intensity measure based on O\*NET's New and Emerging (N&E) Occupations.<sup>6</sup> Lastly, I conduct a falsification exercise similar to Autor et al. (2013) and Hakobyan and McLaren (2016) to detect any presence of confounding factors that affect both changes in the share of new work in management or R&D, and how local labor markets are exposed to Chinese imports.

This paper relates to several different strands of literature. First, it contributes to the studies looking into local labor market adjustments to trade shocks. Existing work have extensively focused on adjustment patterns to trade shocks in terms of estimating mobility costs (Artuc et al., 2010; Artuc and McLaren, 2015), identifying the interaction of other factors (Dix-Carneiro and Kovak, 2017; Dix-Carneiro, 2014), and examining long-term labor

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<sup>5</sup>As suggested by theories looking into competition and technological innovation, the results differ across countries: the effects are positive in Europe (Bloom et al., 2016a), China (Brandt et al., 2017; Bombardini et al., 2018), South Korea (Ahn et al., 2018); and negative in North America (Chakravorty et al. (2017) finds insignificant effects of Chinese import competition on patent counts.)

<sup>6</sup>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. I also use this measure to check the validity of the constructed new work measure in various ways: new work intensive occupation titles, occupational and industry distribution.

market and life outcomes ([Autor et al., 2014, 2019](#); [Pierce and Schott, 2020](#)). In this paper, I focus on how firm-level re-optimizing strategies in response to import shocks affect local labor market demands through new work. And given the skill-complementarity of new work, the analysis also speaks to important implications on inequality in the post-shock labor market experience across worker groups.

Second, it is related to a recent body of work empirically studying the impact of import competition on innovation. Conventional measures of firm innovation activities focus on R&D expenditure, patent citations/counts ([Cohen, 2010](#); [Kogan et al., 2017](#); [Hall et al., 2005](#); [Moser, 2016](#), etc.), or survey on business strategies ([Kueng et al., 2016](#)). In this paper, I argue that measuring innovation of different types by examining new work in different occupation categories provides a more comprehensive analysis on examining various innovation activities.

Finally, it relates to a small yet important strand of studies on new work. [Lin \(2011\)](#) is the first to use job titles to identify new work in the data where he focuses on examining the role of agglomeration in the adaptations of new work. While his paper uses revisions to occupation classifications reported in census documents (1980-2000) to construct data on new work, this strategy can be employed to study data from different sources where revision documents are not readily available. More recently, [Atalay and Sarada \(2020\)](#) uses extensive data on newspaper ads and identifies new work using the number of job title appearances over time. They propose new work as a measure of technology adoption and study firm-level characteristics associated with decisions to adopt new technology.

This paper is organized as follows. In section 2, I discuss sources of data and measurement of new work; and further present empirical facts of new work for post-2000's. In section 3, I empirically examine the effects of Chinese import shocks on emergences of new work in local labor markets. I also include several robustness checks. In section 4, I discuss future plans for the study and conclude.

## 2 Data and Construction of Measures

The baseline data is constructed using the Decennial Censuses 1980, 1990, 2000 5% sample and American Community Surveys (ACS) 2005-2018 (Ruggles et al., 2020). I use job titles in 1980, 1990, and 2000, constructed by Lin (2011),<sup>7</sup> which are originally published in the Dictionary of Occupation Titles, the Census Bureau’s Classified Index of Industries and Occupations respectively. I expand the job title data by adding those published in 2016 in the O\*NET database,<sup>8</sup> to include information on the recent decade.

I also use online job vacancy ads (2010-2020) from Burning Glass Technologies (henceforth BG), which provides the near-universe of online job ads collected from around 40,000 job boards. Each posting contains detailed information on the job characteristics (employer name, occupation, geography, skill and education requirements, wage and non-wage benefits, etc.). The data overrepresents occupations and industries requiring greater skill (Hershbein and Kahn, 2018). While the aggregate number of job ads demonstrates an increasing trend, the occupation and industry distributions remain stable over time.

### 2.1 Identification of New Work

Job titles reflect the content of skill, task, and responsibilities at workplace. The need to create new job titles may arise as the production process requires an application of new knowledge and technologies; or a novel combination of tasks due to technological change, innovation in management, changes in the firm organization, etc. Building on Lin (2011), I exploit the emergence of new job titles in each decade to identify new work, employing the Continuous Bag of Words (CBOW) model. This strategy allows me to: (i) measure pairwise similarity (distance) between job titles based on the context of their appearances in large texts such as Google news, Wikipedia, etc.; and (ii) identify the newly emerged job titles that significantly differ from all existing job titles in the past.<sup>9</sup>

The CBOW model is one of the Word2Vec algorithms which provide numerical representations of words. The key is to generate word-specific vectors by examining the surrounding

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<sup>7</sup>I download from the following link: <https://sites.google.com/site/jeffrlin/newwork>.

<sup>8</sup>The ONET publishes, for each SOC code, a list of reported job titles in “Sample of Reported Titles” and “Alternate Titles” sections.

<sup>9</sup>To a certain extent, changes in the occupation classified system itself can reveal information about new work. However, merging and splitting of occupation codes may arise due to other reasons such as growing supply of workers in particular jobs or revisions to improve the classifications. For this reason, Lin (2011) focuses on occupation “titles” which better reveal the task content of jobs and relies on official documents on conversion tables (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) and string matching methods to identify new work.

words appeared in large texts. In other words, the model uses surrounding words as inputs to predict the target word.<sup>10</sup> 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 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.

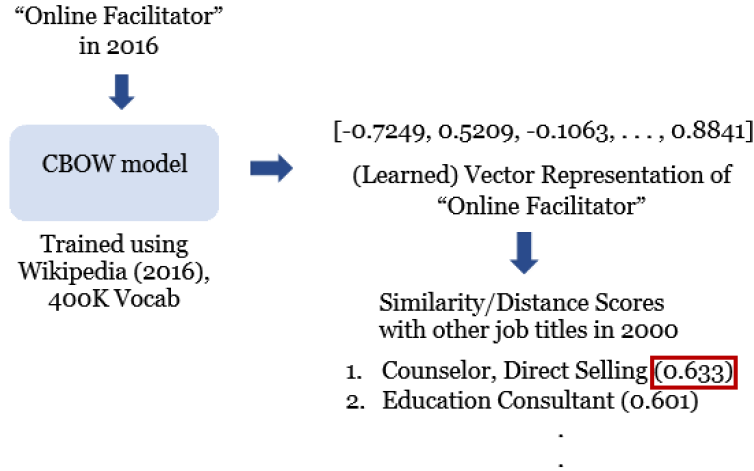


Figure 1: Continuous Bag of Words (CBOW) model on Job Titles

As the CBOW model assigns similar vectors to words that are close in meaning, job titles<sup>11</sup> reflecting similar tasks demonstrate high similarity numerically. Therefore, I define an intensity measure of newness for job titles that captures how distant each job title ( $x$ ) is from all existing ones in the past period ( $y \in Y$ ):

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

By construction, this intensity score is a continuous measure, which can be interpreted as the probability that a particular job title is not observed in the previous period, and therefore, is new. I employ the model on job titles observed in 1980, 1990, 2000, and 2016 and construct new work intensity score for each decade. Due to differences in the data source, the levels and distributions of new work intensity differ over time, as shown in the histograms below. This potentially reflects important changes in the labor market over time,

<sup>10</sup>In Skip-gram, the target word is used to predict the surrounding words.

<sup>11</sup>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; and convert all letters to lower cases.

which may be difficult to separately identify from the source fixed effects. However, the empirical analyses of this paper mainly study new work emerged after 2000 and do not hinge on comparing new work over time.

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 1: Summary Statistics

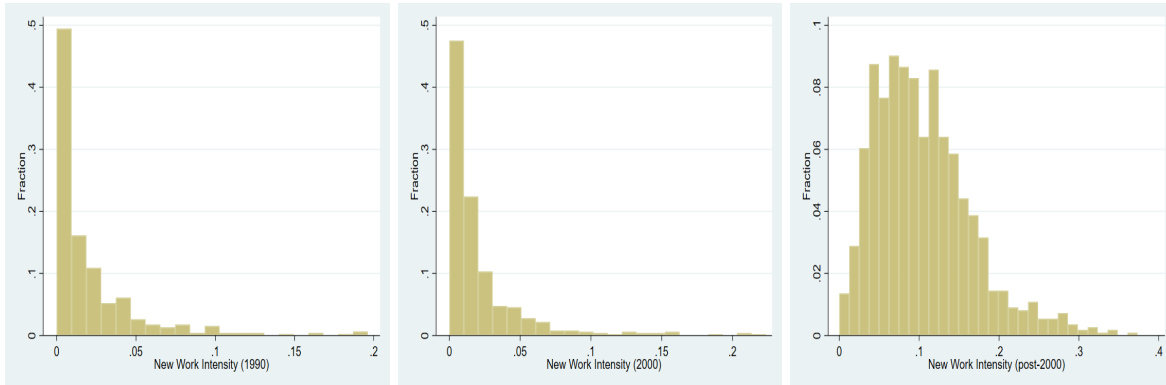


Figure 2: Histogram of New Work Intensity over Time

Nonetheless, past job titles are useful, checking the robustness of the new measure. In particular, I examine the correlations in the new work intensity scores between my measure and new work identified by Lin (2011) for years 1990 and 2000. In Table 2, I show the correlations between the two measures for the two time periods. The correlation coefficients are close to 0.75 at statistical significance level of 1%.<sup>12</sup> As the newness of an occupation title in Lin (2011) is constructed as a binary measure identified using official revision documents, the discrepancy partly stems from comparing a continuous measure to a binary one.

<sup>12</sup>To test the sensitivity of the measure with respect to the type of word embedding models employed, I obtain new work intensity scores using Glove and Fasttext respectively. As shown in Table 2, the value of correlation coefficients, which vary between 0.72 and 0.74, show similar levels to those compared with measures obtained using CBOW.



Employed Text Embedding Methods	1990	2000
CBOw	0.7540*	0.7483*
GloVe <sup>a</sup>	0.7434*	0.7294*
Fasttext <sup>b</sup>	0.7202*	0.7310*

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

<sup>a</sup> Pre-trained word vectors obtained using GloVe, an “unsupervised learning algorithm for obtaining vector representations for words” (Pennington et al., 2014)

<sup>b</sup> Pre-trained word vectors obtained using <https://fasttext.cc/>

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

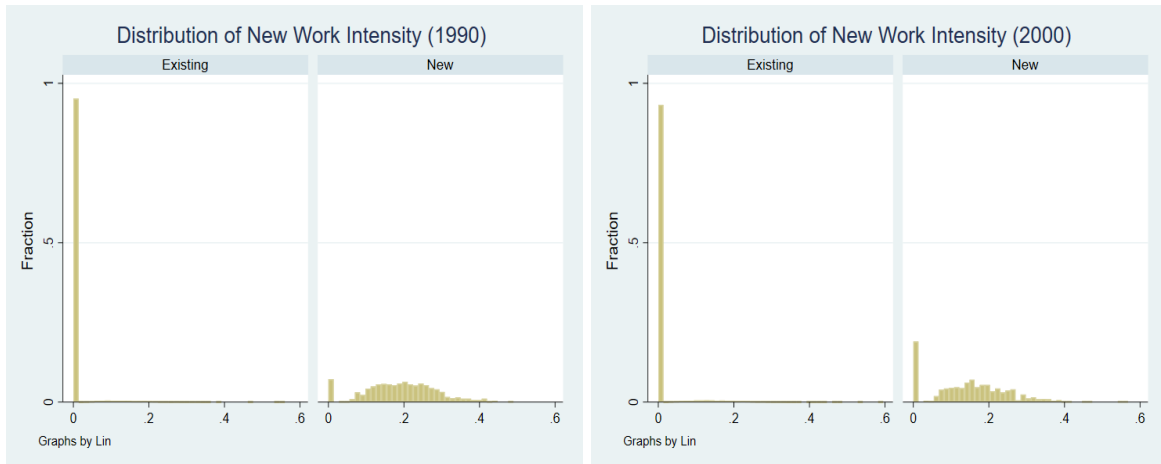


Figure 3: Distribution of Job Titles by New Work Measures of Lin (2011)

As shown in Figure 3, measurement issue is another factor explaining the differences. While more than 95% of what Lin (2011) identifies as new corresponds to a non-zero newness score in my measure, the CBOw model is able to find matching job titles in the past for a small fraction of it.<sup>13</sup> The two methods mostly agree on what is considered as existing work. However, 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 do a manual inspection of titles and draw a threshold below which I assign zero’s to the intensity measure.

As an alternative way to ensure robustness, I use the “New and Emerging (N&E) Occupations” identified in the O\*NET data released in 2006 and 2009 to verify that the empirical analyses in later sections deliver consistent results employing either measure. 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”

<sup>13</sup>Through manual inspection, I find that the direct matching seems to have failed due to the ordering of words, punctuations, conjunctions, and abbreviations.

are classified in this category.<sup>14</sup> Using this data, 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.

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 3: Example New and Emerging Job Titles

## 2.2 Stylized Facts of New Work

To better understand the content of new work, I begin by discussing example job titles that the model identifies with high new work intensity. As shown in Table 4, the nature of new work in different occupation groups reveals substantial heterogeneity, reflecting various channels through which the demand for new work arises. For example, innovation and R&D activities to develop new product lines may require novel tasks among computer scientists or engineers. Also, the adoption of information technology and AI machines/robots 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. Of course, 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.

<sup>14</sup>See <https://www.onetcenter.org/reports/NewEmerging.html> for further details.

Occupation Types	Example Job Titles Identified as New
Managerial (SOC 11, 13, 23)	E-Learning Manager, Brownfield Redevelopment Specialist, Global Supply Chain Director, Demand Generator Manager, Renewable Energy System Finance Specialist, Green Material Value-Added Assessor, Sustainable Business Operations Specialist, International Trade Specialist, Environmental Conflict Manager, Life Care Planner, Data Abstractor
Technological (SOC 15, 17)	Pay-Per-Click Strategist, Search Engine Optimization Strategist, Electronic Transaction Implementer, Data Warehouse Architect, Voice Over Internet Protocol Engineer, Softcopy Photogrammetrist, Green Building Energy Engineer, Underwater Robotacist, Solar Photovoltaic Designer, Manufacturing Production Technician
Admin Support, Sales (SOC 41, 43)	Solar Energy Consultant and Designer, Internet Marketer, Online Content Coordinator, Ocean Export Coordinator, Reprographics Technician, Debug Technician
Production (SOC 49, 51, 53)	Solar Panel Technician, Immersion Metal cleaner, Digital Proofing and Platemaker

Table 4: Example Job Titles with High New Work Intensity Scores by Occupation Types (classified using SOC 2 digits)

The aggregate demand of new work depends on the magnitude of each channel which differentially generates the demand for different new work types across occupations (extensive margin) as well as employment within each job category (intensive margin). In Figure 4, I provide the distributions of new work intensity by 2 digit SOC occupation codes<sup>15</sup> and find significant variation in new work. Note that occupations that require greater skill tend to show a higher average new work intensity scores.

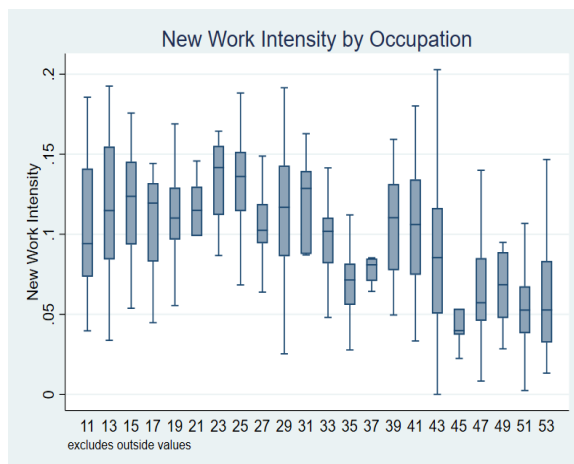


Figure 4: New work intensity by Occupations

Average intensity scores are weighted by occupation-specific national employment using the Occupation Employment Survey in 2010.

<sup>15</sup>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 for more details.

To unpack skill intensity across different skill types, I use rich skill descriptors obtained from O\*NET as well as skill requirements listed in BG job ads. The rest of the empirical analyses I present employs new work intensity measures aggregated at the occupation-level.<sup>16</sup> To further highlight the differences between new and existing work, I work with a binary indicator which identifies occupations in the top quartile of new work intensity scores as new and the rest as existing work.

### 2.2.1 Content of New Work

First, I follow [Deming and Kahn \(2018\)](#) and search for keywords and phrases in BG job ads to examine skill requirements in the following dimension: cognitive, social, character, writing, customer service, project management, people management, financial, computer. To investigate the differences in the intensity of skill demand, I run a series of bivariate ordinary least squares regressions for different skill categories. For each skill category and detailed occupation pair, I compute the share of job ads with the corresponding skill requirement, which is the dependent variable. And the explanatory variable is a binary indicator variable for new work intensity. As shown in Figure 6, occupations intensive in new work show greater demand in different areas of cognitive and social skills, but the differences are insignificant for skills related to customer services and what BG defines as specialized skills.

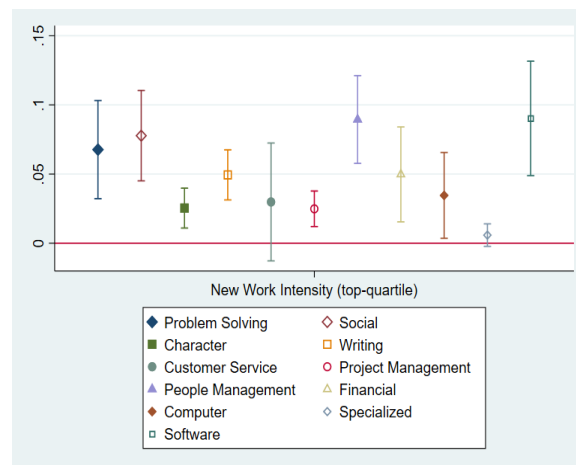


Figure 6: Skill Characteristics of New work: post-2000 (left) and 2000 (right)

An alternative approach to investigate the content of new work is to examine whether new work features intensity in skills that are complementary to recent developments in

<sup>16</sup>This is mainly because the empirical exercises require merging employment data from IPUMS-USA, which record employment at detailed occupations, not job titles level. BG reports job titles in each job vacancy ad; however, the current work does not utilize titles information from BG.

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 different categories of skill: non-routine cognitive, non-routine analytical, non-routine manual, non-routine interpersonal, routine cognitive, routine manual.<sup>17</sup> The dependent variables are now average scores in each skill category. As shown in Figure 7 (left),<sup>18</sup> new work emerged post-2000's 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. I also provide an over time comparison by running the same regression for new work emerged between 1990 and 2000 (Figure 7, right). Results are qualitatively similar; however, the magnitudes of the coefficients are greater in all skill categories for the analysis of new work emerged after 2000. In the Appendix, 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.

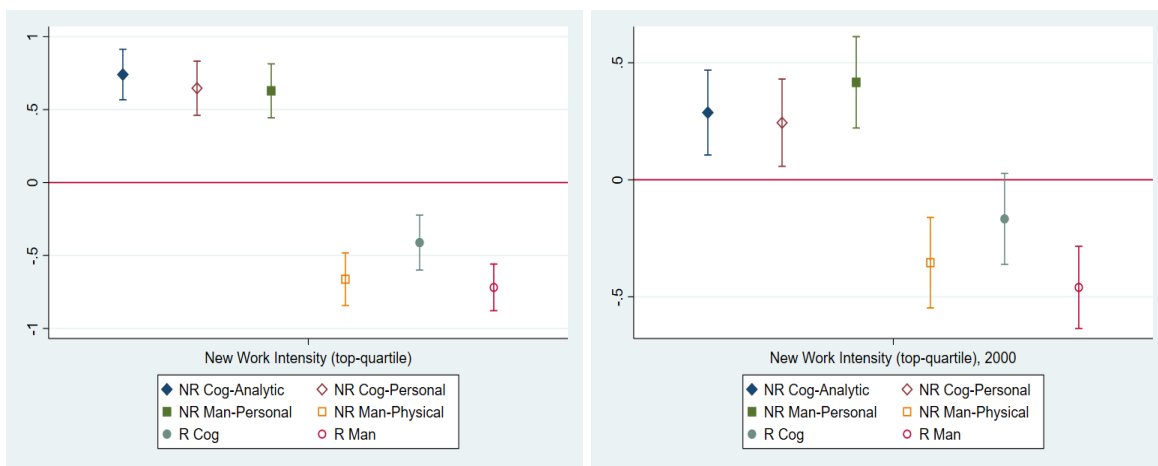


Figure 7: Skill Characteristics of New work: post-2000 (left) and 2000 (right)

### 2.2.2 Skill Premium of New Work

The content of new work examined so far implies important complementarities with individual ability to perform tasks requiring greater skill in various aspects, particularly those that complement recent technological changes. Hence, it is not surprising to find a concentration of workers with college education and beyond in new work employment: the

<sup>17</sup>All measures are normalized to have mean zero.

<sup>18</sup>In the Appendix, I include results repeat the exercises employing measures of new work identified using N&E occupations, which delivers quantitatively similar facts.

share has increased since 2000 and exceeds 50% in 2015 (Figure 8).<sup>19</sup>

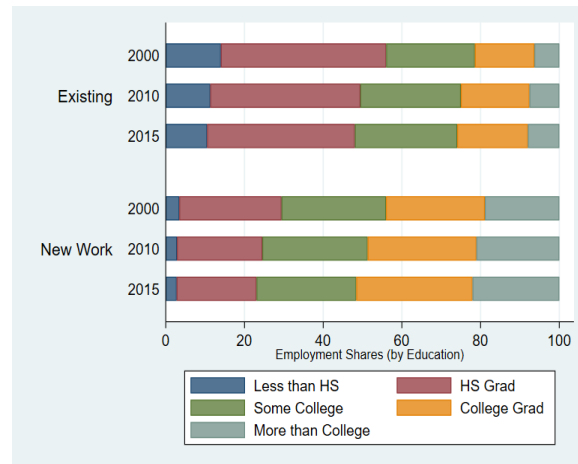


Figure 8: Employment shares of New and Existing Work

This is consistently shown in Figure 9 (left) where I plot the new work intensity score constructed at the occupation level against the wage percentile in year 2015.<sup>20</sup> Using wage as a proxy for skill, the implication remains the same: high-skill workers tend to be employed in occupations intensive in new work. Moreover, I find that there is a positive and significant correlation between occupational wage growth between 2000 and 2015 and the occupational intensity in new work (Figure 9, right).

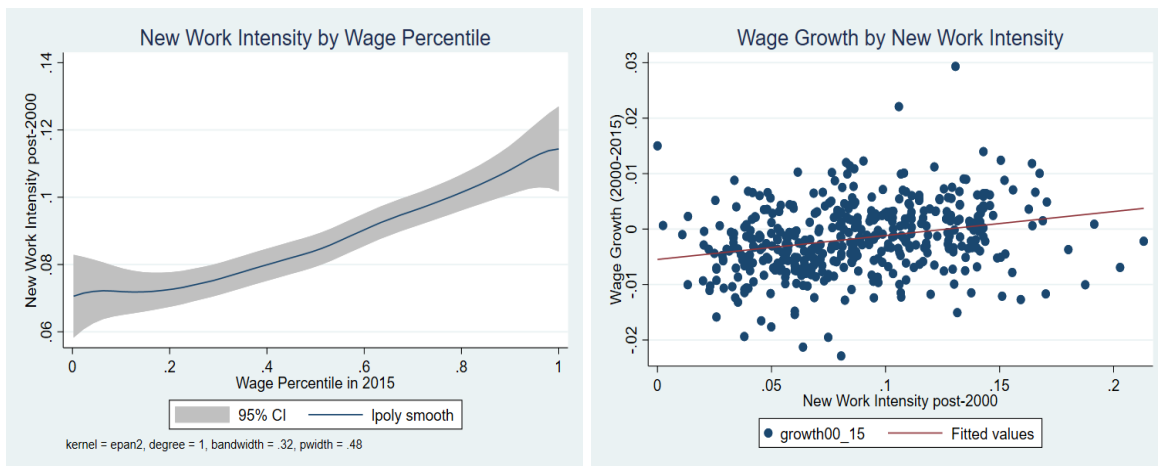


Figure 9: New Work and Skill Percentile (left), Wage Growth (right)

<sup>19</sup>In the Appendix, I 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.

<sup>20</sup>Wages are CPI-adjusted to the base year of 2000.

To further examine the extent to which new work intensity explains variations in wages, I regress individual log(wages) on new work intensity scores. For columns (1) and (2) in Table 5, I pool individual data on wage for years 2005-2018 using the Census sample and ACS respectively. In columns (3)-(6), the analysis is done cross-sectionally focusing on a single year: for (3) and (4), I use data for year 2010; for (5) and (6), year 2015. 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 controls and industry fixed effects. Standard errors are clustered at the 3 digit census occupation-level.

	(1)	(2)	(3)	(4)	(5)	(6)
New Work	4.222*** (0.792)	2.037*** (0.427)	4.177*** (0.788)	1.963*** (0.428)	4.234*** (0.807)	2.094*** (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

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

<sup>a</sup> 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 5: Wage regressions for New Work post-2000's

Examining columns (1)-(6), 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% increase in wages for otherwise observationally similar workers. Comparing those in occupations with new work intensity scores at the 5th and 95th percentile, the difference in new work intensity (0.137) explains wage differences by 28%. As shown in columns (4) and (6), the estimated wage premium is larger in year 2015 compared to 2010: one standard deviation increase in new work intensity score is associated with 12.5% in 2010 and 0.9 percentage points higher in 2015.<sup>21</sup> The significant

<sup>21</sup>In the Appendix, 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

skill premium of new work further highlights its potential consequences on inequality: the gap between those with comparative advantage in adapting to new tasks and those without increases in job opportunities and wage compensation.

So far, I have examined how new work is identified in the data, what the skill content is, and why its adaptation matters from the perspective of labor market inequality. In the next section, I discuss what induces the adaptation of new work, focusing on the role of globalization.

### 3 Import Competition and New Work

Examining the employment distribution across broad industry categories, I find that workers employed in new work intensive jobs are mainly concentrated in professional services. It is worth mentioning the nontrivial share of manufacturing in the new work employment, particularly given the stark decline in manufacturing employment in the past few decades (Bernard et al., 2006; Acemoglu et al., 2015; Autor et al., 2016; Pierce and Schott, 2016, etc.). Taking a closer look at the distribution of new work within the manufacturing sector, I find that employment of new work is concentrated in high-skill professionals, managers, and administrative occupations, though a significant share of employment consists of operators, fabricators and laborers.

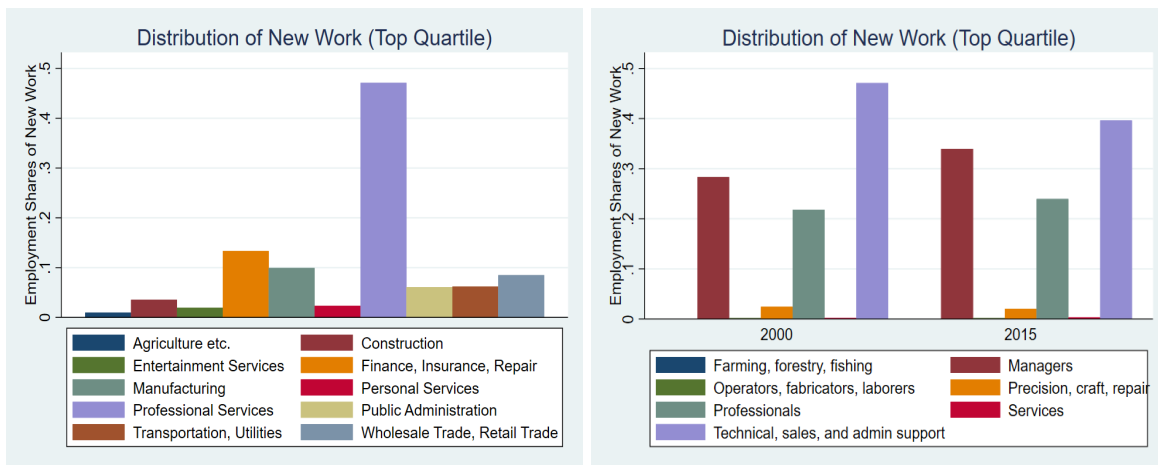


Figure 10: New Work by Broad Occupation (left) and Industry (right) Groups (year = 2010)

intensity measures constructed using the CBOW model, comparing similarity scores between job titles from the previous decade respectively. I obtain qualitatively similar results using measures constructed by Lin (2011).



### 3.1 Possible Mechanisms

There are various mechanisms<sup>22</sup> through which import competition can affect the extent to which firms employ new knowledge, skills, and technologies in various aspects of firm operation: product development, business strategies, organization of production, etc. As for new work in technological jobs that closely reflect firms' operation in R&D and developing patents or new product lines, existing theories (Aghion et al., 2005) provide possible mechanisms in which the impact differs depending the distribution of technological advancements across firms.<sup>23</sup>

Mechanisms suggested by the literature on X-efficiency and firm organization are potentially useful in investigating changes in the firm-level demand of new work in managerial and administrative occupations: innovation in management practices and firm organization. Studies on X-efficiency (Leibenstein, 1978; Chen and Steinwender, 2017) argue that intensified competition may incentivize firms to reduce managerial slack and exert more effort in improving managerial practices. And there are also influential work focusing on management as a technology that affects firm productivity and demonstrate the positive relationship between competition and management (Bloom and Van Reenen, 2007, 2010; Bloom et al., 2013, 2016b). Firm-level demand in hiring jobs that newly combines managerial tasks may arise due to firms' restructuring the organization or hierarchical structure of the firm in response to import shocks (Caliendo et al., 2020b,a).

It is important to note that any complementarity between import competition at the product market level and technology adoption or offshoring/outsourcing (Bernard et al., 2018) which effectively alters the set of tasks performed in-house can further increase the demand in new work. Therefore, controlling for these channels would be important in following analyses. In addition, the average effect of competition on new work is also driven by entry and exit of firms where the low-productivity firms select out of the market. While the data does not allow us to observe these channels of creative destruction competition possibly induces, it is important to keep this aspect in mind with the subsequent analyses.

### 3.2 Identification of Import Competition

To identify import competition, I exploit China's unprecedented emergence in the world economy in early 2000's (Autor et al., 2016) using the industry-level gaps in the Normal Trade Relations (NTR) rates and the non-NTR rates (Pierce and Schott, 2016). Upon China's

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<sup>22</sup>Shu and Steinwender (2018) provides an extensive review on the impact of trade on firm productivity and innovation.

<sup>23</sup>While firms that are in neck-in-neck competition have greater incentives to innovate in order to escape competition, technological laggards with no hopes of catching up would decrease investments in innovation as increased competition already reduces profits.

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, therefore, were expected to be more affected by China’s entry to the world market, and consequently, local labor markets with heavy reliance on these hard hit industries being more exposed to the shock.

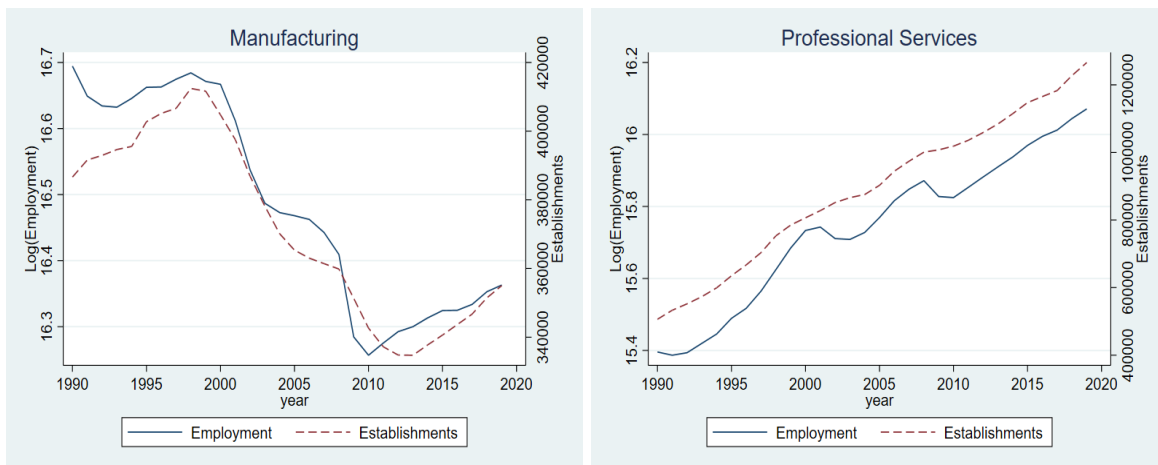


Figure 11: Trends in employment and establishments (Data Source: QCEW 1990-2019)

### 3.3 Empirical Specification

Similar to [Topalova \(2010\)](#), [Kovak \(2013\)](#), [Pierce and Schott \(2020\)](#), the local labor market exposure measure is constructed apportioning trade shocks using local initial industry compositions,

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

where the  $\text{NTR Gap}_{j,1999}$  is constructed measuring the difference between the non-NTR rate and the NTR rate for industry  $j$  in 1999; and further weighted by the industry shares in the tradable sector in commuting zone  $i$  in year 2000.<sup>24</sup> Note that the measure is time-invariant. As noted in [Pierce and Schott \(2016\)](#) and [Handley and Limao \(2017\)](#), variation in the NTR gap is driven by the initial rates set in 1930, which mitigates endogeneity concerns.

Using the local labor market import exposure measures, I first look into the magnitude of the China shock on local manufacturing employment and wages over time (1990-2018)

<sup>24</sup>Following [Autor et al. \(2013\)](#), I use the County Business Patterns data to construct industry mixes in each commuting zone.

by running the following regression for each year:

$$\Delta y_{it,2000} = \beta_{0t} + \beta_{1t} \text{NTR Gap}_{i,1999} + \eta_{st} + e_{it} \quad (3)$$

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  $\eta_{st}$  are the state fixed effects. Due to data availability for years 1991-2004 in IPUMS-USA, I use employment and wage data from QCEW for this exercise. In the following graph, I plot the  $\beta_1$  coefficients and show how the negative effects on U.S. local manufacturing employment and wages demonstrate persistence over time. [Autor et al. \(2014\)](#) discusses heterogenous adjustment patterns across worker groups where low-wage and high-wage individuals differ in their post-China shock response<sup>25</sup> which constitutes an important channel through which the import shocks persist over time. The magnified impact over time in the above results resonate with [Dix-Carneiro and Kovak \(2017\)](#), which shows how the prolonged effects of trade on the Brazilian labor market has amplified in magnitude over 20 years.

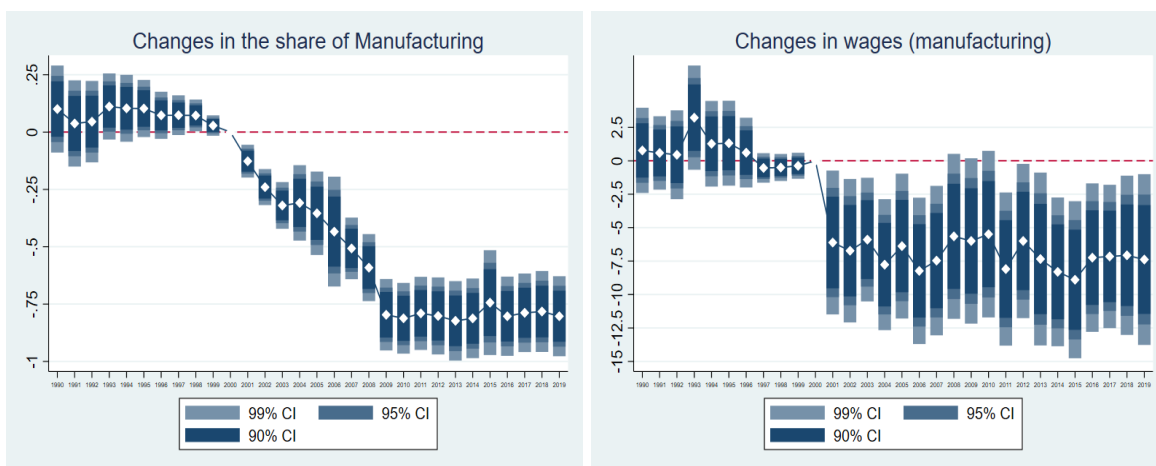


Figure 12: Changes in Manufacturing Employment and Wages (Data Source: QCEW 1990-2019)

Next, I turn to the baseline specification to study whether local labor market exposures to Chinese imports have induced adaptation of new work and the coefficient of interest is a vector of  $\beta_1$  estimated for the sample period:

$$\Delta y_{iot,2000} = \beta_0 + [\text{NTR Gap}_{i,1999} \times I^t] \beta_1 + I^t + \mathbf{X}'_{i,2000} \beta_2 + \eta_R + e_{iot} \quad (4)$$

The dependent variable  $\Delta y_{iot}$  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

<sup>25</sup>They find that low-wage individuals relocate within manufacturing and even continue to stay in industries that face increasing import competitions from China. This is contrary to the high-wage individuals who manage to quickly move out of the trade exposed sector, minimizing loss in earnings.

2000. Shares are constructed focusing on occupations in the top quartile of new work intensity. I control for commuting zone specific characteristics in 2000.<sup>26</sup> It is important to note that any complementarity between import competition at the product market level and technology adoption or offshoring (Bernard et al., 2018) which effectively alters the set of tasks performed in-house can further increase the demand in new work. Therefore, I additionally include the initial share of routine-intensive occupations and that of offshorable occupations as controls. Following Autor and Dorn (2013), I construct occupational indices of routineness and offshorability and define occupations at the top quartile of each index as routine and offshorable respectively. As increased levels of competitions can drive out small and less productive firms, which would change the average effects even without any changes from surviving firms, I add changes in the number of operating establishments at the commuting zone level in each year as controls.

Finally, I examine whether Chinese imports have any heterogeneous effects across occupation groups:

$$\Delta y_{iot,2000} = \beta_0 + [\text{NTR Gap}_{i,1999} \times I^t] \beta_1 + [\text{NTR Gap}_{i,1999} \times I^t \times I^{occ}] \beta_2 + I^t + \mathbf{X}'_{i,2000} \beta_3 + \eta_R + e_{iot} \quad (5)$$

where  $I^{occ}$  is an indicator for task types defined at broad occupation categories (2 digit)<sup>27</sup> and interacted with the NTR Gap and time dummies. I run this specification separately for the different occupation types. Thus, the coefficient of interest, which is a vector of  $\beta_2$  estimated for the sample period, aims to capture the effect of import shocks on a particular occupation type relative to all other occupations.<sup>28</sup>

The identification is threatened if there are any correlations between pre-existing differences in the occupation-specific employment demand across local labor markets and regional NTR Gaps. For example, it is concerning if an increased demand for managerial occupations 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 Chinese import tariffs. As the ACS lack local labor market information for years 2001-2004 and annual data leading up to 2000, I use the Occupational Employment Survey (OES) 1997-2018 and run equation (4) only controlling for the time fixed effects.<sup>29</sup> I show in the Appendix that there are no

<sup>26</sup>Controls include education (the share of less than high-school, high-school graduates, some college, 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)

<sup>27</sup>There are four main categories I focus on: managerial (11, 13, 23 in SOC), technological (15, 17 in SOC), administrative support/sales (41, 43 in SOC), and manual production (49, 51, 53 in SOC).

<sup>28</sup>To examine the sensitivity of the results with respect to imposing common coefficients for  $\beta_0, \beta_3$  and the fixed effects, I run the specification for each year and include results in the Appendix.

<sup>29</sup>Note that OES provides MSA-level occupational employment data. CPS is an alternative source to obtain

apparent pre-existing trends detected across all occupation groups in labor demand. To further mitigate concerns related to pre-existing trends and possible confounding factors, I check whether the results are sensitive to adding past changes in the new work share (1980-1990 and 1990-2000) as controls. I also perform falsification exercises, which I discuss in detail in the next section.

### 3.4 Main Results

The graphs below summarize the estimation results for equations (4) and (5). Each graph plots the point estimates of the coefficient of interest including 90%, 95%, and 99% confidence intervals. 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 the Appendix. Examining equation (4), the estimated effects of the China shock on local labor market adoption of new work are positive across all years but some insignificant in the estimates. 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 0.975 percentage points (ppt) in 2010, 1.599 ppt in 2015, and 2.028 ppt in 2018. The coefficient values remain relatively stable over time, and estimated changes in 2005 persist or slightly increase in subsequent years. As discussed above, import competition may induce new work adaptations in a heterogeneous manner depending on the types of new work. Therefore, the average effects, which confounds the composition effect of different occupation types, merit further investigation through equation (5).

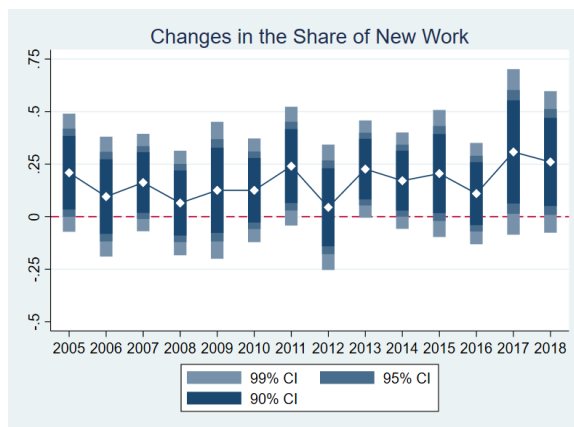


Figure 13: Changes in the share of new work

Beginning with new work in managerial roles, the coefficients ( $\beta_2$ ) are near the value of MSA-level occupational employment during the period; however, the survey nature of the data makes it more nosier than OES.

zero and insignificant in 2005-2007; however, they become positive and significant in 2008, which persist and amplify in magnitude over time (Figure 14, left). One standard deviation increase in import exposures new work in managerial roles by 1.089 ppt in 2010, 2.231 ppt in 2015, and 2.168 ppt in 2018, larger than 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. The finding on managerial new work resonates with the theoretical mechanisms demonstrating positive effects of competition on firm-level efforts to improve management (e.g. [Chen and Steinwender, 2017](#); [Bloom et al., 2013, 2016b](#), etc.) and to reorganize (e.g. [Caliendo et al., 2020a,b](#), etc.)

The results significantly differ for new work in technological jobs. The estimated effects are negative and statistically significant across all years. Unlike managerial work, the estimated coefficient values do not vary significantly over time. Exposure of Chinese imports deters new work adaptations in this group by 1.306 ppt in 2010, 1.175 ppt in 2015, and 1.300 ppt in 2018, smaller than other occupations. Although new work in technological jobs corresponds to a broader notion than traditional innovation measures, the findings are consistent with the existing empirical work<sup>30</sup> examining the effects of import competition on innovation using measures of R&D expenditure or patent data in the U.S. ([Autor et al., 2020](#); [Hombert and Matray, 2018](#); [Xu and Gong, 2017](#))

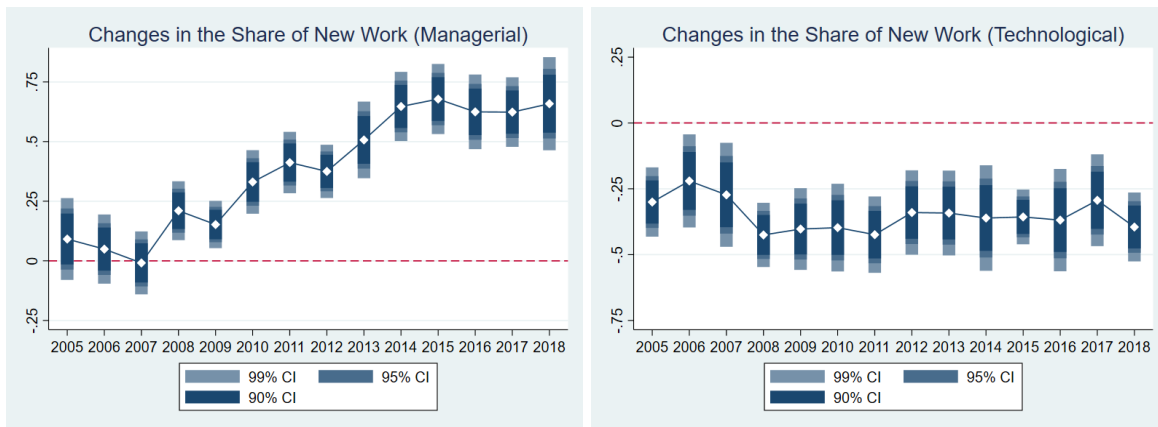


Figure 14: Changes in the share of managerial (left) and technological (right) new work

Next, I look into occupations in production and sales/administrative support. Similar to technological jobs, the estimated effects are negative and statistically significant; how-

<sup>30</sup>As mentioned above, implications of the theory provide ambiguous results on the effect of import competition on innovation efforts: the effects are positive in Europe ([Bloom et al., 2016a](#)), China ([Brandt et al., 2017](#); [Bombardini et al., 2018](#)), South Korea ([Ahn et al., 2018](#)); and negative in North America ([Autor et al., 2020](#); [Hombert and Matray, 2018](#); [Kueng et al., 2016](#); [Xu and Gong, 2017](#)). Note that [Chakravorty et al. \(2017\)](#) finds insignificant effects of Chinese import competition on patent counts.

ever, the magnitude of coefficients increase over time for both occupation groups. New work adaptations are discouraged by greater exposure of Chinese imports in both groups compared to the rest of the occupations: they decrease by 0.283 ppt in 2010, 0.740 ppt in 2015, and 1.135 ppt in 2018 for production occupations; and by 0.684 ppt in 2010, 1.056 ppt in 2015, and 1.178 ppt in 2018 for sales/administrative support jobs. The magnitudes of coefficient values are smaller in the beginning few years compared to those obtained in the analysis with technological jobs; however, reach similar levels closer to the end of the sample period. Interpreting adaptation of new work as firm-level efforts to save cost, the negative effects are consistent with what existing work (Kueng et al., 2016; Bena and Simintzi, 2015) find on the effect of competition on process innovation.

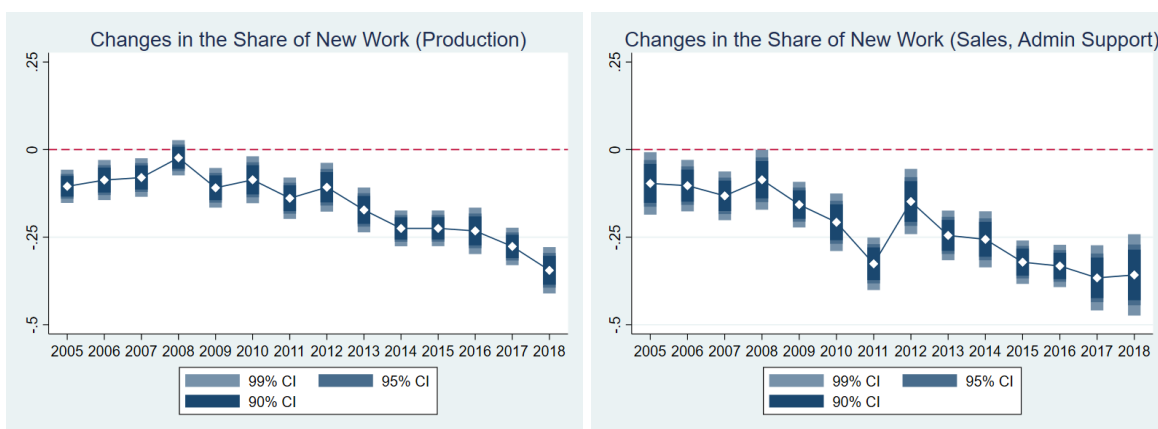


Figure 15: Changes in the share of new work in production (left) and admin support (right)

### 3.5 Robustness Exercises

To check the validity of the main results, I conduct robustness exercises by employing alternative measures of import shocks and new work; and by conducting a falsification exercise similar to Autor et al. (2013) and Hakobyan and McLaren (2016). All results using alternative measures and validation exercises support the main findings reported in the previous sections and are included in the Appendix.

#### 3.5.1 Alternative Measures

**New & Emerging Work** In attempts to check the sensitivity of the results due to measurement error in new work, I iterate the exercise using new work intensity measures based on O\*NET's New and Emerging (N&E) Occupations.<sup>31</sup> As discussed in Section 2, I create an

<sup>31</sup>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.



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.<sup>32</sup>

**New Work Intensity Score** The main results are based on examining the share of new work using a binary variable assigned based on the new work intensity scores. Here, I preserve the continuous measure and weight it by employment shares to obtain the average new work intensities. The dependent variable becomes the change in new work intensities in commuting zone  $i$  for occupation group  $o$ .

$$\Delta \text{New Work Intensity}_{iot,2000} = \sum_{m \in o} \frac{L_{mit}}{L_{it}} \times \text{New Work Intensity}_m \quad (6)$$

**Import Competition from China** I begin by employing an alternative measure of import shocks following [Autor et al. \(2013\)](#) where local exposure to the China shock are captured as follows:

$$\Delta \text{IPW}_{it} = \sum_j \frac{L_{ijt}}{L_{jt}} \frac{\Delta M_{j,2000-2007}}{L_{it}} \quad (7)$$

where the measure of import<sup>33</sup> exposure per worker in region  $i$  is constructed by weighting the changes in the level of industry imports by the industry share in each region  $i$  and normalizing by the total employment in region  $i$ .

Due to unobserved shocks to U.S. product demand, which can be correlated with (i) innovation or creation of new work and (ii) U.S. imports, I follow the instrument variable approach of the their work and construct instruments:

$$\Delta \text{IPW}_{it} = \sum_j \frac{L_{ijt-1}}{L_{jt-1}} \frac{\Delta M_{jt}^H}{L_{it-1}} \quad (8)$$

U.S. imports are instrumented using imports from the country of interest to high-wage countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, Switzerland) and further weighted by the industry composition and employment in the previous period in each region.

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<sup>32</sup>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.

<sup>33</sup>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.



### 3.5.2 Validation Exercises

First, to verify that the estimated effects on changes in the new work share for each occupation category are not driven by pre-existing demand of new work in the past, I run equation (5) using changes in the share of new work that has emerged in between 1980 and 1990 instead of post-2000's. This exercise is to ensure that the estimated effects are not merely picking up long-run trends in the demand for particular jobs. Second, I conduct a falsification exercise similar to [Autor et al. \(2013\)](#) and [Hakobyan and McLaren \(2016\)](#) and regress past changes of new work on measures of future import shocks from China. This aims to detect any presence of confounding factors that affect both changes in the share of new work and how local labor markets are exposed to Chinese imports.

## 4 Conclusion

In this paper, I study the effect of import competition on a previously unexplored dimension of U.S. local labor market adjustments: the emergence of new work. I focus on how firm-level re-optimizing strategies in response to import shocks affect local labor market demands through new work which involves employing new knowledge, skills, and technologies. Using measures of new work, which I construct through the emergence of job titles, I find that intensified competition due to China's entry to the world market induces adaptation of new work in managerial roles while deters technological ones. The effects persist over time and are robust to different specifications or measurements as well as validation exercises.

The persistent and positive effect of managerial new work which magnifies over time gives rise to recognizing an important adjustment channel through which firms respond to import shocks and shape local labor market demand for skill in the long-run. Further examining changes in the skill, task, and technology requirement for managers using job posting data and studying heterogeneity across different firm characteristics would be a promising way to extend the current analysis.

In addition, given the skill-complementarity of new work where I find skill premium in wages as well as an increasing share of college-educated workers over time, it is important to further investigate consequences of labor market inequality that results from trade-induced creation or adaptation of new work. This contributes to understanding a potentially important mechanism through which globalization increases the gap at the frontier in terms of seizing opportunities, resulting in very different the post-shock labor market experience and outcome across worker as well as firm groups.

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# Appendices

## Appendix A Data: Tables and Graphs

### A.1 Job Titles in New Work

#### A.1.1 Example

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

A time-consistent classification of occupations (occ2010) from IPUMS USA is employed.

Table A.1: Example New Job Titles

SOC codes	Occupation Titles	SOC codes	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.2: Occupation Codes with the most job titles in new work



## A.2 Content of New Work

### A.2.1 Skill Characteristics

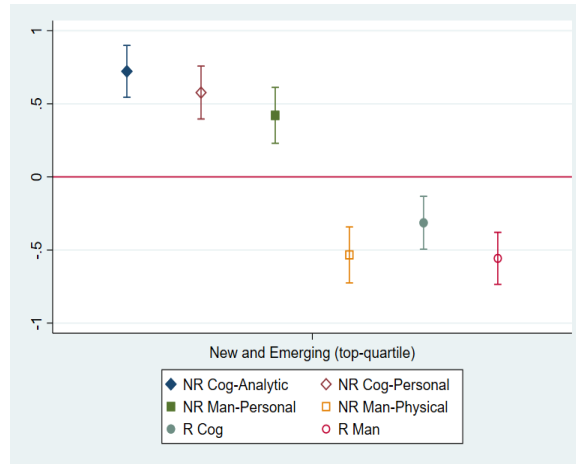


Figure A.1: Skill Characteristics of New Work (New and Emerging)

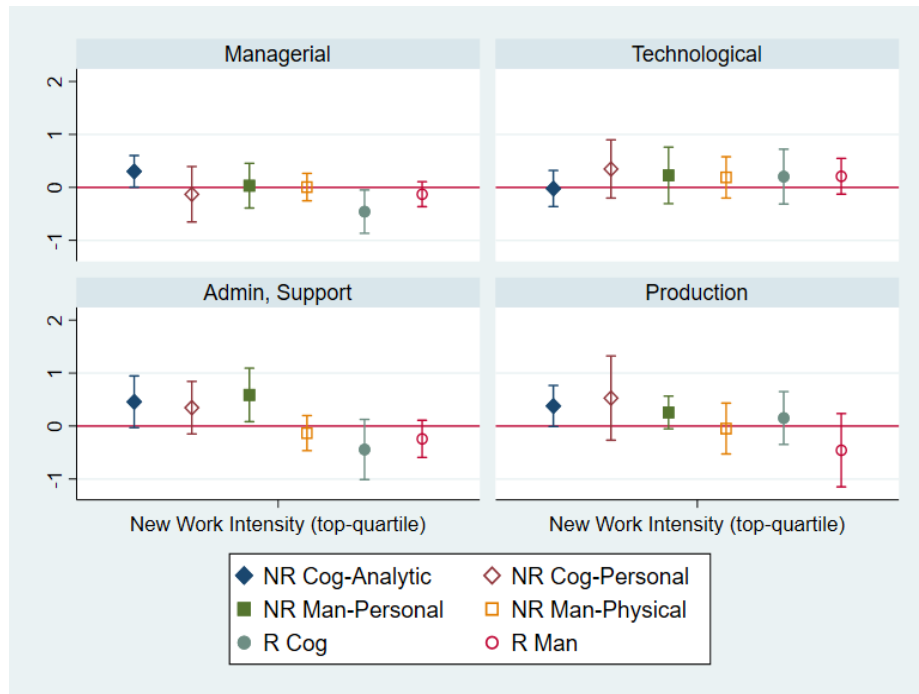


Figure A.2: Skill Characteristics of New Work by Occupations

## A.2.2 Demographic Distribution of New Work

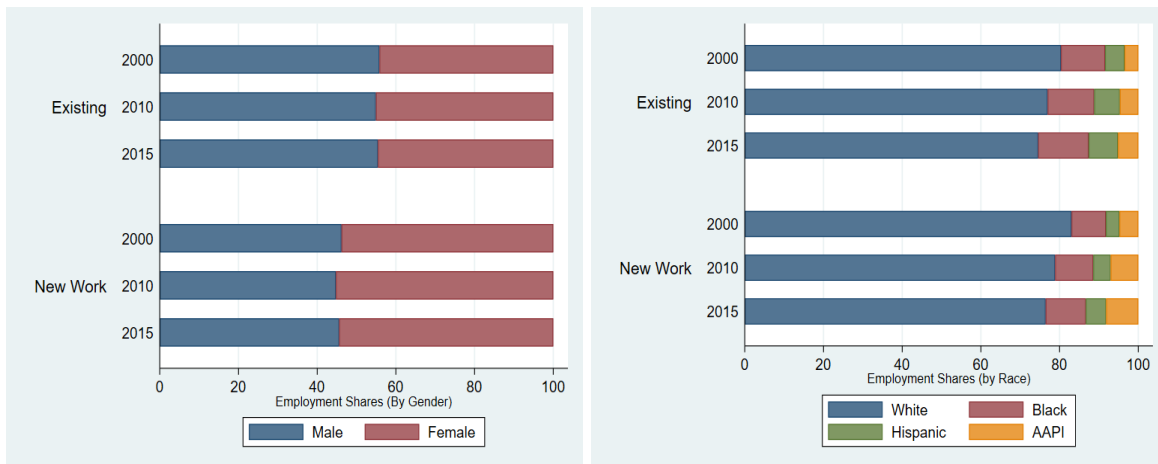


Figure A.3: Employment shares of New (top quartile of new work intensity) and Existing Work

## A.2.3 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*** (0.846)	1.141*** (0.420)	0.820*** (0.116)	0.408*** (0.0601)	2.470 (1.709)	1.729** (0.826)	1.043*** (0.337)	0.414*** (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

<sup>a</sup> 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.3: Wage regressions for New Work (2000, 1990)

## A.3 Estimation Results

### A.3.1 Summary Statistics

	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 A.4: Summary Statistics

### A.3.2 Regression Results: Table

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

### A.3.3 Pre-existing trends: OES data

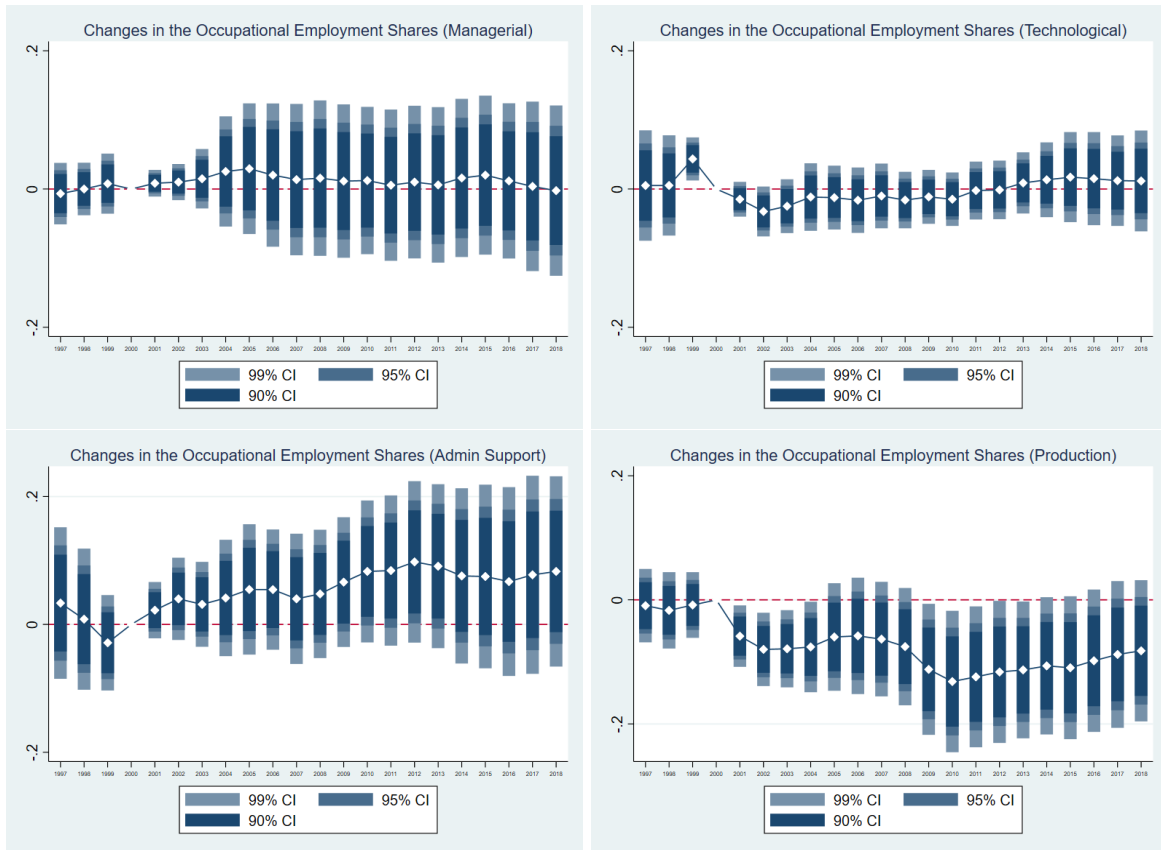


Figure A.4: Changes in the share of new work by occupational roles

### A.3.4 Pre-existing trends: adding controls

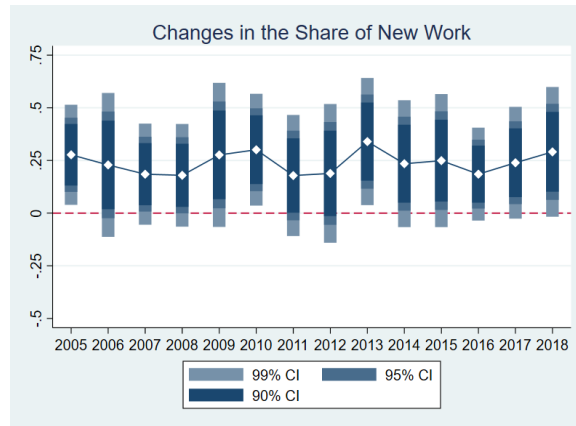


Figure A.5: Changes in the share of new work

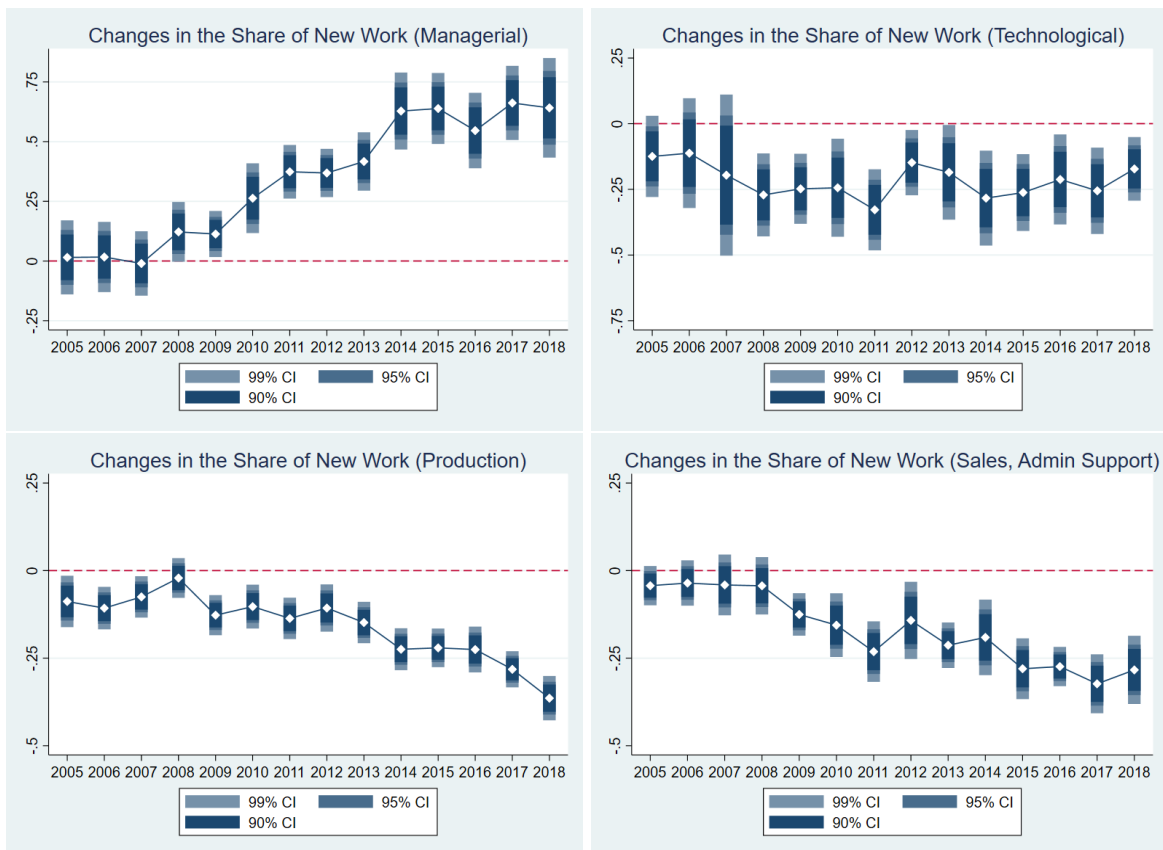


Figure A.6: Changes in the share of new work by occupational roles

### A.3.5 Manufacturing Sector Only

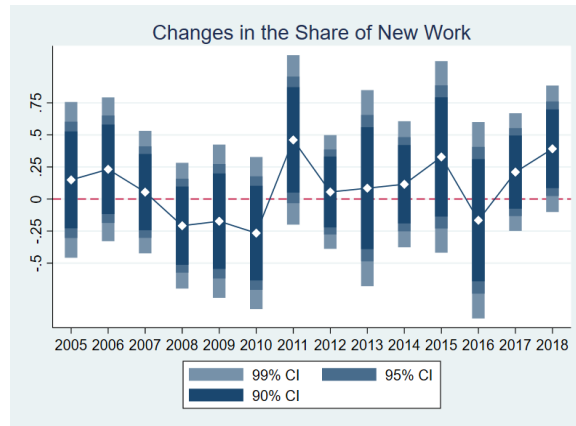


Figure A.7: Changes in the share of new work: manufacturing

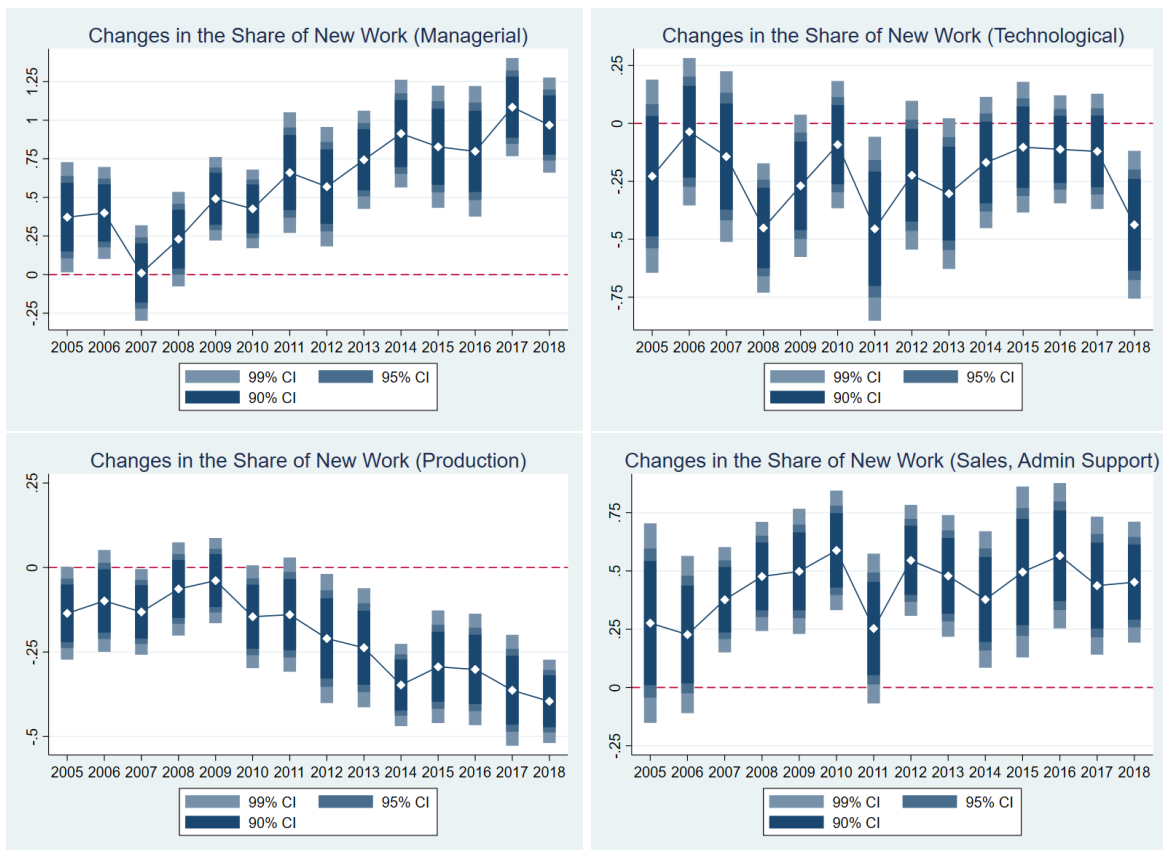


Figure A.8: Changes in the share of new work: manufacturing



## A.4 Robustness Results

### A.4.1 N&E Occupations

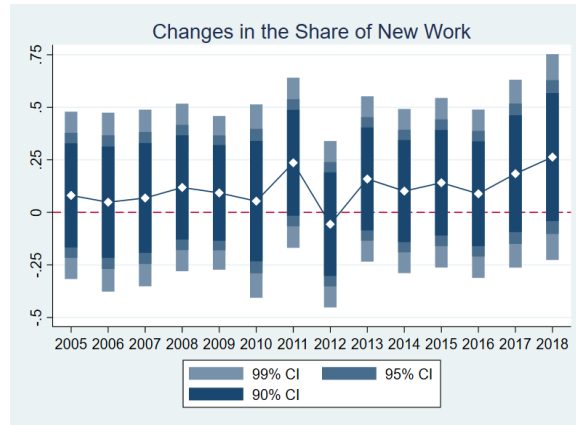


Figure A.9: Changes in the share of N&E

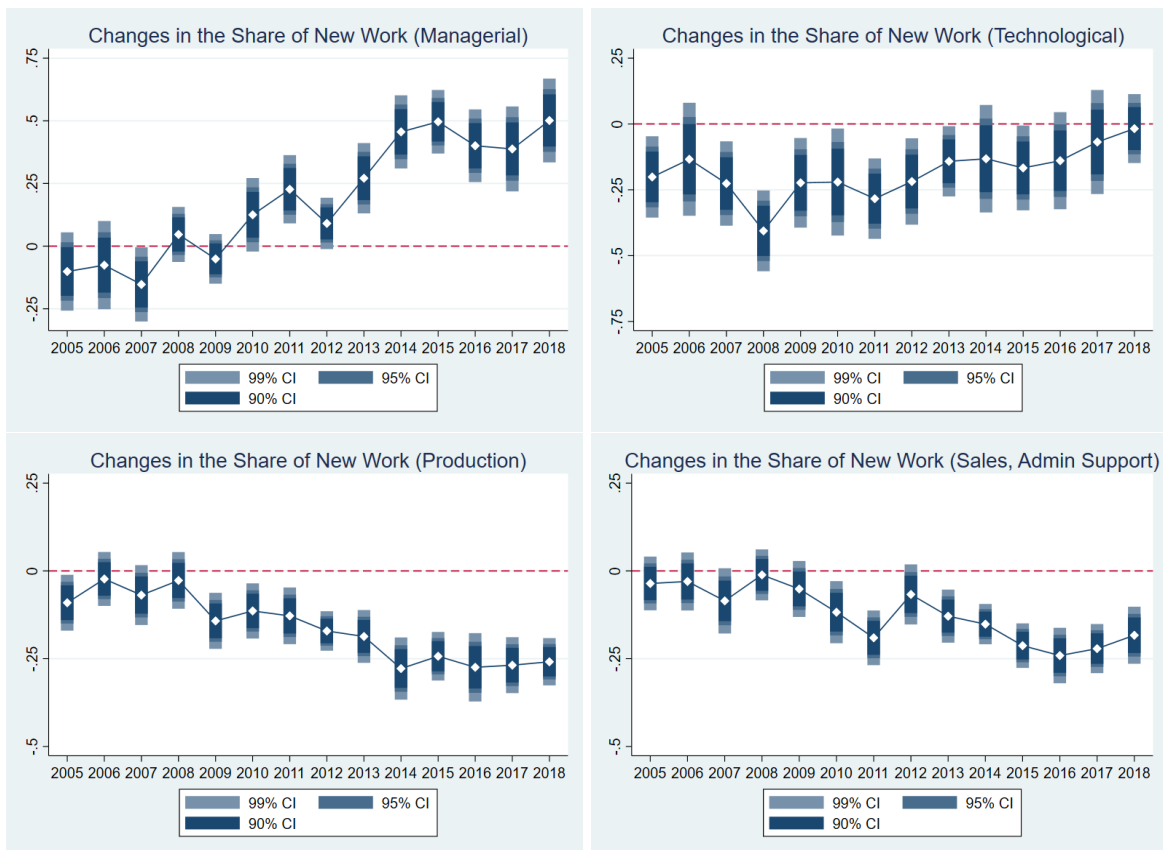


Figure A.10: Changes in the share of N&E

## A.4.2 New Work (Continuous Measure)

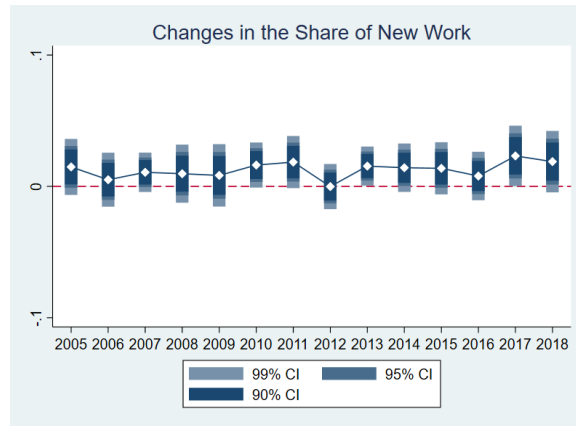


Figure A.11: Changes in the share of new work

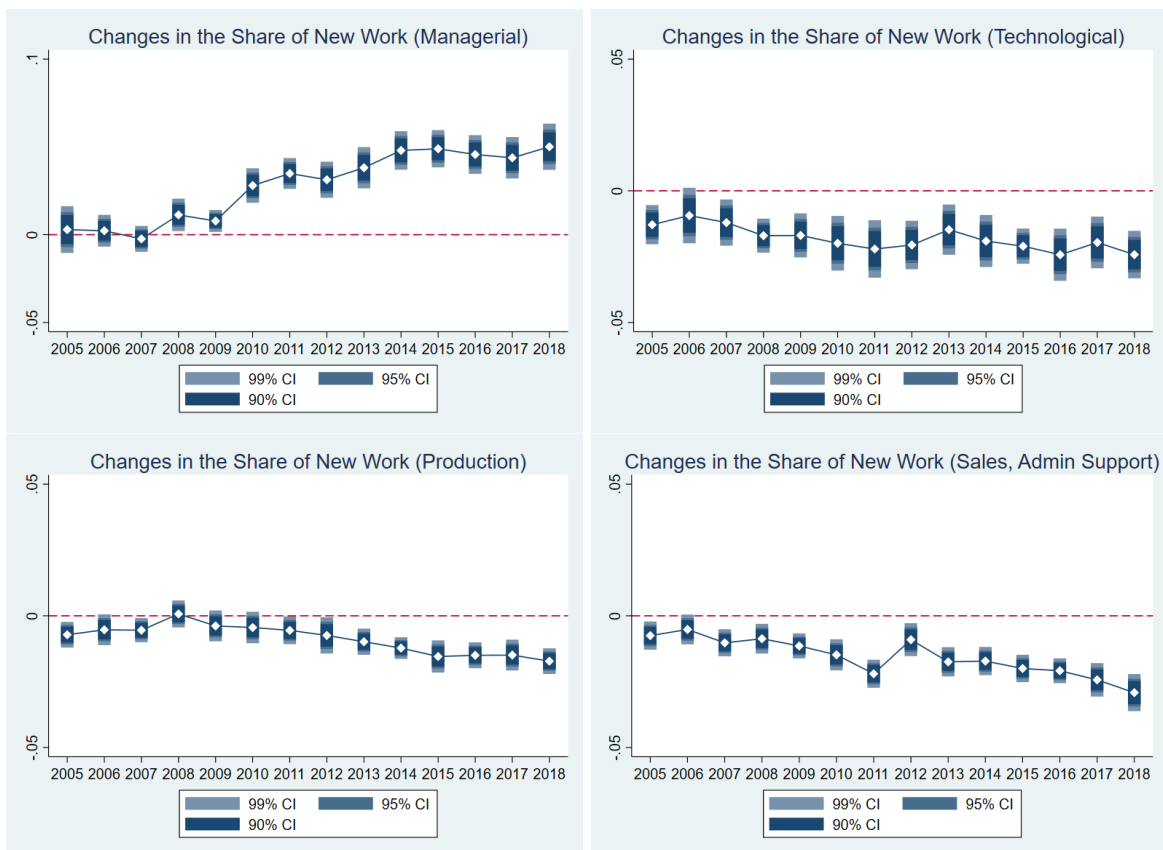


Figure A.12: Changes in the share of new work by occupational roles

### A.4.3 Alternate Measure of Import Shocks

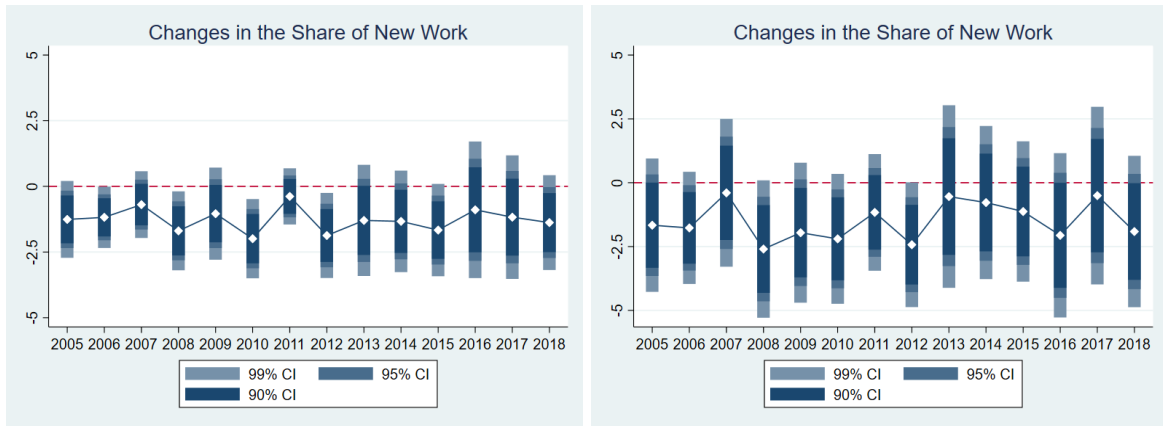


Figure A.13: Changes in the share of new work: OLS (left), IV (right)

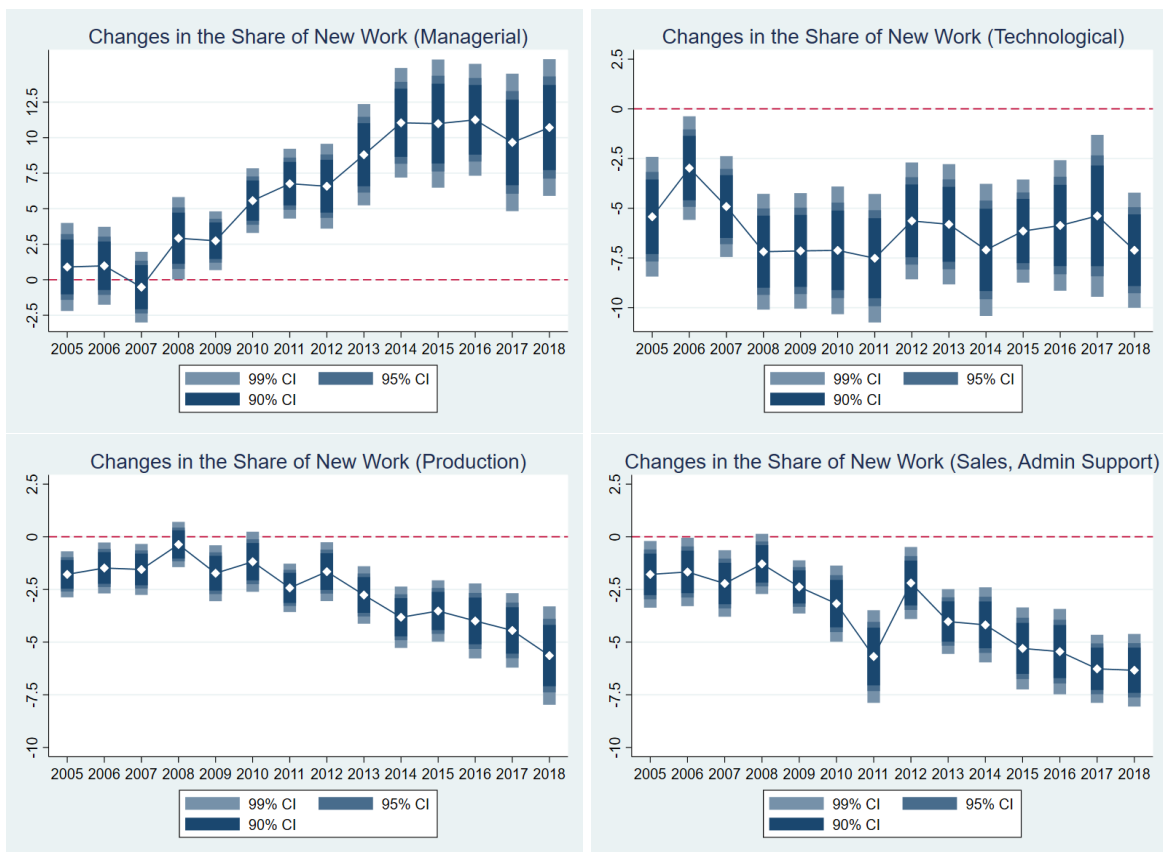


Figure A.14: Changes in the share of new work by occupational roles: OLS

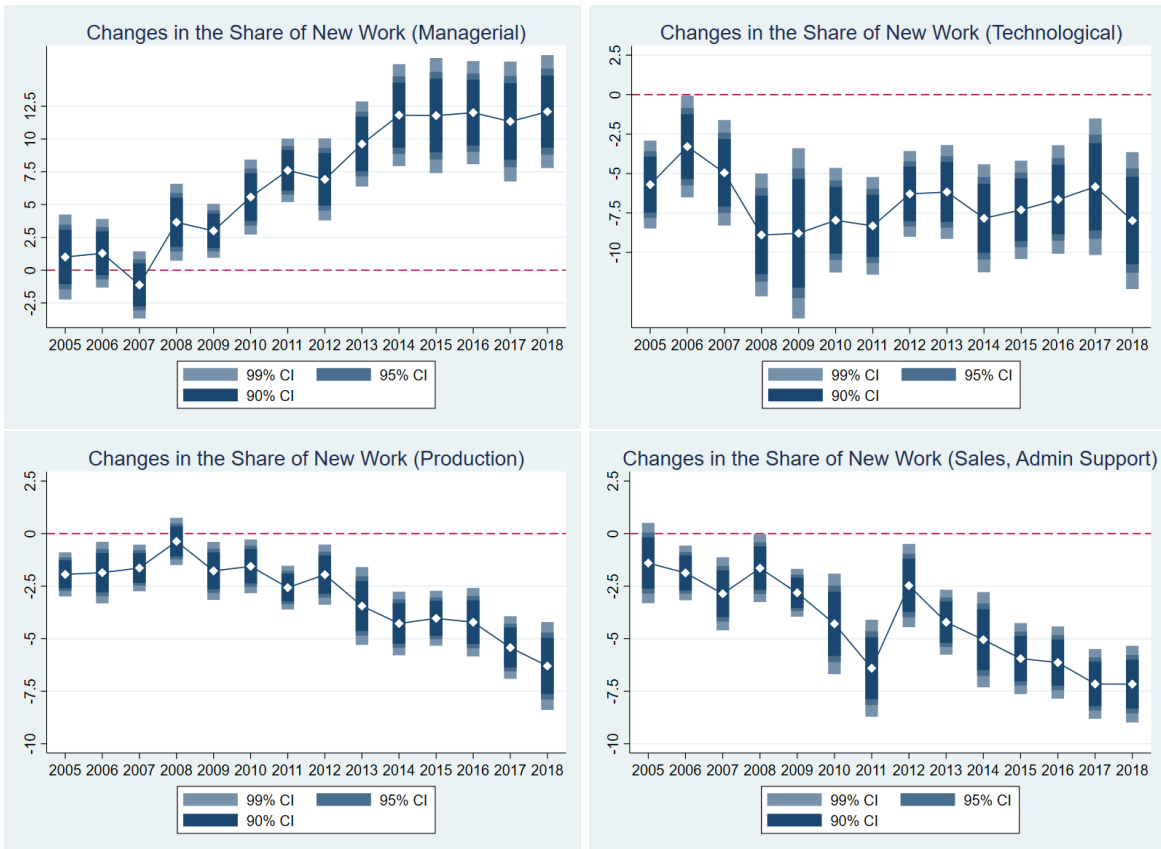


Figure A.15: Changes in the share of new work by occupational roles: IV

#### A.4.4 Alternative Specification: Estimation by Year

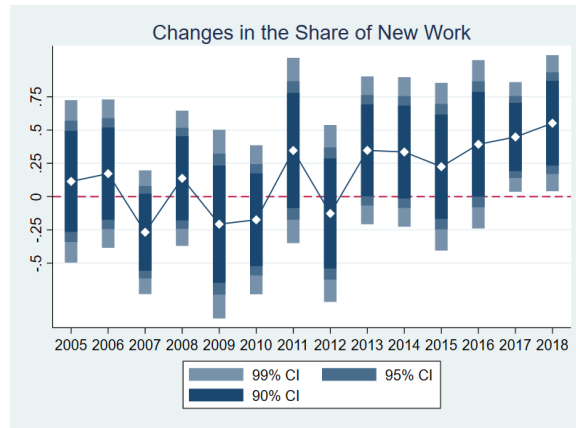


Figure A.16: Changes in the share of new work

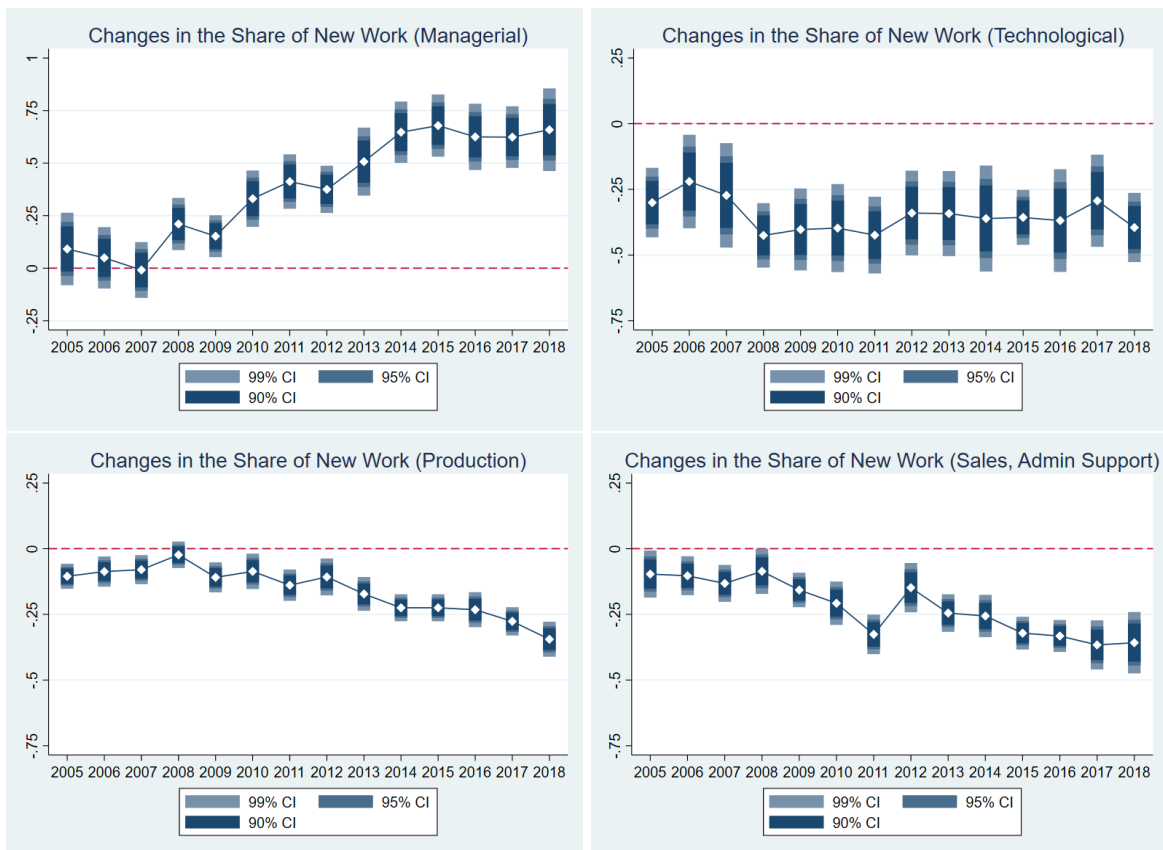


Figure A.17: Changes in the share of new work by occupational roles

### A.4.5 Validation Exercises

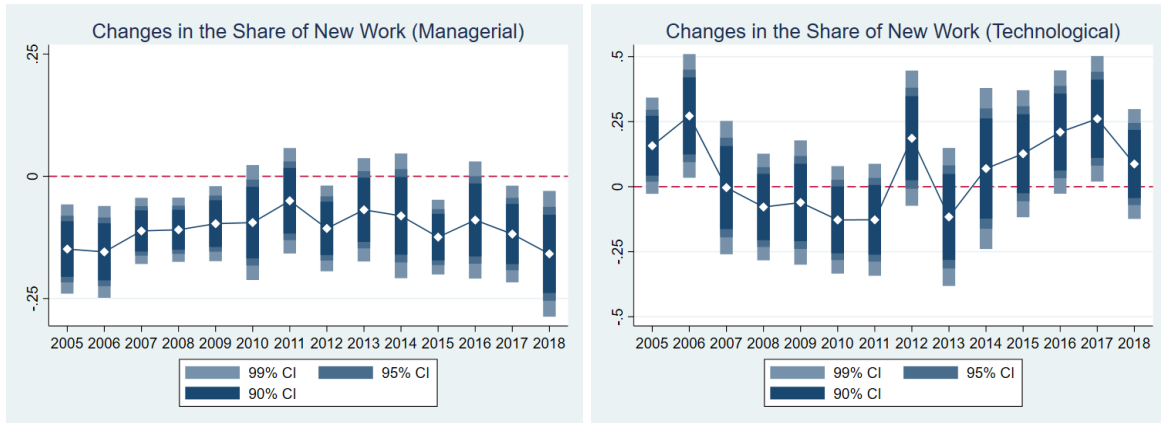


Figure A.18: Changes in the share of new work by occupational roles

$\Delta$ 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 $\times$ 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 A.5: Falsification Exercise