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Robots, computers, and the gender wage gap

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ABSTRACT

We analyze the effects of two automation technologies, industrial robots and computing equipment, on the gender wage gap in US local labor markets between 1990 and 2015. We find distinct impact of robot and computer capital: an increase in robots decreases male wage more than female wage, whereas an increase in computers reduces female wage more than male wage. According to our estimates, one additional unit of robot per thousand workers reduces gender wage gap by 0.3 log points, and by contrast an increase in computer capital by one million dollars per thousand workers increases gender wage gap by 4.1 log points.

1. Introduction

Technological progress in automation is poised to change the future of labor market. Two leading automation technologies, industrial robots and computing equipment, have advanced rapidly since the 1990s.[1] As Fig. 1 shows, the stock of robots in the US increased more than fourfold and the stock of capital on computing equipment rose more than 14 times between 1995 and 2015.[2] Recent studies have linked the growth in robots (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2019) and computers (Krueger, 1993; DiNardo and Pischke, 1997; Autor et al., 1998; 2003) to significant effects on employment and wages. The literature has also suggested a more nuanced view of the impact of technological progress on

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[1] The International Federation of Robotics (IFR) defines an industrial robot as "an automatically controlled, re-programmable, and multipurpose manipulator programmable in three or more axes, which can either fixed in place or mobile for use in industrial automation applications." The IFR collects information on both industrial and service robots. A service robot is defined as a robot that performs useful tasks for humans or equipment excluding industrial automation application. The publicly available IFR data do not provide information on the use of service robots. Industrial robots are distinct from other types of machinery and equipment in that they are fully autonomous machines that do not need a human operator and they can be reprogrammed to perform multiple tasks and adapted to different applications. Computing equipment includes computers and all other automatic data processing machines, as well as peripheral equipment such as storage units and accessories, based on the European Classification of Products by Activity (Jäger, 2018).

[2] The spread of robotics and computing technologies is expected to accelerate over the decades to come (Ford, 2015). For example, Boston Consulting Group (BCG, 2015) has projected that the world stock of robots may quadruple by 2025. According to a forecast from the International Data Corporation (IDC, 2018), spending on cloud computing infrastructure will grow at an annual growth rate of 10.8 % in the next five years.

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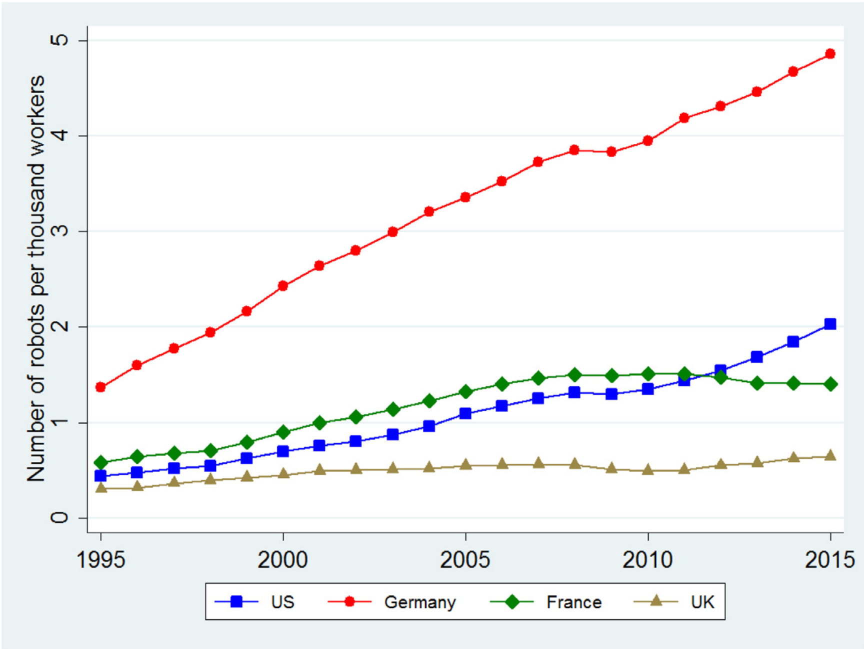
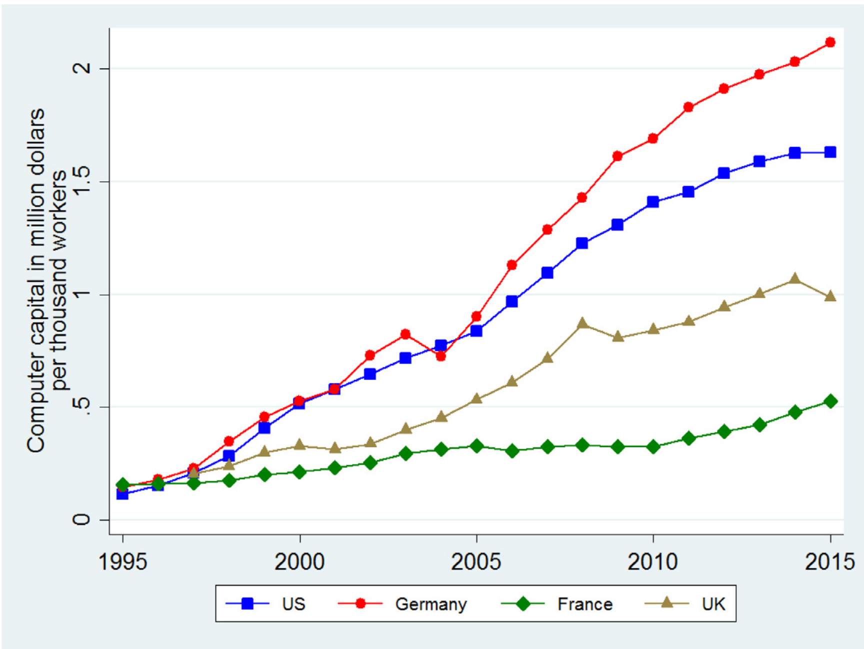


(a) Robot Capital



(b) Computer Capital

Fig. 1. Trends in Robot and Computer Capital in the United States and Europe. *Notes:* Robot capital is measured by operational stock of industrial robots per thousand US-equivalent workers. Computer capital is measured in million 2010 US dollars per thousand US-equivalent workers. The robot data come from the IFR, and the computer capital and employment data come from the EUKLEMS. The EUKLEMS reports capital stock in each country's home currency. We use the corresponding exchange rates to convert all values to 2010 US dollars.

the demand for different types of skills, measured either by different education groups (e.g., Katz and Murphy, 1992; Krusell et al., 2000; Autor et al., 2008; Michaels et al., 2004) or by different occupations (e.g., Autor and Dorn, 2013; Goos et al., 2009; Goos and Manning, 2007; Spitz-Öener, 2006) and investigated its contribution to wage inequality. If new technologies have different complementarity with various skills and have distinct effects on the demand for them, we would expect that technological progress may also affect male and female wages differently. In this paper, we examine the impact of robots and computers on the gender wage gap in US local labor markets.

We first document that there are rapid growth and considerable variation in the adoption of robot and computer capital across industries and across local labor markets, proxied by commuting zones (CZs) in the US. We construct our measure of robot adoption in a CZ using data from the IFR on the increase in the stock of industrial robots across industries weighted by each industry's baseline employment share in the CZ from the Census. Our measure of computer adoption uses data on computing equipment across industries from the EUKLEMS, also weighted by each industry's baseline employment share. We show that male workers are more likely to be employed in industries that use more robots, whereas female workers are more likely to be employed in industries that use more computers.

We find that male and female workers cluster into occupations that require different skills. Using data from the Census and the Dictionary of Occupational Titles (DOT), we show that female workers are disproportionately employed in occupations that require relatively more brain skills. Male workers, by contrast are overrepresented in occupations that require high brawn skills. We further show that at the industry level, the adoption of robots is positively correlated with an industry's brawn skill requirement but is uncorrelated with its brain skill requirement. The adoption of computers, by contrast is uncorrelated with an industry's brawn skill requirement and positively associated with its brain skill requirement. These empirical evidence corroborates the view that robot capital is more substitutable for brawn skills in which men have a comparative advantage, whereas computer capital is more substitutable for brain skills in which women have a comparative advantage.

We develop a simple conceptual framework to illustrate the effects of robot and computer capital on the gender wage gap. Incorporated into the model are different features of robots and computers consistent with the data: robots are more substitutable for brawn labor, whereas computers are more substitutable for brain labor. Following Galor and Weil (1996), we focus on a simplified description of the gender differences in factor endowments: while men and women have equal quantities of brain skills, men have more brawn skills. The more robot capital does an economy accumulate, the higher the rewards of brain skills relative to brawn skills. Similarly, the accumulation of computer capital implies higher rewards of brawn skills relative to brain skills. Therefore, the model predicts that, all other things being equal, in regions with more robot capital, gender wage gap is lower; whereas in regions with more computer capital, gender wage gap is higher. The simple framework provides guidance for estimating the impact of robots and computers on the gender wage gap across US local labor markets.

In order to focus on the changes in robot and computer capital driven by technological advances, we use robot adoption trends in several European economies that are ahead of the US in robotics to instrument robot adoption in the US. We use the industry-specific initial level of computer intensity, which presumably captures the industrys inherent reliance on computers for technological reasons, as an instrument for computer adoption in the US. Exploiting these sources of variations and using combined data from the IFR, EUKLEMS, and Census, we find systematic evidence that the adoption of robot and computer capital has significant and sizable effects on the gender wage gap. We show that an increase in the stock of robots decreases male wage more than female wage, leading to a reduction in the gender wage gap; whereas an increase in computer capital reduces female wage more than male wage and has a positive effect on the gender wage gap. One additional unit of robot per thousand workers is estimated to decrease gender wage gap by 0.3 log points, and an increase in computer capital by one million dollars per thousand workers is estimated to increase gender wage gap by 4.1 log points.

The existence of gender wage differentials in the US labor market is well documented (Altonji and Blank, 1999; Blau and Kahn, 2006; 2017). The principal explanations for the trends and persistence in gender wage gap include differences in human capital variables (Altonji and Blank, 1999), computer use and skill-biased technological change (Weinberg, 2000; Card and DiNardo, 2002), deunionization (Blau and Kahn, 2006), employment selection (Mulligan and Rubinstein, 2008), attitude towards bargaining and competition (Gneezy et al., 2003; Babcock and Laschever, 2009), working hours (Goldin, 2014; Erosa et al., 2017), as well as gender segregation (Bayard et al., 2003; Blau and DeVaro, 2007). Most closely related to our work is the recent literature that uses the task-based framework introduced by Autor et al. (2003) to explain the narrowing of the gender wage gap. Bacolod and Blum (2010) and Yamaguchi (2018) show that an increase in the prices of skills in which women have a comparative advantage and a decrease in the prices of skills in which men have a comparative advantage can account for a significant portion of the narrowing gender gap. Borghans et al. (2014) and Ge and Zhou (2018) focus on the importance of people skills and their returns in accounting for changes in the gender wage gap. Black and Spitz-Öener (2010) directly compare women's work (measured by job tasks) to that of men using survey data from West Germany and investigate the potential role of workplace computerization on occupation task requirements. Beaudry and Lewis (2014) find that changes in skill prices driven by PC adoption are important in explaining the decline in the gender wage gap. In this paper, we rely on data from the IFR and EUKLEMS to directly measure two potentially skill-biased technological changes, namely robots and computers, which enable us to exploit plausible exogenous changes in technology adoption and estimate their impact on the gender gap in local labor markets. Our data also allow us to consider several alternative explanations, such as overall capital deepening and changes in trade exposure.

The rest of this paper is organized as follows. Section 2 describes the data, highlighting some key data patterns that inform subsequent analyses. Section 3 outlines a simple conceptual framework that links the adoption of robotics and computing technologies to gender wage gap. Section 4 discusses the empirical specifications and presents our results. Section 5 provides the conclusion.

2. Data and descriptive statistics

In this section, we first introduce our data sources, summarize the construction and measurement of our key variables, and describe relevant data patterns of robot capital, computer capital, and gender wage gap in the US. Then we present simple statistical evidence that is consistent with two assumptions. First, males have a comparative advantage in brawn skills, whereas females have a comparative advantage in brain skills; second, robot capital is more substitutable for brawn labor than for brain labor, whereas computer capital is more substitable for brain labor than for brawn labor. These assumptions imply that the adoption of robotics and computing technologies may have differential effects on male and female wages. We will investigate these relationships in Section 3 through a simple theoretical framework and form empirical specifications and bring them to the data in Section 4.

2.1. Data on Robot and computer capital

The best accessible data source on the use of robots is the one collected by the IFR, which compiles data on robots by surveying global robot suppliers (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2019). The IFR data consist of counts of industrial robots installation and operational stock by industry, country, and year, covering over 50 countries since 1993. For the United States, the IFR collects country-level data since 1993 and reports industry-specific data after 2004.[3]

Our computer capital data are taken from the EUKLEMS database. The EUKLEMS includes measures of economic growth, productivity, employment, capital formation and technological change at the industry level for all European Union (EU) member states and the US in its latest 2017 release (Jäger, 2018). Data for most European countries come from Eurostat, whereas US data are from the Bureau of Economic Analysis (BEA). Total capital is decomposed into ten asset types: computing equipment, communication equipment, transport equipment, other machinery and equipment, total non-residential investment, residential structures, computer software and databases, research and development, cultivated assets, and other intellectual property products. We use computing equipment as our definition for computer capital.

We measure robot capital by the number of robots per thousand workers, using the operational stock of industrial robots from the IFR and employment data from the EUKLEMS.[4] Computer capital is measured in million of 2010 US dollars per thousand workers, using the computing equipment stock and employment figures from the EUKLEMS.[5] We compare the US robot and computer capital intensity with major EU countries between 1995 and 2015 in Fig. 1a and b.[6] Fig. 1a shows that the US lags significantly behind Germany (as well as Italy and Sweden, not shown in Fig. 1a) in the adoption of robotics technologies. The number of industrial robots per thousand workers was much higher in Germany (1.36) than those in France (0.58), the US (0.44), and the UK (0.31) in 1995. There has been a fast increase in robot capital since the 1990s but Germany has maintained its leading position relative to the US and other EU countries over time. By 2015, the number of industrial robots per thousand workers was at 2.03 in the US, in contrast to 4.86 in Germany. Comparing the US to France and the UK, robot use in the US has caught up with and surpassed France since 2012 and has been consistently ahead of the UK. In contrast, Fig. 1b shows that the US has a leading position in computing technology. Despite being slightly behind

[3] The robots data for the United States are not distinguishable from those for North America in the IFR data before 2004. Following the literature, we use the North America data to proxy US robot use as the US accounts for more than 90% of the entire robot use in North America. In the empirical analysis, we implement an IV procedure to correct for potential bias due to measurement error.

[4] There are several standard types of industrial robots based on their mechanical structures: articulated robots, Cartesian robots, parallel robots, SCARA (selective compliance assembly robot arm), and cylindrical robots, among which the articulated robots account for more than half of the total operational stock. The IFR reports counts of industrial robots installation and operational stock, but has no information on robot prices. As argued by Acemoglu and Restrepo (2019), in principle robots in different sectors may have different capabilities and values, but in practice they are fairly similar in these dimensions. Robot prices of different types fall in the range of $24,000 per robot to about $80,000 with an average unit price of $44,000 in 2017. Acemoglu and Restrepo (2019) further show that adjusting robot quantities using differences in robot prices across industries generates similar results. The statistical method to construct the operational stock of industrial robots takes capital obsolescence into consideration by withdrawing robots from service after 12 years.

[5] According to the EUKLEMS data, computing equipment grew the fastest between 1990 and 2015 by more than 29 times, whereas total capital increased by 2.3 times during the same period. Standard perpetual inventory method (PIM) is used to construct capital stock of computing equipment. Specifically, gross captial stock is calculated as the weighted average of capital investment in previous years, of which the service life has not yet expired. The weights constitute the relative efficiency of capital investments of different vintage. In the formula, $A_t = \sum_{\tau=0}^{T} \theta_\tau I_{t-\tau}$, where A_t denotes gross capital stock at time t, I_t represents capital investment, θ_τ is the relative efficiency of a capital investment of vintage τ, and T denotes the expected service life. If the relative efficiency of capital investment declines geometrically, then gross capital stock at time t can be estimated by $A_t = (1-\delta)A_{t-1} + I_t$, where δ is the capital depreciation rate. The depreciation rate for computing equipment is 31.19%. The price of computer capital at time t is estimated by $p_t = r_t p_{t-1}^I + \delta p_t^I$, where r_t is the real rate of return, defined as the nominal rate of return adjusted for asset-specific capital gains, p_t^I denotes the investment price of buying a unit of capital, and δ is the rate of depreciation. More details on the methods to estimate the value of capital services can be found in Timmer et al. (2007).

[6] Employment is measured as the number of US equivalent workers in 1990 in all countries in Fig. 1a and b. More specifically, the EUKLEMS reports total working hours in a year in each industry in a country. We divide working hours in an industry in a country by working hours per worker in the corresponding US industry in 1990 to obtain the country's number of US equivalent workers.

Table 1
Robot Capital by Industry in the United States, 1993–2015.

Industries	Robot Capital			Change in Robot Capital	
	1993	2000	2015	1993–2000	2000–2015
All industries	0.34	0.70	2.03	0.36	1.33
Manufacturing					
Automotive	25.81	53.38	129.40	27.57	76.02
Metal products	2.70	5.59	8.28	2.89	2.69
Plastics and chemicals	1.72	3.56	10.60	1.84	7.04
Electronics	1.51	3.12	14.69	1.61	11.56
Food and beverages	1.12	2.31	6.55	1.19	4.24
Apparel and textiles	0.00	0.00	0.07	0.00	0.07
Wood and furniture	0.00	0.00	0.17	0.00	0.17
Paper and publishing	0.00	0.00	0.14	0.00	0.14
Glass and minerals	0.00	0.00	0.92	0.00	0.92
Basic metals	0.00	0.00	8.87	0.00	8.87
Industry machinery	0.00	0.00	2.53	0.00	2.53
Aerospace	0.00	0.00	0.72	0.00	0.72
Miscellaneous manufacturing	0.00	0.00	16.31	0.00	16.31
Nonmacufacturing					
Agriculture	0.00	0.00	0.04	0.00	0.04
Mining	0.00	0.00	0.06	0.00	0.06
Utilities	0.00	0.00	0.09	0.00	0.09
Construction	0.00	0.00	0.02	0.00	0.02
Education and research	0.00	0.00	0.08	0.00	0.08
Services	0.00	0.00	0.00	0.00	0.00

Notes: Robot capital is measured by the number of robots per thousand workers. The number of robots comes from the IFR and the number of workers in each industry comes from the EUKLEMS.

Germany, the US has been consistently ahead of almost all other EU countries in computer capital intensity. By 2015, the US computer capital intensity was at 1.63 million dollars per thousand workers, much higher than those in France (0.53) and the UK (0.99).

Robot and computer capital are not evenly distributed across industries in the US.[7] Table 1 shows the number of robots per thousand workers in each of the IFR industries. The first three columns compare robot intensity across industries in 1993 (the first year robot data are available from IFR), 2000, and 2015, respectively. The automotive industry had the highest number of robots per thousand workers at 25.81 in 1993, which was much higher than all other industries and followed by metal products (2.70), plastics and chemicals (1.72), and electronics (1.51). Many manufacturing industries and all non-manufacturing industries used no industrial robot in 1993 according to the IFR. By 2015, the number of robots per thousand workers reached 129.40 in the auto industry, followed by miscellaneous manufacturing (16.31), electronics (14.69) and plastics and chemicals (10.60). The last two columns of Table 1 show the change in robot intensity in each industry over time. Those industries with higher initial robots per thousand workers, such as automotive, electronics, plastics and chemicals, tend to experience larger increase in robot use over time. In addition, the increase in robot capital accelerated after year 2000.

Table 2 shows computer capital intensity measured in million dollars per thousand workers in each of the 24 EUKLEMS industries from 1990 to 2015. The finance and insurance industry had the highest computer capital intensity at 0.12 million dollars per thousand workers in 1990. Refined petroleum products, electronics, chemicals and chemical products were among the other industries that had high computer intensity in 1990. All industries experienced rapid rise in computer capital intensity between 1990 and 2015, but the growth rate varied greatly across industries. The information and communication industry's computer capital intensity increased from 0.06 in 1990 to 1.50 in 2000 and 7.61 in 2015, claiming leading position in computer capital. Other industries that have experienced fast growth in computer capital intensity include mining, finance and insurance, and refined petroleum products. Overall, industries with higher initial computer capital tend to experience higher growth in computer capital over time. We also observe an accelerated increase in computer capital intensity between 2000 and 2015 compared to the 1990s.

Male and female workers sort themselves into different industries. In Table 3, we present the proportions of male and female workers employed in several high robot intensity industries (including automotive, electronics, metal products, plastics and chemicals, and basic metals) and several high computer intensity industries (including information and communication, finance and insurance, professional and scientific works, refined petroleum products and electronics) between 1990 and 2015. We use data from the Integrated Public Use Micro Samples (IPUMS) 5% Census samples of 1990 and 2000, and three-year pooled American Community Survey (ACS) 2009–2011 and 2014–2016 to represent 2010 and 2015, respectively (Ruggles et al., 2015). Among all employed workers between age 16 and 64, the proportion working in high robot industries declined from 6.18% in 1990 to 4.26% in 2015 (Table 3, Panel A). This trend is consistent and reflects the fact that high

[7] Appendix A provides detailed descriptions of industry-level data construction.

Table 2
Computer Capital by Industry in the United States, 1990–2015.

Industries	Computer capital			Change in computer capital	
	1990	2000	2015	1990–2000	2000–2015
All industries	0.06	0.52	1.63	0.46	1.11
Manufacturing					
Refined petroleum products	0.11	0.60	5.31	0.49	4.71
Electronics	0.07	0.65	2.56	0.57	1.92
Chemicals and chemical products	0.07	0.72	2.07	0.65	1.35
Transport equipment	0.05	0.25	0.75	0.20	0.51
Industrial machinery	0.05	0.45	0.72	0.40	0.27
Basic metals and metal products	0.03	0.17	0.50	0.14	0.33
Wood and paper	0.03	0.21	0.64	0.18	0.43
Food and beverages	0.02	0.19	0.71	0.17	0.52
Plastics	0.02	0.14	0.65	0.12	0.51
Miscellaneous manufacturing	0.02	0.14	0.47	0.12	0.33
Apparel and textiles	0.01	0.08	0.22	0.07	0.14
Nonmanufacturing					
Finance and insurance	0.12	1.62	4.73	1.50	3.11
Professional and scientific works	0.07	1.13	2.90	1.06	1.76
Information and communication	0.06	1.50	7.61	1.44	6.11
Mining	0.06	0.57	6.45	0.51	5.88
Utilities	0.05	0.34	1.52	0.29	1.18
Whole sales and retails	0.05	0.42	1.47	0.37	1.05
Social services	0.01	0.17	1.18	0.16	1.01
Real estate	0.01	0.40	2.33	0.39	1.93
Recreational services	0.01	0.14	0.60	0.13	0.46
Transportation and storage	0.01	0.31	0.97	0.30	0.66
Accommodation services	0.01	0.06	0.42	0.05	0.37
Agriculture	0.00	0.05	0.18	0.04	0.14
Construction	0.00	0.11	0.28	0.11	0.17

Notes: Computer capital is measured in million dollars per thousand workers. Data on computer capital and the number of workers in each industry come from the EUKLEMS.

Table 3
Employment Shares in High Robot and High Computer Industries.

	1990	2000	2010	2015
	Panel A: High robot industries			
All workers	6.18	5.73	4.50	4.26
Male	8.04	7.53	6.23	6.02
Female	3.94	3.69	2.63	2.37
	Panel B: High computer industries			
All workers	11.69	11.61	12.22	11.65
Male	10.14	10.61	11.89	11.64
Female	13.55	12.75	12.60	11.67

Notes: Microdata come from the IPUMS 5% Census samples of 1990 and 2000, and three-year pooled ACS 2009–2011 and 2014–2016 to represent 2010 and 2015. High robot industries include automotive, electronics, metal products, plastics and chemicals, and basic metals. High computer industries include information and communication, finance and insurance, professional and scientific works, refined petroleum products and electronics.

robot industries have experienced more adoption of robots over time (Table 1) and thus more labor has been replaced by robots in these industries. The proportions of male workers employed in high robot industries are more than twice as much compared to the proportions of female workers. In 2015, 6.02% of male workers were employed in high robot industries, whereas only 2.37% of female workers worked in the same industries. The fraction of workers in high computer intensity industries was relatively stable between 1990 and 2015 (Table 3, Panel B). Female workers are more likely than male workers to be employed in high computer intensity industries, although the gender difference seems shrinking over time. Given that male and female workers are distributed in industries with different robot and computer capital intensity, the labor market impact of robots and computers may vary across gender.

2.2. Commuting zone data

The concept of commuting zones (CZs) was first introduced in Tolbert and Sizer (1996) and has been used as a definition of local labor markets (e.g., Autor and Dorn, 2013). A CZ is a cluster of counties with strong commuting ties. In practice, a CZ usually contains several counties, but a county may also sit on the borders of several CZs. Unlike Metropolitan Statistical Areas (MSAs), CZs cover the entire US including both metropolitan and rural areas. The commuting ties within CZs can also capture industrial similarities. In this study, we focus on the 722 CZs covering the continental US. To match the Census and ACS micro data from IPUMS to CZs, we use the procedures provided by Autor and Dorn (2013) to assign counties or Census Public Use Micro Areas (PUMAs) to CZs.[8]

Our worker sample consists of non-institutionalized civilian employed workers between age 16 and 64. Annual working hours are computed by the product of weeks worked times usual number of hours per week from the 1990 Census and the 2014–2016 ACS. We calculate individual hourly wage by dividing annual earnings by total working hours, and define gender wage gap in a CZ as the log difference between the average of male hourly wages and the average of female hourly wages in the region.[9] Fig. 2a illustrates the variations in gender wage gap across CZs in 1990. The darker color represents larger gender wage gap in the CZ. The gender wage gap varies significantly across local labor markets, ranging from 14 to 42 log points. Fig. 2b shows the decline of gender wage gaps across CZs between 1990 and 2015. The darker color corresponds to larger decline in the gender gap. At the national level, gender wage gap declined by 10 log points from 26 in 1990 to 16 in 2015. The change in gender wage gap varies substantially across regions. The gender wage gap narrowed by more than 20 log points in some CZs, whereas in some other CZs the gender wage gap barely changed or even increased between 1990 and 2015. In our empirical analysis, we will investigate the effects of various socioeconomic factors at the local labor market, including robot and computer adoption, on the observed changes in the gender wage gap.

We use change in robot capital in industry i between time t_0 and t_1 to measure the adoption of robotics technology in the industry. More specifically,

$$\Delta RA_{i,(t_0,t_1)} = \frac{R_{i,t_1} - R_{i,t_0}}{L_{i,1990}} - g_{i,(t_0,t_1)} \frac{R_{i,t_0}}{L_{i,1990}}, \tag{1}$$

where $R_{i,t}$ is the number of robots in industry i at time t, $L_{i,1990}$ is the number of workers (in thousands) in industry i in the baseline year of 1990, and $g_{i,(t_0,t_1)}$ is the output growth rate between t_0 and t_1 in industry i. The employment counts and output growth rates by industry come from the EUKLEMS dataset. The robot adoption measure in Eq. (1) takes into account industry-level variations in robot use while keeping baseline employment fixed at 1990 level ($L_{i,1990}$) and adjusting for the overall expansion of industry-specific output $\left(g_{i,(t_0,t_1)}\right)$.[10]

Robot adoption in a CZ j between time t_0 and t_1 is defined as the sum of industry-level robot adoption weighted by each industry's baseline employment share. More specifically,

$$\Delta RA_{j,(t_0,t_1)} = \sum_i \frac{L_{ij,1990}}{L_{j,1990}} \Delta RA_{i,(t_0,t_1)}, \tag{2}$$

where $\frac{L_{ij,1990}}{L_{j,1990}}$ is the employment share of industry i in CZ j and $\Delta RA_{i,(t_0,t_1)}$ is defined in Eq. (1).

Similarly we measure computer adoption in industry i between time t_0 and t_1 as:

$$\Delta CA_{i,(t_0,t_1)} = \frac{C_{i,t_1} - C_{i,t_0}}{L_{i,1990}} - g_{i,(t_0,t_1)} \frac{C_{i,t_0}}{L_{i,1990}}, \tag{3}$$

where $C_{i,t}$ is the computer capital stock (in million dollars) in industry i at time t, $L_{i,1990}$ and $g_{i,(t_0,t_1)}$ have the same definitions as those in Eq. (1). Again, the computer adoption measure keeps baseline employment fixed and adjusts for industry-specific output growth.[11] Analogous to Eq. (2), we define computer adoption in a CZ j between time t_0 and t_1 as follows

$$\Delta CA_{j,(t_0,t_1)} = \sum_i \frac{L_{ij,1990}}{L_{j,1990}} \Delta CA_{i,(t_0,t_1)}, \tag{4}$$

where $\frac{L_{ij,1990}}{L_{j,1990}}$ is the industry employment share and $\Delta CA_{i,(t_0,t_1)}$ is defined in Eq. (3).

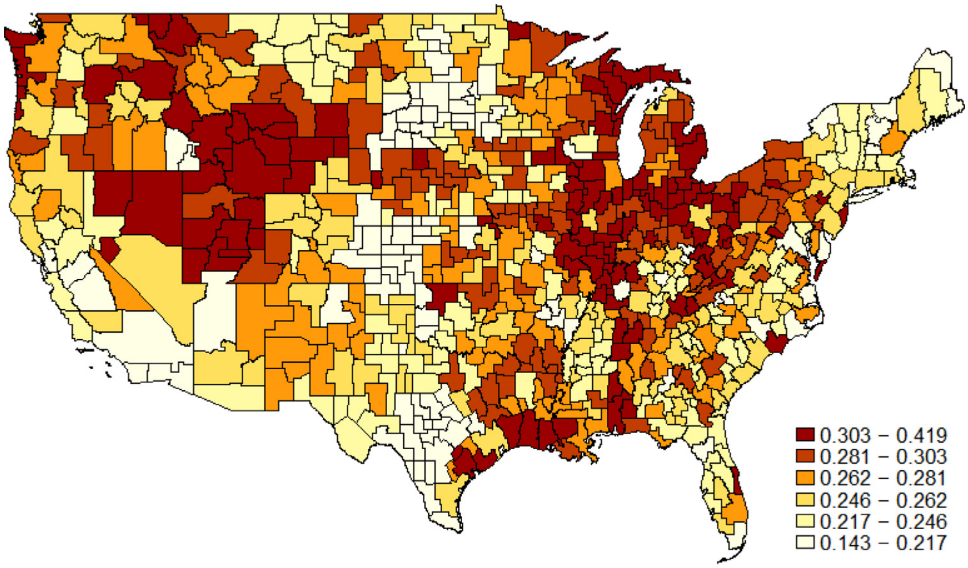
Fig. 3a shows the variations in robot adoption defined in (2) between 1993 and 2015 across US CZs. The darker color corresponds to higher level of robot adoption. As the automotive industry has a dominant position in robot use, areas that

[8] Autor and Dorn (2013) provide the crosswalks between counties (or PUMAs) and CZs between 1990 and 2010. For 2015, we first use the information on how PUMA borders changed between 2010 and 2015 from the Bureau of Census to match PUMAs in 2015 to PUMAs in 2010, then assign PUMAs to CZs.

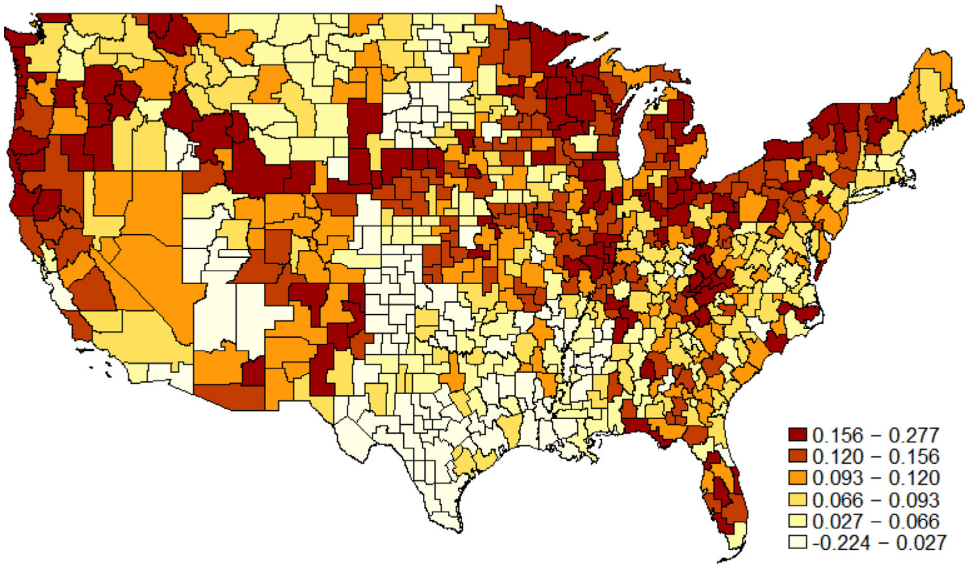
[9] Earnings are top coded in the census and ACS data. We adjust top-coded annual earnings to 1.5 times of the top codes. To control for extreme values in hourly wage, we assign the 99th percentile value to all observations above the 99th percentile and assign the 1st percentile value to all values below the 1st percentile.

[10] Note that we use employment from a fixed base year (1990) instead of current year to calculate change in robot capital measured by the number of robots per thousand workers. Alternatively, change in robot capital may be calculated by $\frac{R_{i,t_1}}{L_{i,t_1}} - \frac{R_{i,t_0}}{L_{i,t_0}}$, in which if $R_{i,t_1} = R_{i,t_0}$ and $L_{i,t_1} < L_{i,t_0}$, then $\frac{R_{i,t_1}}{L_{i,t_1}} > \frac{R_{i,t_0}}{L_{i,t_0}}$. That is, in an industry with a steady number of robots but a shrinking workforce, it appears as if the industry adopts more robots over time. This is the reason why we use the number of workers from 1990 in our calculation for change in robot capital in Eq. (1), as well as for the statistics in Fig. 1a and b. Because the number of robots was low in 1993, the adjustment term $g_{i,(t_0,t_1)} \frac{R_{i,t_0}}{L_{i,1990}}$ is not quantitatively important. Between 1993 and 2015, 96.4 percent of the variation in robot adoption across industries as measured in Eq. (1) is driven by the increase in the first term, $\frac{R_{i,t_1} - R_{i,t_0}}{L_{i,1990}}$.

[11] The adjustment term $g_{i,(t_0,t_1)} \frac{C_{i,t_0}}{L_{i,1990}}$ in Eq. (3) is also not quantitatively important; 98.5 percent of the variation in computer adoption across industries is driven by the change in computer intensity captured by the first term in (3), $\frac{C_{i,t_1} - C_{i,t_0}}{L_{i,1990}}$. When we re-estimate our models by using alternative measures for robot adoption and capital adoption without including the corresponding adjustment terms, we obtain similar results.



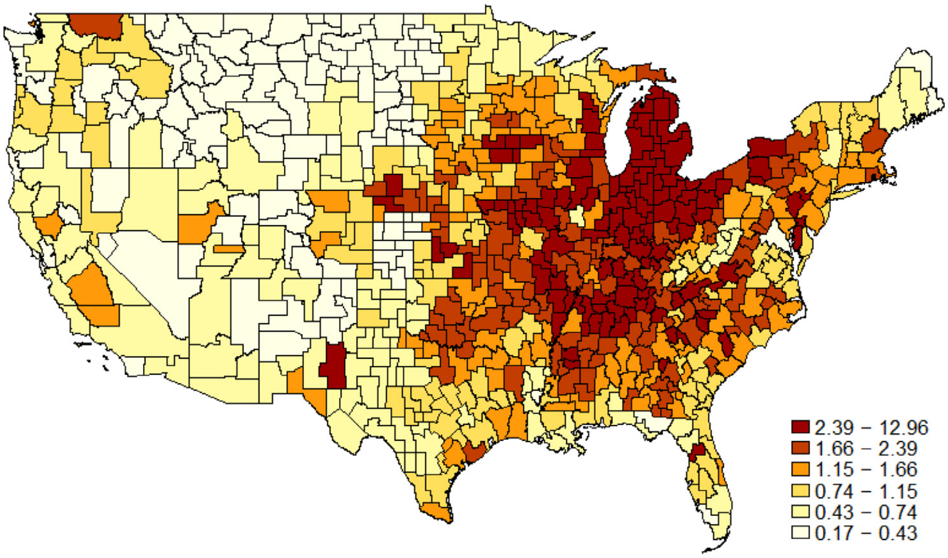
(a) Gender Wage Gap in 1990



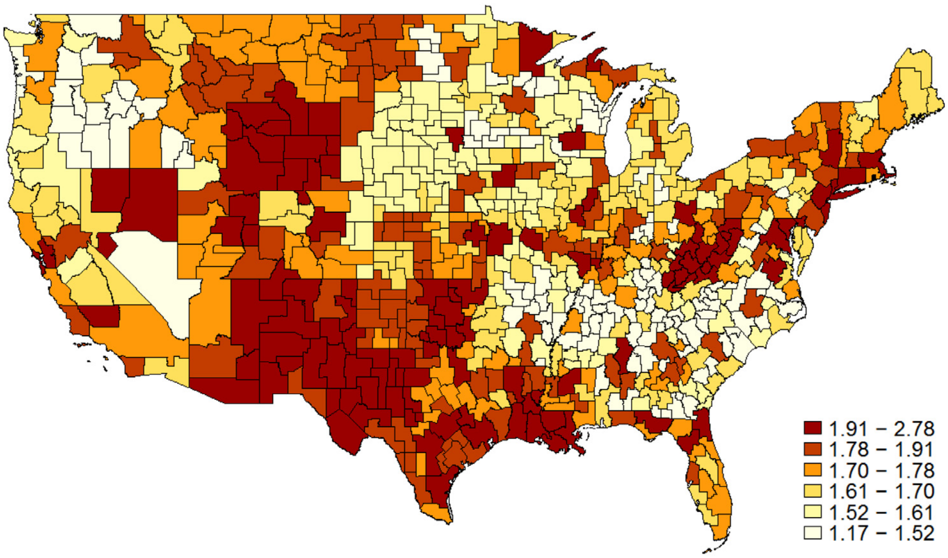
(b) Decline in Gender Wage Gap, 1990–2015

Fig. 2. Gender Wage Gap across Commuting Zones. *Notes:* The data come from the 1990 Census and the 2014–2016 ACS. Hourly wage is computed by dividing annual earnings by total working hours for non-institutionalized civilian employed workers between age 16 and 64. Gender wage gap in a commuting zone is defined as the log difference between the average of male hourly wages and the average of female hourly wages in the region.

host auto manufacturers and auto parts suppliers have the highest robot adoption. Most of the CZs with the highest robot adoption cluster in the states of Michigan, Ohio, and Indiana. Besides the areas around the Great Lakes, CZs with high robot adoption are less clustered. In the CZs with the lowest robot adoption, agriculture industry tend to account for the largest employment share in the region. Similarly, Fig. 3b shows the variations in computer adoption defined in (4) between 1990 and 2015, with darker color representing higher computer adoption. The regional variations in computer adoption are also largely driven by the distribution of industries across CZs. For example, many CZs in Louisiana and Texas have high computer adoption because the concentration of petroleum and mining industries is high. New York City has high computer adoption because of its heavy concentration in financial industry, whereas the California bay area also has high computer adoption because of its booming electronics industry. Both figures reveal significant heterogeneity across CZs.



(a) Robot Adoption, 1993–2015



(b) Computer Adoption, 1990–2015

Fig. 3. Robot and Computer Adoption across Commuting Zones. *Notes:* The robot data come from the IFR and the computer capital data come from the EUKLEMS. Robot (computer) adoption in a commuting zone is defined as the sum of industry-level robot (computer) adoption weighted by each industry's 1990 employment share in the commuting zone.

We construct a measure for overall capital deepening in a CZ by using industry-specific total capital stock (per thousand workers) from EUKLEMS weighted by each industry's employment share in the CZ, in the same way as those in Eqs. (2) and (4). This variable is used to control for other non-robot non-computer automation technologies. We follow Autor et al. (2013) to construct a measure of US local labor market exposure to Chinese imports. We obtain industry level Chinese imports from Comtrade, and then project them to CZ level by using each industry's employment share in a CZ as weights. The (change in) exposure to Chinese imports is defined as

$$\Delta IPW_{jt} = \sum_i \frac{L_{ijt}}{L_{jt}} \frac{\Delta M_{it}}{L_{it}}, \tag{5}$$

where L_{it} is the start of period (year t) employment in industry i, ΔM_{it} is the observed change in US imports from China in industry i between the start and end of the period, and $\frac{L_{ijt}}{L_{jt}}$ is the employment share of industry i in CZ j at time t. We also

Table 4
Top Occupations by Gender, with Skill Measures.

Occupation description	Employment in 1990	% female	% male	Brain skills	Brawn skills
Top ten female occupations					
Secretaries	183,610	98.88	1.12	88	48
Dental hygienists	3,442	98.34	1.66	53	20
Kindergarten teachers	12,065	98.13	1.87	64	45
Dental assistants	8,310	97.72	2.28	60	3
Receptionists	34,102	96.22	3.78	41	22
Child care workers	35,849	96.18	3.82	37	3
Typists	27,547	95.16	4.84	39	35
Registered nurses	84,476	94.66	5.34	84	65
Household cleaners and servants	13,620	94.35	5.65	5	32
Licensed practical nurses	19,658	94.23	5.77	50	65
Top ten male occupations					
Bus engine mechanics	13,258	0.84	99.16	42	91
Heavy equipment mechanics	9,557	0.94	99.06	43	92
Heating mechanics	8,780	1.13	98.87	42	67
Drillers of oil wells	1,809	1.15	98.85	24	82
Paving equipment operators	3,731	1.24	98.76	23	91
Railroad brake operators	1,536	1.35	98.65	23	65
Plumbers	22,100	1.41	98.59	46	90
Concrete workers	3,028	1.43	98.57	25	80
Roofers and slaters	7,971	1.46	98.54	27	91
Elevator installers	1,149	1.54	98.46	28	92

Notes: The table reports the top ten occupations for male and female, along with mean skill measures, using 1990 US Census microdata and the 1977 DOT. Brawn skills and Brain skills are standardized into percentile values corresponding to their ranks in the 1970 skill distributions.

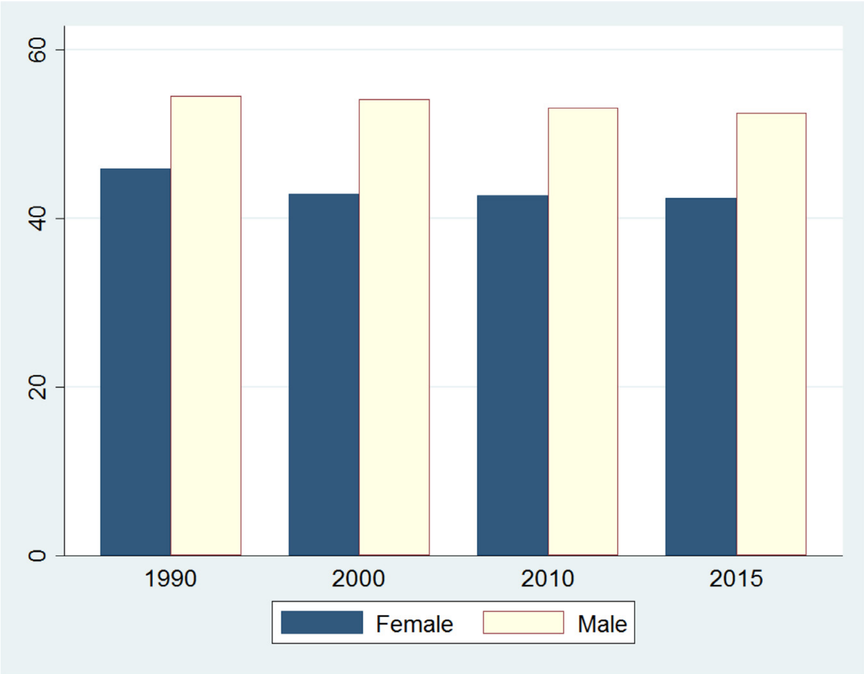
consider other CZ characteristics that may affect gender wage gap. For each CZ, we collect information on total population, shares of population with different education levels, races, genders, and ages in 1990 from the Census data. We rely on share of employment in manufacturing, fraction of female workers in manufacturing employment, and fraction of employment in routine occupations in a CZ to control for differences in industry structure. We also construct changes in the share of college graduates by gender between 1990 and 2015 in each CZ to account for changes in skill supply. Table A1 presents summary statistics on commuting zone gender wage gap, technological changes, and other characteristics.

2.3. The substitutions between technologies and skills

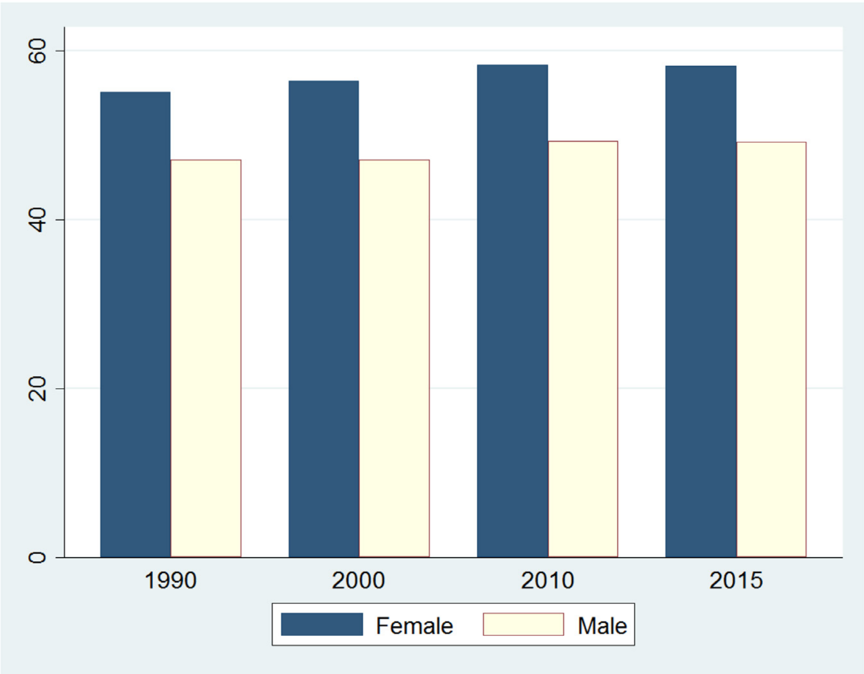
We construct measures of brawn skills and brain skills by using information on skill requirements at detailed occupational level and assuming that workers are matched to jobs that require skills they have, following the pioneer work by Autor et al. (2003). We begin with the 1990 US Census, which identifies each person's occupation. Using the 1977 DOT, we construct a measure for brawn skills in each occupation by combining five DOT variables, including eye-hand-foot coordination, motor coordination, finger dexterity, manual dexterity, and physical strength. A measure for brain skills is constructed by combining multiple DOT variables: GED reasoning, GED math, GED language, verbal aptitude, numerical aptitude, temperaments on DCP (direction, control and planning for an activity), FIF (interpreting feeling, ideas, facts in terms of personal viewpoint), INFLU (influencing people in their opinions, attitudes or judgment about ideas or things), SJC (making generalizations, evaluations, or decisions based on sensory or judgmental criteria), MVC (making generalization, judgments, or decisions based on measurable or verifiable criteria), and DEPL (dealing with people beyond giving and receiving instructions). We standardize our brawn and brain skills measures by taking the average of the relevant DOT variables into percentile values corresponding to their ranks in the 1970 skill distributions. We choose 1970 as the base year for our standardization because it reflects the distribution of skills before the recent progress in robot and computing technologies.

Table 4 examines the relationship between gender and skills. The table reports top ten occupations for each gender and their skill content using the 1990 Census data. The occupations with the largest shares of female workers (such as secretaries, dental hygienists, and kindergarten teachers) typically have high percentile scores on brain skills and low percentile scores on brawn skills, with household cleaners and servants being the only exception. By contrast, the occupations with the largest shares of male workers (such as mechanics, oil drillers and operators) score high on brawn skills and score low on brain skills. Therefore, if the only contribution of robot was to replace brawn skills, it should hurt male workers more than female workers. Similarly, if computer capital was to substitute brain skills, it should hurt female workers more than male workers.

We further explore the relationship between gender and skills in Fig. 4, which presents gender differences in average brawn skills and brain skills between 1990 and 2015. We find that males on average have much higher brawn skills (Fig. 4a) and much lower brain skills than females (Fig. 4b). Average brawn skills have declined slightly for both males and females, whereas average brain skills have increased since 1990. The gender differences in brawn and brain skills in Fig. 4 are not driven by the differences in a few industries. Fig. 5a plots the male and female difference in brawn skills across industries

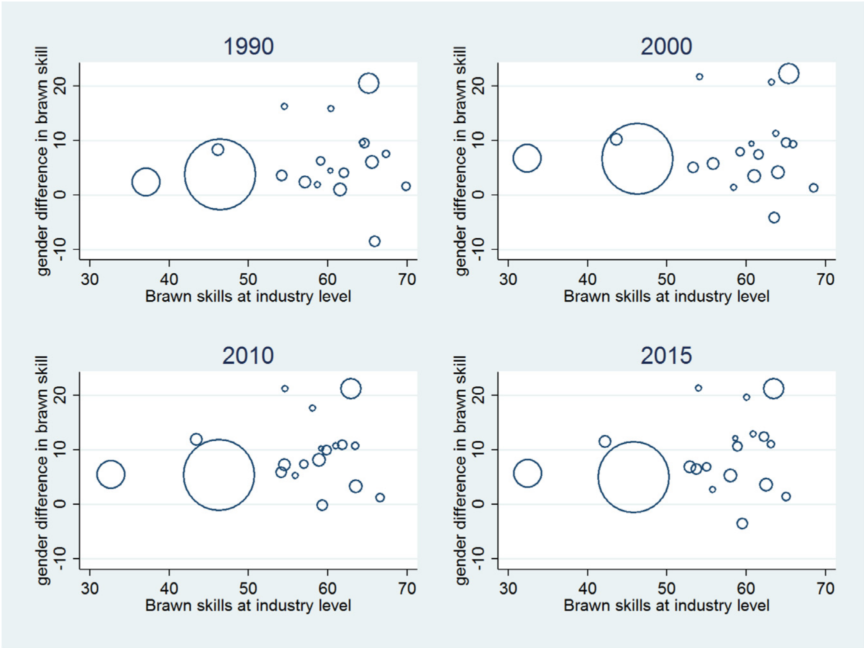


(a) Brawn Skills by Gender

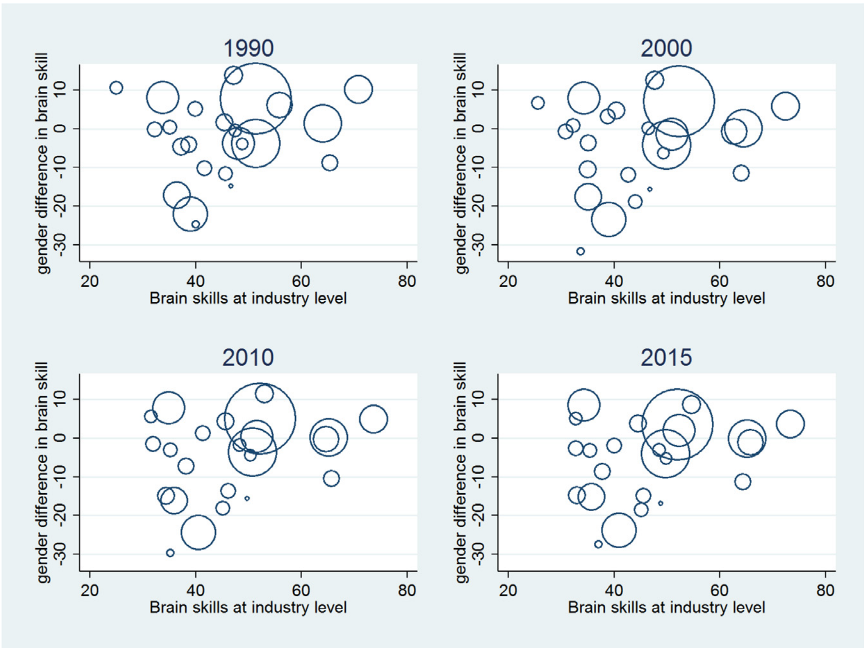


(b) Brain Skills by Gender

Fig. 4. Gender Differences in Brawn and Brain Skills. *Notes:* The data come from the 1990 and 2000 censuses, 2009–2011 and 2014–2016 ACS, and the 1977 DOT. Brawn skills and brain skills are standardized into percentile values corresponding to their ranks in the 1970 skill distributions.



(a) Gender Differences in Brawn Skills



(b) Gender Differences in Brain Skills

Fig. 5. Gender Differences in Brawn and Brain Skills Across Industries. *Notes:* The data come from the 1990 and 2000 censuses, 2009–2011 and 2014–2016 ACS, and the 1977 DOT. Brawn skills and brain skills are standardized into percentile values corresponding to their ranks in the 1970 skill distributions.

ordered by their brawn skill requirement in 1990, 2000, 2010, and 2015, respectively.[12] We find that males have higher brawn skills than females in almost all industry in all years, and gender differences in brawn skills tend to be higher in industries with higher brawn skill requirement. Fig. 5b plots the male and female difference in brain skills across industries ordered by their brain skill requirement in each year. In most industries, females on average have higher brain skills than males. Gender differences in brain skills tend to be higher in industries with lower brain skill requirement.

Figs. 6 and 7 provide evidence on the substitutions between technologies and skills. Fig. 6a shows the correlation between 1990 brawn skill requirement in an industry with robot adoption in the industry, and Fig. 6b depicts the analogous relationship between brain skill requirement with robot adoption. We find a positive correlation between initial brawn skill requirement and robot adoption over time, but no relationship between brain skill requirement and robot adoption. That is, industries that required higher brawn skills in 1990 are more likely to adopt robotics technology over time, but the initial brain skill requirement in an industry is not associated with robot adoption. Fig. 7a and b show the correlations between initial skill requirements and computer adoption across industries and reveal no correlation between initial brawn skill requirement and computer adoption and a positive correlation between brain skill requirement and computer adoption. Industries with higher brain skill requirements are more likely to adopt computer technology. These empirical evidence is consistent with the notion that robot capital is more substitutable for brawn skills and computer capital is more substitutable for brain skills.

3. Conceptual framework

In this section, we discuss the potential effects of different technological changes on wages. Our conceptual framework is based on two postulates that are consistent with the data. First, robot capital is more substitutable with brawn labor than with brain labor, whereas computer capital is more substitutable with brain labor than with brawn labor. Second, males have a comparative advantage in brawn skills, and females have a comparative advantage in brain skills. We will investigate the relationships between robot and computer adoption and gender wage gap in a simple model and form empirical specifications based on them. In the subsequent empirical analysis, we will also consider the effects of other socioeconomic variables, such as overall capital deepening and trade exposure, on the gender wage differentials.

We consider a production model with two task inputs, manual and cognitive, that are used to produce output Y. The tasks are carried out by four factor inputs. Two of these factors are labor inputs: brawn labor (L_A) and brain labor (L_B), and they are supplied by workers of different gender ($g = f, m$). The other two factors of production are robot capital (R) and computer capital (C), which have different substitution elasticities with the two labor inputs. Manual tasks are completed by brawn labor and robot capital, whereas cognitive tasks are completed by brain labor and computer capital. The aggregate output at time t is generated by combining all inputs using the following technology:

$$Y_t = z_t (R_t^{\rho} + L_{At}^{\rho})^{\beta/\rho} (C_t^{\theta} + L_{Bt}^{\theta})^{(1-\beta)/\theta}, \tag{6}$$

where z_t is an efficiency parameter, β is manual tasks' share and $1-\beta$ is cognitive tasks' share in the production process, respectively. In this specification, the elasticity of substitution between robot capital and brawn labor is $1/(1-\rho)$, the elasticity of substitution between computer capital and brain labor is $1/(1-\theta)$, whereas the elasticity of substitution between robot capital and brain labor and that between computer capital and brawn labor are 1. We model robots as being more likely to replace brawn labor and computers as being more likely to substitute brain labor, thus $1/(1-\rho) > 1$, and $1/(1-\theta) > 1$. By implication, robot capital is a relative substitute for brawn labor and a relative complement to brain labor, whereas computer capital is a relative substitute for brain labor and a relative complement to brawn labor.

There is a continuum of unit mass female workers, f, and a continuum of unit mass male workers, m. Each worker of gender g is endowed with brawn skills L_A^g and brain skills L_B^g, and they supply labor inelastically. We assume that men and women have the same amount of brain skills ($L_B^f = L_B^m$), but men are on average stronger than women physically and have a comparative advantage in brawn skills ($L_A^f < L_A^m$) (Galor and Weil, 1996; Pitt et al., 2012; Rendall, 2018).[13]

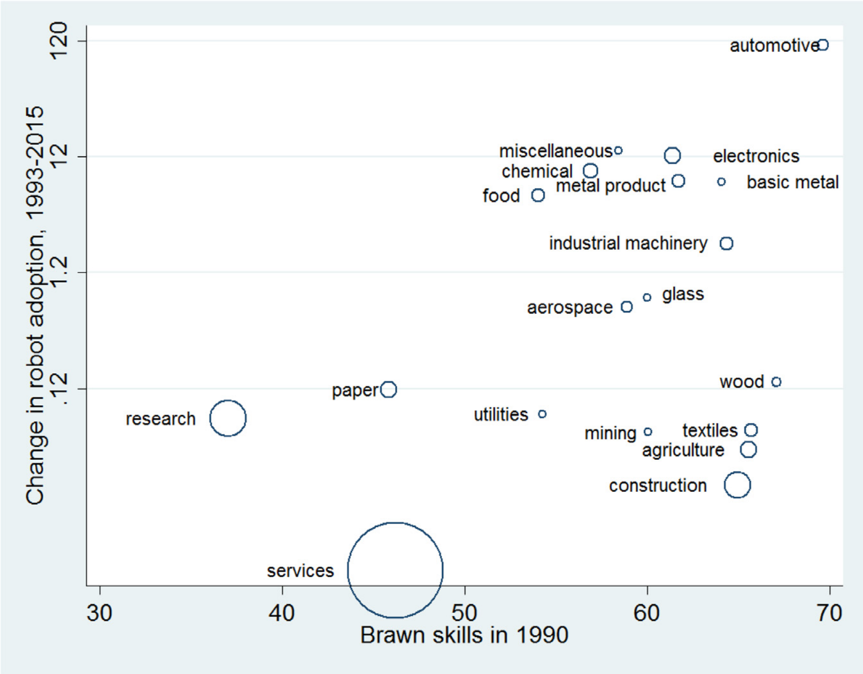
Following Autor and Dorn (2013), the production function of robot and computer capital are given by $R_t = Y_{Rt} e^{\delta_R t}$ and $C_t = Y_{Ct} e^{\delta_C t}$, where Y_{Rt} and Y_{Ct} are the amount of final good allocated to produce robot and computer capital, respectively. The parameters δ_R and δ_C are positive constants that capture technological progress in producing new robot and computer capital. Both types of capital are assumed to fully depreciate between periods. Market competition and the zero profit condition imply that the real prices of capital (P_{Rt}, P_{Ct}) are equal to average cost, that is, $P_{Rt} = Y_{Rt}/R_t = e^{-\delta_R t}$, $P_{Ct} = Y_{Ct}/C_t = e^{-\delta_C t}$. At time $t = 0$, the prices of capital are normalized to 1. Over time, the (quality-adjusted) prices of robot and computer capital go down continuously as its production efficiency increases.

Without loss of generality, utility is assumed to be linear in consumption. Given P_{Rt} and P_{Ct} at time t, the social planner chooses the level of capital (R_t, C_t) to maximize aggregate utility and solves the following problem:

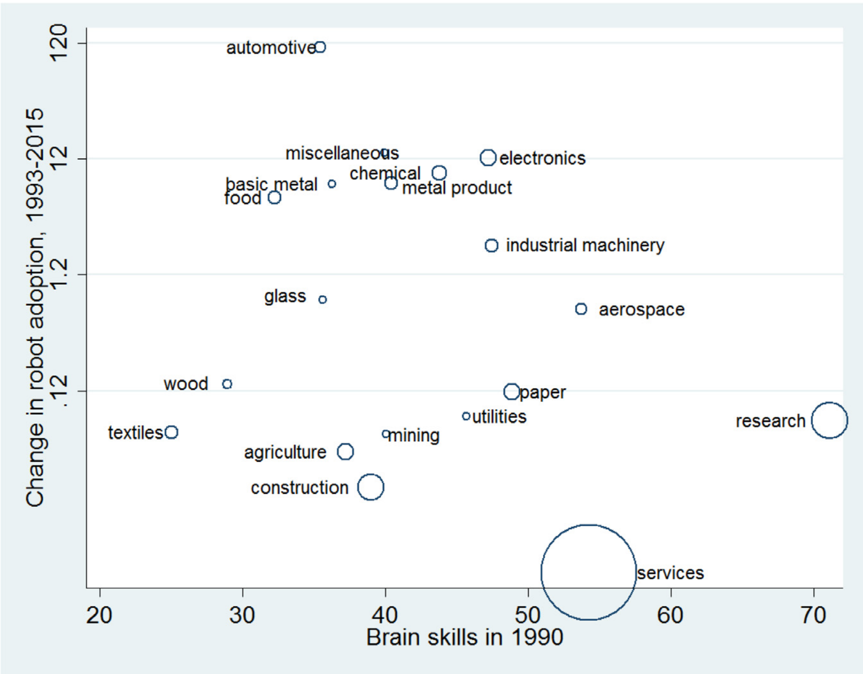
$$\max_{R,C} Y_t - P_{Rt} R_t - P_{Ct} C_t, \tag{7}$$

[12] The brawn skill requirement in an industry is the weighted average of occupation-specific brawn skill requirement within the industry.

[13] Besides the evidence shown in Table 4, Figs. 4 and 5, Mathiowetz et al. (1985) show that men have higher grip strength than women on average in a US study, and Pitt et al. (2012) find similar patterns in Bangladesh. Therefore, the gender difference in physical strength is likely originated from biological differences rather than cultural or economic differences.

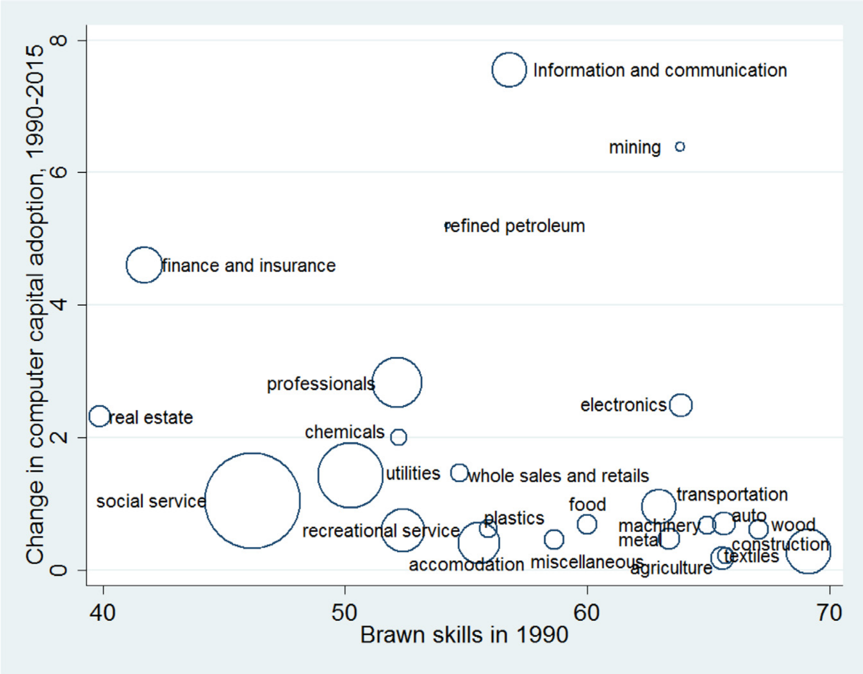


(a) Brawn Skills and Robot Adoption

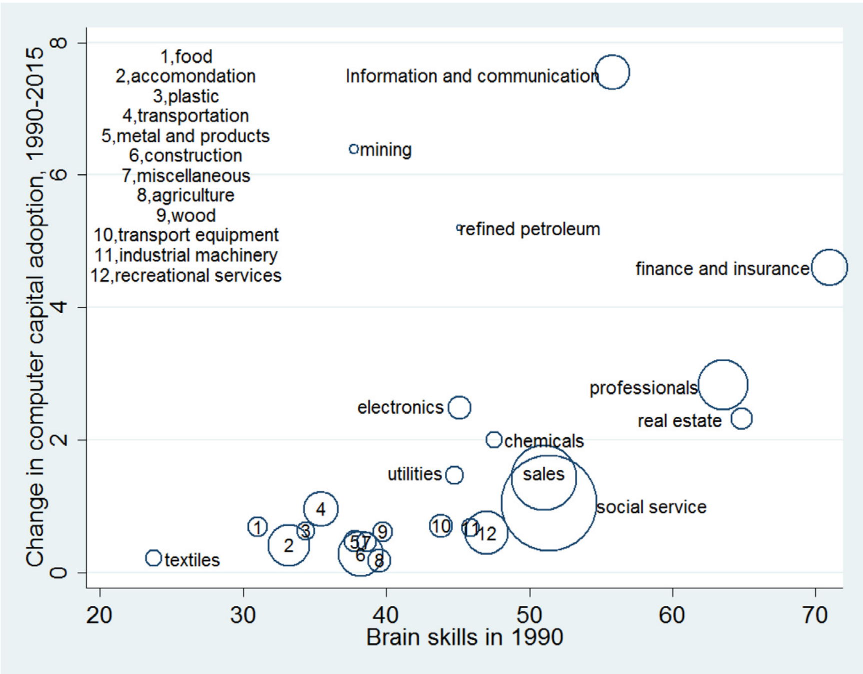


(b) Brain Skills and Robot Adoption

Fig. 6. Substitutions between Robot Capital and Skills. *Notes:* The robot data come from the IFR, and the data on skills come from the 1990 census and the 1977 DOT. Brawn skills and brain skills are standardized into percentile values corresponding to their ranks in the 1970 skill distributions.



(a) Brawn Skills and Computer Adoption



(b) Brain Skills and Computer Adoption

Fig. 7. Substitutions between Computer Capital and Skills. *Notes:* The computer capital data come from the EUKLEMS, and the data on skills come from the 1990 census and the 1977 DOT. Brawn skills and brain skills are standardized into percentile values corresponding to their ranks in the 1970 skill distributions.

where Y_t is given by Eq. (6). The first order conditions imply that

$$\partial Y_t/\partial R_t = e^{-\delta_R t}, \text{ and } \partial Y_t/\partial C_t = e^{-\delta_C t}. \tag{8}$$

We can show that

$$\frac{\partial R_t}{\partial t} > 0, \text{ and } \frac{\partial C_t}{\partial t} > 0. \tag{9}$$

Over time, as the prices of robot and computer capital go down, there is wider adoption and more production of both robots and computers.[14]

Factor prices are determined by marginal products of per unit of labor input as following:

$$w_{At} = z_t \beta L_{At}^{\rho-1}(R_t^\rho + L_{At}^\rho)^{\beta/\rho-1}(C_t^\theta + L_{Bt}^\theta)^{(1-\beta)/\theta}, \tag{10}$$

$$w_{Bt} = z_t(1-\beta)L_{Bt}^{\theta-1}(R_t^\rho + L_{At}^\rho)^{\beta/\rho}(C_t^\theta + L_{Bt}^\theta)^{(1-\beta)/\theta-1}. \tag{11}$$

It is immediate from Eq. (10) that the effect of robots adoption on brawn labor wage is ambiguous. In particular, $\partial w_{At}/\partial R_t < 0$, if $\rho > \beta$; and $\partial w_{At}/\partial R_t > 0$, if $\rho < \beta$. When the elasticity of substitution between robots and brawn labor is large and satisfies $\rho > \beta$ (in the extreme case they become perfect substitutes when $\rho = 1$), the rise in robots would increase manual tasks inputs and push down the marginal product of brawn labor. In contrast, when the elasticity of substitution between robots and brawn labor is small such that $\rho < \beta$, robots and brawn labor would become relative complements in the production and the rise in robots would increase the marginal product of brawn labor. Because robots and brain labor are productive complements, the wage paid to brain labor rises with wider adoption of robots, i.e., $\partial w_{Bt}/\partial R_t > 0$. Similarly, we can show that brawn labor wage increases with computers, but the effect of computer adoption on brain labor wage depends on the elasticity of substitution between computer and brain labor.

The relative skill premium between brain and brawn skills (π) can be expressed as a function of input ratios:

$$\pi_t = \frac{w_{Bt}}{w_{At}} = \frac{1-\beta}{\beta}\left[\frac{\left(\frac{R_t}{L_{At}}\right)^\rho + 1}{\left(\frac{C_t}{L_{Bt}}\right)^\theta + 1}\right]\left(\frac{L_{At}}{L_{Bt}}\right). \tag{12}$$

The brain skill premium depends on the relative supply of brain and brawn labor inputs L_{At}/L_{Bt}. Relatively faster growth of brain labor input reduces the brain skill premium. The brain skill premium also depends on the relative supply of robot capital and brawn labor and the relative supply of computer capital and brain labor. Under the assumptions that brawn labor is more substitutable for robots and brain labor is more substitutable for computers, we have $0 < \rho, \theta < 1$. In this case, growth in robot capital tends to increase brain skill premium as it increases the relative demand for brain labor input, whereas rise in computer capital tends to decrease brain skill premium as it decreases the relative demand for brain labor input:

$$\frac{\partial \pi_t}{\partial R_t} > 0, \quad \text{and} \quad \frac{\partial \pi_t}{\partial C_t} < 0. \tag{13}$$

Gender-specific wage is determined by skill endowments and marginal products of labor as following:

$$w_t^g = w_{At}L_{At}^g + w_{Bt}L_{Bt}^g, \quad \text{where } g = f, m. \tag{14}$$

Therefore, the impacts of increasing R_t and C_t on female and male wages, w_t^f, w_t^m, are all ambiguous. Gender wage gap can be defined as a function of brain skill premium:

$$\frac{w_t^m}{w_t^f} = \frac{L_{At}^m + L_{Bt}^m \pi_t}{L_{At}^f + L_{Bt}^f \pi_t}. \tag{15}$$

That is, women's relative wage increases in brain skill premium, since women possess relatively more brain skills. As a result, women's relative wage increases with growth in robot capital and decreases with growth in computer capital.[15]

The main goal of this study is to analyze the effect of technological changes, proxied by the growth in industrial robots and computer capital on gender wage gap. From a simple time-series study, some other variables that have trended over time may generate spurious relationship between technological changes and gender wage gap. Therefore, we focus on the local labor market impact of robot and computer capital in our empirical analysis, following studies such as Autor and

[14] Following the literature (e.g., Autor et al., 2003; Autor and Dorn, 2013), the prices of robot and computer are assumed to fall exogenously with time due to technical advances. Analyzing the driving forces of technological advances and the determinants of technology adoption is beyond the scope of current paper and left for future research.

[15] For simplicity, we assume homogeneous skill endowment within each gender group. In Appendix B, we relax this assumption and allow for individual heterogeneous skill endowment, following Autor et al. (2003), Autor and Dorn (2013), and Ottaviano et al. (2013). In this extension, workers sort themselves into different tasks according to comparative advantage, and labor inputs are determined at the labor market equilibrium. Technological advances due to robot and computer adoption directly change the allocation of labor inputs across task types. We show that the implications for the effects of robots and computers on gender-specific wage levels and gender wage gap would be unchanged in the extended model.

Dorn (2013), Autor et al. (2013), and Acemoglu and Restrepo (2019). To guide the subsequent analysis at the level of local labor markets, we consider a large set of geographic regions, $j \in \{1, 2, ..., J\}$ and allow the structure of production to vary across regions. Each region is endowed with a unit mass of male workers and a unit mass of female workers and has the following production function:

$$Y_{jt} = z_{jt}(R_{jt}^{\rho} + L_{Ajt}^{\rho})^{\beta_j/\rho}(C_{jt}^{\theta} + L_{Bjt}^{\theta})^{(1-\beta_j)/\theta}, \tag{16}$$

with $\beta_j \in (0, 1)$. In this specification, each region produces a differentiated product Y_j. A region with a higher β_j produces a product with more intensive use of manual tasks (carried out by robots or brawn labor), whereas a region with a lower β_j has relatively high demand for cognitive tasks (carried out by computers or brain labor).

Next, we analyze the cross-region differences in robot and computer adoption (or production). The first order conditions of region j's social planner's problem are

$$\begin{aligned} &z_{jt}\beta_j(R_{jt}^{\rho} + L_{Ajt}^{\rho})^{\beta_j/\rho-1}(C_{jt}^{\theta} + L_{Bjt}^{\theta})^{(1-\beta_j)/\theta}R_{jt}^{\rho-1} = e^{-\delta_R t},\\ &z_{jt}(1-\beta_j)(R_{jt}^{\rho} + L_{Ajt}^{\rho})^{\beta_j/\rho}(C_{jt}^{\theta} + L_{Bjt}^{\theta})^{(1-\beta_j)/\theta-1}C_{jt}^{\theta-1} = e^{-\delta_C t}, \end{aligned} \tag{17}$$

which yield

$$\frac{R_{jt} + L_{Ajt}^{\rho}R_{jt}^{1-\rho}}{C_{jt} + L_{Bjt}^{\theta}C_{jt}^{1-\theta}} = \frac{\beta_j}{1-\beta_j}e^{(\delta_R-\delta_C)t}. \tag{18}$$

In our simple framework, labor inputs are exogenously given. Eq. (18) implies that as the price of robot or computer capital goes down, i.e., as δ_R or δ_C increases, the demand for robot or computer goes up. Furthermore, we can show that

$$\partial R_{jt}/\partial\beta_j > 0, \text{ and } \partial C_{jt}/\partial\beta_j < 0. \tag{19}$$

That is, in regions with higher demand for manual task input, there is faster adoption of robot capital; and in regions with higher demand for cognitive task input, there is faster adoption of computer capital.

Gender wage gap in region j is given by

$$\frac{w_{jt}^m}{w_{jt}^f} = \frac{L_{Ajt}^m + L_{Bjt}^m\pi_{jt}}{L_{Ajt}^f + L_{Bjt}^f\pi_{jt}}. \tag{20}$$

where the regional skill premium π_{jt} depends on the adoption of robot and computer capital in the region:

$$\pi_{jt} = \frac{1-\beta_j}{\beta_j}\left[\frac{\left(\frac{R_{jt}}{L_{Ajt}}\right)^{\rho}+1}{\left(\frac{C_{jt}}{L_{Bjt}}\right)^{\theta}+1}\right]\left(\frac{L_{Ajt}}{L_{Bjt}}\right). \tag{21}$$

In regions with faster adoption of robots, Eq. (21) implies that brain skill premium is higher. As a result, Eq. (20) predicts that women's relative wage is also higher. Similarly, in regions with faster adoption of computers, brain skill premium and women's relative wage are lower. This inference leads to the main hypothesis derived from the simple conceptual framework that can be tested empirically: *In regions with faster adoption of robot capital, gender wage gap is lower; whereas in regions with faster adoption of computer capital, gender wage gap is higher, all else being held constant.*

4. Empirical analysis

In this section, we first formulate our empirical specification using the simple framework in Section 3 as our guidance. Then we present the effects of robot and computer adoption on gender wage gap across CZs to test the predictions of the model and discuss the quantitative implications of our estimates. Finally, we investigate the robustness of our estimates.

4.1. Empirical specification

The implications of the model in Section 3 can be empirically tested by considering a log linear approximation of Eq. (20) to derive the impact of robot and computer capital on local gender wage gap as follows:

$$GAP_{jt} = \eta_R \ln\frac{R_{jt}}{L_{Ajt}} + \eta_C \ln\frac{C_{jt}}{L_{Bjt}} + \phi \ln\frac{L_{Ajt}}{L_{Bjt}}, \tag{22}$$

where $GAP_{jt} = \ln w_{jt}^m - \ln w_{jt}^f$ is the gender wage gap in region j at time t. Our hypothesis is that $\eta_R < 0$ and $\eta_C > 0$.

Our main empirical specification is based on Eq. (22). In our data, we measure robot and computer capital by the quantities of capital stock per thousand workers (R/L and C/L) and approximate the relative supply of brawn and brain labor inputs by controlling population shares of workers with different gender and other characteristics. We estimate the model in long differences (Δ) over 25 years to focus on the historical trends and smooth out measurement error (Acemoglu and Restrepo, 2019; Autor and Dorn, 2013; Michaels et al., 2004). Some regions had close to zero robot or computer capital in

1990, so their changes in $\ln R/L$ and $\ln C/L$ are enormous. Therefore, we subsitute changes in levels of robot and computer capital rather than logarithms in our empirical specifications. Consequently our key estimating equation is given by:

$$\Delta GAP_{j,(t_0,t_1)} = \alpha_0 + \alpha_1 \Delta RA_{j,(t_0,t_1)} + \alpha_2 \Delta CA_{j,(t_0,t_1)} + \boldsymbol{X}_{j,(t_0,t_1)} \boldsymbol{\Gamma} + \epsilon_{j,(t_0,t_1)}, \tag{23}$$

where $\Delta RA_{j,(t_0,t_1)}$ represents robot adoption as defined in Eq. (2), $\Delta CA_{j,(t_0,t_1)}$ represents computer adoption as defined in Eq. (4), $\boldsymbol{X}_{j,(t_0,t_1)}$ is a vector of regional characteristics and economic variables, and $\epsilon_{j,(t_0,t_1)}$ represents a random error.

Fig. 8 shows the correlations between changes in gender wage gap and the two technological changes across CZs. There appears to be a negative relationship between gender wage gap and robot adoption (Fig. 8a), and a positive relationship between gender wage gap and computer capital adoption (Fig. 8b). The solid lines correspond to fitted lines from linear regressions with CZ population in 1990 (represented by bubble size) as weights. The dashed lines are for unweighted regressions. We fit the following equations:

$$\Delta GAP_{j,1990-2015} = \underset{(0.002)}{-0.077} - \underset{(0.001)}{0.007} \Delta RA_{j,1993-2015}, \tag{24}$$

$$\Delta GAP_{j,1990-2015} = \underset{(0.020)}{-0.251} + \underset{(0.011)}{0.090} \Delta CA_{j,1990-2015}. \tag{25}$$

The point estimate of -0.007 (standard error 0.001) for the robot adoption variable confirms that a CZ's robot adoption is predictive of its decline in gender wage gap, whereas the positive point estimate of 0.090 (standard error 0.011) for the computer adoption variable indicates that the growth in computer capital is associated with an increase in gender wage gap. Although these estimates are supportive of our model's predictions, there are many other observable and unobservable factors that may affect gender wage gap in local labor markets. We examine the links between technological changes and gender wage gap more rigorously in our econometric analysis below.

We augment specification (23) in our subsequent empirical analysis. Since robots and computers are only two specific aspects of recent technological progress, we also investigate the impact of overall capital deepening on gender wage gap. Additionally, we control for trade exposure and various other CZ characteristics and economic variables that may affect gender wage gap. Even after we take into account all these control variables, there are other reasons why the US adoption of robot and computer capital could be subject to measurement error or correlated with the error term $\epsilon_{j(t_0,t_1)}$, leading to biased estimates. For example, any (unobserved) shock to relative labor demand for female workers in a CZ may affect the technology adoption decisions of the industries located in the CZ. To identify the effects of robot and computer adoption on the gender wage gap in US local labor markets, we implement some instrumental variable strategies.

We instrument the US robot adoption using an analogous measure constructed for several European countries that are ahead of the US in robot technology (Acemoglu and Restrepo, 2019), which is meant to capture the exogenous component of robot use driven by technological progress. In particular, the IFR data show that the number of robots per thousand workers in Germany (shown in Fig. 1a), Sweden, and Italy (i.e., *EURO*3) are ahead of that in the US throughout the period between 1993 and 2015. Therefore, we combine the IFR robot data with employment counts and output growth from the EUKLEMS for these countries and define their average robot adoption as follows

$$\overline{\Delta RA}_{i,(t_0,t_1)} = \frac{1}{3} \sum_{c \in EURO3} \left[\frac{R^c_{i,t_1} - R^c_{i,t_0}}{L^c_{i,1990}} - g^c_{i,(t_0,t_1)} \frac{R^c_{i,t_0}}{L^c_{i,1990}} \right], \tag{26}$$

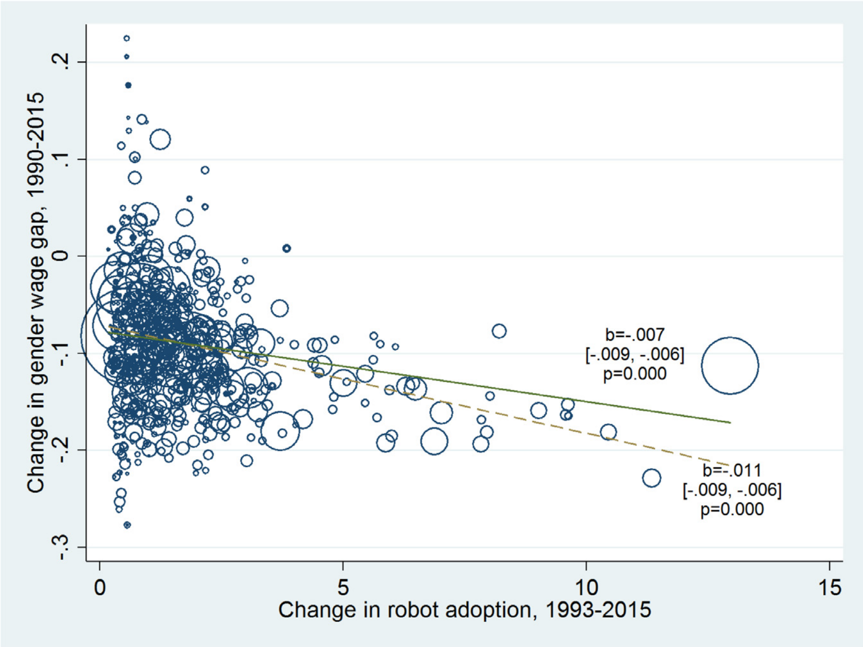
where $R^c_{i,t}$ is the number of robots in industry i in country c at time t, $g^c_{i,(t_0,t_1)}$ is the growth rate of output in industry i in country c between time t_0 and t_1, and $L^c_{i,1990}$ is the baseline employment level.[16] We instrument the US commuting zone robot adoption $\Delta RA_{j(t_0,t_1)}$ in Eq. (23) by

$$\overline{\Delta RA}_{j,(t_0,t_1)} = \sum_i \frac{L_{ij,1990}}{L_{j,1990}} \overline{\Delta RA}_{i,(t_0,t_1)}, \tag{27}$$

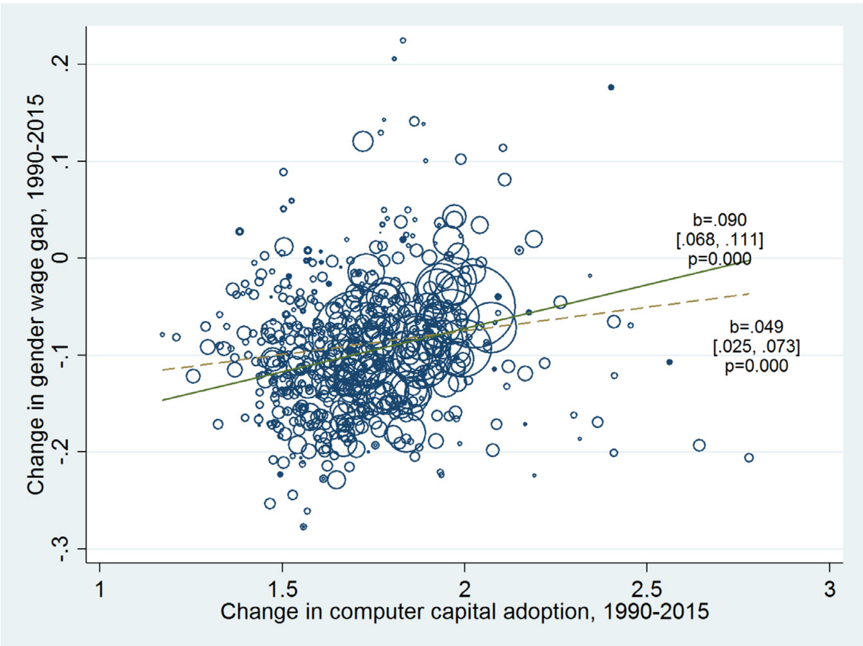
where $\frac{L_{ij,1990}}{L_{j,1990}}$ is the baseline employment share of industry i and $\overline{\Delta RA}_{i,(t_0,t_1)}$ is defined in Eq. (26). In terms of computing technology, the US plays a leading role in the world (Fig. 1b). Therefore, we use the industry-specific initial levels of computer intensity weighted by the baseline employment share of industries in a CZ in the US as an instrument for subsequent growth in computer capital in the CZ defined in (4), following Michaels et al. (2004).

Appendix Figure A1 depicts the first-stage relationships between our main explanatory variables and their corresponding instruments. The top panel reveals the substantial predictive power of the *EURO*3 robot adoption instrument $\overline{\Delta RA}_{j,(t_0,t_1)}$ for US robot adoption $\Delta RA_{j,(t_0,t_1)}$ across CZs, consistent with the notion that US robot adoption is driven by technological advance led by *EURO*3. The bottom panel shows a strong correlation between a CZ's initial computer capital level in 1990 and computer adoption over time $\Delta CA_{j,(t_0,t_1)}$. In the following section, we implement a two-stage least squares (2SLS) IV estimation strategy based on these results.

[16] Acemoglu and Restrepo (2019) use the average robot penetration in five EU countries (*EURO*5), comprising Italy, Sweden, France, Denmark and Finland, to instrument US robot adoption. We exclude France, Denmark and Finland from our measure in Eq. (26) because the US had surpassed these countries in the number of robots per thousand workers by 2015. However, using *EURO*5 average as instrument for US robot adoption does not change our results.



(a) Gender Wage Gap vs. Robot Adoption



(b) Gender Wage Gap vs. Computer Adoption

Fig. 8. Correlations between Gender Wage Gap and Technological Changes. *Notes:* The wage data come from the Census and ACS, the robot data come from the IFR, and the computer capital data come from the EUKLEMS. The solid lines correspond to fitted lines from linear regressions with commuting zone population in 1990 as weights. The dashed lines are for unweighted regressions. Bubble size indicates the 1990 population size in the corresponding commuting zone.

4.2. Estimation results

We estimate specification (23) on the full sample of 722 CZs. Table 5 reports estimation results for a long difference specification between 1990 and 2015, where we regress the change in gender wage gap between 1990 and 2015 on robot and computer adoption for the same period. We instrument robot adoption in the US by the average change in the three leading European countries and instrument computer adoption by initial level of computer intensity as described above and present the 2SLS estimates.[17] The first-stage estimates presented in Panel B of Table 5 suggest our instruments have positive and significant effects on our measures of robot and computer adoption. The *F*-statistics are large, thereby suggesting that these IVs have a high explanatory power for the variables of interest. We weight each observation of CZ by its 1990 population. Standard errors are clustered at the state level to account for spatial correlation across CZs.

The first column of Table 5 provides estimates of a parsimonious specification that only includes geographic dummies for the nine Census divisions as covariates. We estimate a strong negative effect of robot adoption on gender wage gap in a CZ with a coefficient of −0.003 (standard error 0.001) and a strong positive effect of computer adoption on gender wage gap with a coefficient of 0.063 (standard error 0.014). These estimates indicate that an increase of one robot per thousand workers in our robot adoption measure in a CZ is predicted to reduce its gender wage gap by 0.3 log points and an increase of one million dollars per thousand workers in our computer adoption measure is predicted to increase gender wage gap by 6.3 log points.

In the rest of columns in Table 5, we include a set of controls to eliminate potential confounders. In the second column, we add change in total capital in a CZ between 1990 and 2015 as a proxy for other non-robot non-computer technological progress. The effect of total capital on gender wage gap is negative but not statistically different from zero. The inclusion of total capital does not change our estimate of the impact of robot adoption on gender wage gap but reduces our estimate of the impact of computer adoption on gender wage gap to 0.048 (standard error 0.021).

The two most widely cited explanations for the evolution of US wage structure in the 1980s and 1990s are skill-biased technical change and trade with low-wage countries. Of these two, skill-biased technical change was often believed to be the dominant explanation in the 1980s (Katz and Autor, 1999), whereas trade in the form of foreign outsourcing also played a significant role in explaining the rise in wage inequality (Feenstra and Hanson, 1999). In the third column of Table 5, we control for international competition using US exposure to Chinese imports defined in Eq. (5), as trade exposure has been shown to have significant effect on local labor market outcomes in recent decades (Autor and Dorn, 2013) and may affect technology adoption decision (Bloom et al., 2016).[18] To account for the potential endogeneity of US trade exposure, we instrument for the growth in US imports from China using Chinese import growth in eight other high-income countries, following Autor et al. (2013). Specifically, we instrument the import exposure variable ΔIPW_{jt} with a non-US exposure variable ΔIPW_{ojt} that is constructed by

$$\Delta IPW_{ojt} = \sum_i \frac{L_{ijt-1}}{L_{jt-1}} \frac{\Delta M_{oit}}{L_{it-1}}, \tag{28}$$

where imports from China to other eight developed countries (including Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland) by industry (ΔM_{oit}) replaces US imports by industry (ΔM_{it}) in Eq. (5). In addition, employment levels from the prior decade in 1980 are used to replace start-of-period employment levels by industry and region as contemporaneous employment by region may be affected by China trade. Our IV estimates show a negative and insignificant effect of trade exposure to Chinese imports on gender wage gap (column 3).[19] This additional control has little impact on our estimate of the effect of robot adoption. The point estimate remains at -0.003. This specification finds a slightly smaller effect of computer adoption on gender wage than does the corresponding estimate in the second column, but the estimate remains economically large and statistically significant.

The next column includes an additional variable on the share of employment in routine jobs or occupations in 1990 to capture the susceptibility of a CZ's occupations to substitution by technology. Routine occupations are a set of jobs whose primary activities follow a set of rules that make them easy to be automated (Autor et al., 2003). One percentage point increase in the share of employment in routine occupations in a CZ in 1990 is found to decrease gender wage gap in the CZ by 0.4 log points. With this additional control, the point estimates on robot and computer adoption have the same sign and are close in magnitude compared with those in column 3.

In column 5, we augment the regression model with baseline CZ characteristics in 1990, which include the log of population, the shares of population by race, age, and education, share of employment in manufacturing, and share of female workers in manufacturing employment in a CZ. These variables capture the baseline demographic characteristics and industrial structure of a CZ that may affect gender wage gap. The estimated effects of robot and computer adoption on gender

[17] We present the ordinary least squares (OLS) estimates of Eq. (23) in Appendix Table A2.

[18] As a very large proportion of the US imports growth comes from China, recent trade literature has focused on the effects of rising Chinese import competition on the US labor market (Autor et al., 2013; Pierce and Schott, 2016). Autor et al. (2013) also show that the local labor market effects of imports from all low-income countries are almost identical to the effects of China imports alone.

[19] We have also constructed gender-specific trade exposure variables by replacing total employment in Eq. (5) by gender-specific employment and instrumented them by corresponding gender-specific instruments. With the alternative trade exposure measures, the estimated results on the effects of trade exposure, robot and computer adoption on gender wage gap are all very similar to those using the single trade exposure measure.

Table 5
The Effects of Robots and Computers on Gender Wage Gap, 1990–2015.

	(1)	(2)	(3)	(4)	(5)	(6)
Robot adoption	−0.003**	−0.003**	−0.003**	−0.003***	−0.003**	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Computer adoption	0.063***	0.048***	0.047**	0.045**	0.045**	0.041**
	(0.014)	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)
Total capital		−0.000	−0.000	−0.000	−0.000**	−0.000**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trade exposure			−0.095	−0.135	−0.033	−0.040
			(0.078)	(0.098)	(0.086)	(0.084)
% Routine jobs				−0.004***	−0.004***	−0.004***
				(0.001)	(0.001)	(0.001)
Δ Female college share						−0.970***
						(0.166)
Δ Male college share						0.771***
						(0.165)
Census division dummies	yes	yes	yes	yes	yes	yes
Demographics and industry shares					yes	yes
Observations	722	722	722	722	722	722
R-squared	0.28	0.28	0.29	0.31	0.36	0.36
			First-stage results			
Robot adoption	1.530***	1.533***	1.494***	1.544***	1.585***	1.583***
	(0.091)	(0.092)	(0.093)	(0.094)	(0.092)	(0.091)
F-statistics	147.41	159.39	228.91	165.34	134.09	132.86
R-squared	0.92	0.92	0.91	0.92	0.93	0.93
Computer adoption	51.095***	37.017***	36.355***	36.419***	35.225***	35.205***
	(1.825)	(2.013)	(1.862)	(1.876)	(1.832)	(1.913)
F-statistics	184.40	214.36	213.88	253.74	235.29	288.90
R-squared	0.66	0.77	0.79	0.81	0.95	0.96
Trade exposure			1.017***	0.946***	0.938***	0.937***
			(0.159)	(0.198)	(0.236)	(0.237)
F-statistics			20.08	13.51	9.98	9.54
R-squared			0.56	0.57	0.59	0.59

Notes: The table presents 2SLS estimates of the impact of robot and computer adoption on gender wage gap for 1990–2015. In all specifications, we instrument the US robot adoption using the average robot adoption from Germany, Italy, and Sweden and instrument the US computer adoption using its initial computer level in 1990. We also instrument the US trade exposure to Chinese imports using the trade exposure of other developed economies to Chinese imports. All estimates are from regressions weighted by population in 1990. Column 1 only includes Census division dummies. Columns 2–4 add change in total capital, the US trade exposure to Chinese imports, and share of employment in routine jobs. Column 5 adds demographic characteristics of commuting zones (log of population, shares of population with high school, some college, college, and postgraduate education, share of whites, and shares of workers between age 35–49 and 50–64) and employment share of manufacturing and share of female workers in manufacturing employment in 1990. Column 6 includes changes in the shares of workers with at least college education for both genders. We also report the first-stage coefficients and F-statistics in all models. Robust standard errors are in the parentheses. *** and ** stand for significance at the 1% and 5% level, respectively.

wage gap from this augmented model do not change significantly. This outcome suggests that the effects of robot and computer adoption on gender wage gap are robust to the initial differences in demographics and industry structure across CZs.

Our empirical analyses so far have focused on the effects of demand shocks, such as technological changes and trade exposure, on the gender wage gap between 1990 and 2015. During the same time period, skill supplies by gender have also shifted significantly. In particular, college enrollment in the US has increased substantially, and the college gender gap has reversed (Goldin et al., 2006; Ge and Yang, 2013). In column 6 of Table 5, we include two additional controls that measure the changes in college-educated male and female workers' shares in total male and female employment in a CZ, respectively, to control for changes in gender-specific skill supply. Not surprisingly, an increase in female college share is found to substantially reduce gender wage gap, whereas an increase in male college share enlarges gender wage gap. It is reassuring that the additional supply-side controls have little impact on our estimate of the effect of robot adoption. The estimated effect of computer adoption on gender wage gap is a little smaller in column 6, but remains economically and statistically significant.

Table 5 focuses on our main outcome variable, gender wage gap. We present the effects of robot and computer adoption on male and female hourly wages in Table 6. Robot adoption has a statistically significant negative effect on both male and female wages. The impact of robot adoption on male wage is larger than that on female wage, consistent with the notion that robot capital is more substitutable for male labor as males have a comparative advantage in brawn skills. In our preferred specifications with full controls presented in columns 3 and 6 in Table 6, an increase of one robot per thousand workers in our robot adoption measure in a CZ is predicted to reduce male log hourly wage by 0.010 (standard error 0.002) and female log hourly wage by 0.006 (standard error 0.001). Computer adoption also has a negative effect on both male and

Table 6
The Effects of Robots and Computers on Changes in Male and Female Wages.

	Male wage			Female wage		
	(1)	(2)	(3)	(4)	(5)	(6)
Robot adoption	−0.014***	−0.013***	−0.010***	−0.011***	−0.010***	−0.006***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Computer adoption	−0.100***	−0.090**	−0.051	−0.143***	−0.118***	−0.109***
	(0.024)	(0.038)	(0.041)	(0.021)	(0.033)	(0.036)
Total capital		−0.000	−0.000		−0.000	−0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Trade exposure		−0.524***	−0.017		−0.465***	0.053
		(0.152)	(0.027)		(0.135)	(0.076)
% Routine jobs			−0.008***			−0.004***
			(0.002)			(0.001)
Δ College share			1.234***			1.457***
			(0.081)			(0.055)
Census division dummies	yes	yes	yes	yes	yes	yes
Demographics and industry shares			yes			yes
Observations	722	722	722	722	722	722
R-squared	0.32	0.32	0.47	0.28	0.29	0.36
	First-stage results					
Robot adoption	1.530***	1.494***	1.583***	1.530***	1.544***	1.581***
	(0.091)	(0.093)	(0.091)	(0.091)	(0.093)	(0.091)
F-statistics	147.41	230.40	135.27	147.41	227.21	135.10
R-squared	0.92	0.92	0.92	0.92	0.92	0.93
Computer adoption	51.095***	36.348***	40.405***	51.095***	36.355***	35.206***
	(1.825)	(1.962)	(1.919)	(1.825)	(1.962)	(0.1981)
F-statistics	184.40	212.71	244.12	184.4	214.96	246.83
R-squared	0.66	0.79	0.92	0.66	0.79	0.96
Trade exposure		0.997***	0.897***		1.000***	0.910***
		(0.150)	(0.219)		(0.169)	(0.254)
F-statistics		20.41	10.07		19.65	7.74
R-squared		0.52	0.58		0.56	0.58

Notes: The table presents 2SLS estimates of the impact of robot and computer adoption on changes in male and female hourly wages for 1990–2015. In all specifications, we instrument the US robot adoption using the average robot adoption from Germany, Italy, and Sweden and instrument the US computer adoption using its initial computer level in 1990. We also instrument the US trade exposure to Chinese imports using the trade exposure of other developed economies to Chinese imports. All estimates are from regressions weighted by population in 1990. Columns 1 and 4 only include Census division dummies. Columns 2 and 5 add change in total capital and the US trade exposure to Chinese imports. Columns 3 and 6 include share of employment in routine jobs, demographic characteristics of commuting zones (log of population, shares of population with high school, some college, college, and postgraduate education, share of whites, and shares of workers between age 35–49 and 50–64) and employment share of manufacturing and share of female workers in manufacturing employment in 1990, and change in the gender-specific share of workers with at least college education. We also report the first-stage coefficients and F-statistics in all models. Robust standard errors are in the parentheses. *** and ** stand for significance at the 1% and 5% level, respectively.

female wages. But the impact on female wage is significantly larger than that on male wage, indicating that computer capital is more substitutable for female labor. An increase of one million dollars per thousand workers in our computer adoption measure in a CZ reduces male log hourly wage by 0.051 in the specification with full controls (column 3) even though the estimate is not statistically significant. The same change in computer adoption lowers female log hourly wage significantly by 0.109 (column 6). Therefore, the recent automation technologies, as measured by robot and computer adoption, are substitutes with both male and female labor, but the elasticities of substitution are significantly different by gender, leading to changes in gender wage gap.

We can combine the estimates in Table 5 with changes in robot and computer adoption presented in Fig. 3a and b to conduct a "back-of-the-envelope" calculation on how much the technological changes in robots and computers can account for the observed change in the gender wage gap in the US.[20] According to the estimates from our preferred specification with full controls in column 6 of Table 5, the adoption of one additional robot per thousand workers in a CZ reduces its gender wage gap by 0.3 log points relative to other CZs. An average increase in the number of robots per thousand workers from 0.34 in 1990 to 2.03 in 2015 would lead to a decline in gender wage gap by 0.51 [$= 0.3 \times (2.03 - 0.34)$] log points, accounting for approximately 6% of the observed decline in gender wage gap between 1990 and 2015. The adoption of one additional million dollars computer capital per thousand workers in a CZ increases its gender wage gap by 4.1 log points

[20] The "back-of-the-envelope" calculations need to be interpreted cautiously because they are based on point estimates and simple extrapolation, and the IV estimator is known to identify only the local treatment effect (Imbens and Angrist, 1994). Thus, the quantitative implications are only suggestive.

Table 7
The Effects of Robots and Computers on (Pre-exposure) Gender Wage Gap in 1970–1990.

	(1)	(2)	(3)	(4)	(5)	(6)
Robot adoption 1990–2015	−0.002	−0.002	−0.002	−0.001	−0.001	−0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Computer adoption 1990–2015	−0.009	−0.006	−0.004	−0.003	−0.003	−0.003
	(0.025)	(0.040)	(0.039)	(0.041)	(0.049)	(0.047)
Total capital 1990–2015		0.000	0.000	0.000	0.000	0.000
		(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Trade exposure 1990–2015			−0.254	−0.214	0.179	0.163
			(0.207)	(0.262)	(0.214)	(0.187)
% Routine jobs in 1970				−0.005***	−0.013***	−0.013***
				(0.001)	(0.002)	(0.002)
Δ Female college share						−0.368**
						(0.151)
Δ Male college share						0.175
						(0.155)
Census division dummies	yes	yes	yes	yes	yes	yes
Demographics and industry shares					yes	yes
Observations	722	722	722	722	722	722
R-squared	0.15	0.16	0.16	0.19	0.42	0.43

Notes: The table presents 2SLS estimates of the impact of robot and computer adoption on past change in gender wage gap between 1970–1990. In all specifications, we instrument the US robot adoption using the average robot adoption from Germany, Italy, and Sweden and instrument the US computer adoption using its initial computer level in 1990. We also instrument the US trade exposure to Chinese imports using the trade exposure of other developed economies to Chinese imports. All estimates are from regressions weighted by population in 1970. Column 1 only includes Census division dummies. Columns 2–4 add change in total capital, the US trade exposure to Chinese imports, and share of employment in routine jobs in 1970. Column 5 adds demographic characteristics of commuting zones (log of population, shares of population with high school, some college, college, and postgraduate education, share of whites, and shares of workers between age 35–49 and 50–64) and employment share of manufacturing and share of female workers in manufacturing employment in 1970. Column 6 includes changes in the shares of workers with at least college education for both genders between 1970 and 1990. For comparison with our main results, the outcomes are scaled to a 25-year equivalent change. Robust standard errors are in the parentheses. *** and ** stand for significance at the 1% and 5% level, respectively.

relative to other regions. An average increase in computer adoption from 0.06 (in 1990) to 1.63 (in 2015) million dollars per thousand workers would lead to an increase in gender wage gap by 6.44 $[= 4.1 \times (1.63 - 0.06)]$ log points. That is, the average gender wage gap would have been 6.44 percentage points lower if there were no growth in computer capital between 1990 and 2015.

4.3. Robustness checks

Over the time period that we examine, gender wage gap in the US experienced a secular decline. One concern for our analysis is that some (unobserved) common causal factor is behind both the decline in gender wage gap and the adoption of robot and computer capital. For example, gender wage gap in the CZs that adopt more robot or computer capital could have been on a downward or upward trend because of social economic changes such as international competition and other technological changes. Thus, our estimates might confound the impact of robot and computer adoption with pre-existing CZ trends. To verify that our results capture the period-specific effects of robot and computer adoption, we conduct a falsification exercise in Table 7 by regressing *past* changes in gender wage gap between 1970 and 1990 in a CZ on *future* robot and computer adoption between 1990 and 2015. The estimates provide little evidence suggesting pre-trends. All specifications in Table 7 show that there is no quantitatively or statistically significant association between robot or computer adoption and pre-1990 change in gender wage gap.

We conduct a series of additional robustness checks in Table 8. We present estimates of the more detailed specification in column 6 of Table 5 that exploits geographic variations in robot and computer adoption conditional on changes in total capital, trade exposure and employment share of routine occupations, and with controls on Census division dummies, population demographics, baseline industry employment shares, and changes in gender-specific skill supplies. Panel A of Table 8 shows the effects of robot and computer adoption on gender wage gap, and Panels B and C show the corresponding effects on male and female hourly wages. Column 1 estimates an unweighted regression model. We have an estimated coefficient of -0.003 (standard error 0.001) on robot adoption and an estimated coefficient of 0.039 (standard error 0.021) on computer adoption, which are not statistically different from the baseline estimates. The estimated effects on gender-specific wage are also similar between the weighted and unweighted regressions.

In Fig. 3a and b, the presence of large variations in the adoption of robot capital and computer capital across CZs is apparent. One concern is that our results are driven by a number of CZs with very high robot or computer adoption. In col-

Table 8
Robustness Checks.

	Unweighted	No top robot CZs	No top computer CZs	No top robot and computer CZs	Effects between 1990–2007	Stacked Differences
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Change in gender wage gap					
Robot adoption	−0.003**	−0.002**	−0.003**	−0.002**	−0.004**	−0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Computer adoption	0.039**	0.036*	0.033*	0.033*	0.050**	0.064**
	(0.021)	(0.022)	(0.020)	(0.020)	(0.029)	(0.032)
Observations	722	712	712	702	722	1444
R−squared	0.53	0.52	0.53	0.47	0.30	0.22
	Panel B: Change in male wage					
Robot adoption	−0.011***	−0.009***	−0.011***	−0.010***	−0.013***	−0.012***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Computer adoption	−0.068**	−0.065*	−0.068**	−0.062**	−0.109***	−0.091**
	(0.035)	(0.036)	(0.037)	(0.032)	(0.045)	(0.040)
Observations	722	712	712	702	722	1444
R-squared	0.48	0.44	0.46	0.44	0.45	0.24
	Panel C: Change in female wage					
Robot adoption	−0.006***	−0.006**	−0.005***	−0.006**	−0.008***	−0.009***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Computer adoption	−0.113***	−0.119***	−0.114***	−0.114***	−0.152***	−0.156***
	(0.036)	(0.036)	(0.035)	(0.035)	(0.043)	(0.051)
Observations	722	712	712	702	722	1444
R-squared	0.37	0.35	0.36	0.35	0.35	0.28

Notes: The table presents 2SLS estimates of the impact of robot and computer adoption using alternative specifications. In all specifications, we instrument the US robot adoption using the average robot adoption from Germany, Italy, and Sweden, instrument the US computer adoption using its initial computer level in 1990, instrument the US trade exposure to Chinese imports using the trade exposure of other developed economies to Chinese imports, and include all the control variables as the specification in column 6 of Table 5. Panel A presents results for change in gender wage gap. Panels B and C present results for change in male and female hourly wage, respectively. Column 1 presents results from an unweighted regression. Column 2 presents results excluding the top one percent commuting zones with the highest robot adoption. Column 3 presents results excluding the top one percent commuting zones with the highest computer adoption. Column 4 presents results excluding both types of commuting zones. Column 5 presents results for the period 1990–2007. Column 6 presents stacked-differences estimates for two periods, 1990 to 2000 and 2000 to 2015. We scale the outcomes in columns 5–6 to a 25-year equivalent change. Robust standard errors are in the parentheses. ***, **, and * stand for significance at the 1%, 5% and 10% level, respectively.

umn 2 of Table 8, we exclude the top one percent CZs with the greatest robot adoption from our sample and re-estimate the model. The coefficient estimate on robot adoption becomes −0.002 (standard error 0.001) and the coefficient on computer adoption decreases slightly to 0.036 (standard error 0.022). The negative effect of robot adoption and the positive effect of computer adoption on gender wage gap are not due to the CZs with very large robot adoption. Column 3 demonstrates that our results are not driven by the CZs with very large computer adoption either by re-estimating the model after excluding the top one percent CZs with the highest computer adoption. When we exclude both the top one percent CZs with the highest robot adoption and the top one percent CZs with the highest computer adoption in column 4 of Table 8, the results remain robust.

We estimate a long-difference specification for 1990–2015 in our baseline specifications. To examine the potentially confounding effects of the Great Recession, column 5 of Table 8 presents results for a shorter time window that ends in 2007. We rescale the outcomes to a 25-year equivalent change in column 5 so that the estimates are comparable with other specifications. The estimated effects have the same signs and are modestly larger for the pre-Great Recession period.

In the last column of Table 8, we consider an alternative specification in which we stack the first differences for the two periods, 1990 to 2000 and 2000 to 2015, and include separate time dummies for each period. The stacked-differences model explores the variations in robot and computer adoption between these two time periods. It is reassuring that we still estimate (after converting to a 25-year equivalent change for consistency) a negative impact of robot adoption and a positive impact of computer adoption on gender wage gap.

5. Conclusion

The rapid development of automation technologies in recent decades suggests that the labor market consequences of technological change may be substantial. Much previous research has studied the effects of skill-biased technological change on wages for worker of different education or occupations. In this paper, we estimate the impact of two leading automation technologies, industrial robots and computing equipment, on changes in the gender wage gap between 1990 and 2015 on US local labor markets. Results suggest that one more unit of robot per thousand workers would decrease gender wage gap by 0.3 log points, and the increase of robots would account for 6% of the total reduction in the gender wage gap between 1990 and 2015. By contrast, an increase in computer capital by one million dollars per thousand workers is estimated to increase gender wage gap by 4.1 log points. The gender wage gap would have been 6.4 percentage points lower if there were no growth in computer capital between 1990 and 2015.

The present study focuses on the effects of robots and computers on the gender wage gap in the US. Although gender wage differentials worldwide have fallen substantially over time, the gaps persist and their sizes vary considerably (Blau and Kahn, 1992; Weichselbaumer and Ebmer, 2005). Using microdata from 22 countries over the 1985–1994 period, Blau and Lawrence (2003) find that a country's wage structure and collective bargaining are related to the gender pay gap. The meta-analysis by Weichselbaumer and Ebmer (2005) shows that most of the decrease in gender pay gap is due to better labor market endowments of females. Although technological changes in most other countries are not as rapid as those in the US, the fundamental forces governing technological change and labor market outcomes are likely to be similar. Whether the different aspects of technological changes identified in the US context can explain changes in gender pay gaps in other countries remains an important topic for future research.

Declaration of Competing Interest

No relevant or material financial interests that relate to the research described in this paper.

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Appendix A. Description of industry-level data

The IFR reports the use of robots at two or three digit level within manufacturing and at one digit level for non-manufacturing industries. Following Acemoglu and Restrepo (2019), we use robot data for 19 IFR industries in this study. Within manufacturing, the IFR covers 13 disaggregated industries: food and beverages; textiles (including apparel); wood and furniture; paper and printing; plastic and chemicals; glass and non-metals; basic metals; metal products; industrial machinery; electronics; automotive; shipbuilding and aerospace; and miscellaneous manufacturing. The IFR miscellaneous manufacturing industry covers industries in divisions 32 and 33 of the International Standard Industrial Classification (ISIC) and includes industries such as jewelry, sports goods, games and toys, dental instruments, and repair and installation of machinery and equipment. Outside manufacturing, there are six broad industries: agriculture, forestry and fishing; mining; utilities; construction; education, research and development; and services. Robot use data are not available at industry level before 2004 for the US. We use the distribution across industries in 2004 to split the previous years' total number of robots into the IFR industries.

Due to confidentiality concern, the IFR does not report robot data for a particular industry in a country if the number of suppliers to the industry is less than four. Instead, the IFR categorizes these robots as unspecified. The percentage of unspecified robots has decreased significantly from over 50% in 1993 to less than 20% in 2015. We use the proportions across industries in the specified data from 2015 as weights and allocate the unspecified robots to each industry. Alternatively, one can use the proportions across specified industries in each year as weights to allocate the unspecified robots, which would allow the composition of unspecified robots to change with the specified industries. However, many non-manufacturing industries have zero entries before 2015, which may be the result of data unreported for confidentiality concern rather than the actual absence of robots in these industries. Thus using the alternative variable weights may allocate unspecified robots to manufacturing industries disproportionately, especially in early years. We have tried to use variable weights to allocate unspecified robots, and the distribution of robots across industries is very similar to that reported in this paper.

The EUKLEMS releases capital data at two-digit NACE industry level within manufacturing sector and at one-digit level outside manufacturing sector.[21] We construct computer capital data for 24 industries. Within manufacturing, there are 11 industries: electronics; industrial machinery; chemical products; petroleum products; transport equipment; basic metal and metal products; food and beverages; wood and paper; plastics; apparel and textiles, and miscellaneous manufacturing. Besides agriculture, mining, utilities, construction, we have computer data on 9 disaggregated service industries: information and communication; transportation and storage; finance and insurance; real estate; professional and scientific works; wholesale and retail trade; social services; recreational services; accommodation services.

Appendix B. Model extension

In the simple conceptual framework presented in Section 3, skill endowments are homogeneous among workers with the same gender, and workers are bound to given skills and corresponding tasks. We now consider an extension of the framework, in which workers are endowed with different skills and will choose tasks according to their comparative advantage.

[21] NACE is the statistical classification of economic activities in the European Community, derived from the French term "nomenclature statistique des activités économiques dans la Communauté européenne". US data are originally reported under the North American Industry Classification System (NAICS) and converted to the NACE system.

We consider the same production function as in Eq. (6) and leave the time dependence of variables t implicit for ease of notation. There is a continuum of income-maximizing workers, each of whom inelastically supplies one unit of labor. Workers have heterogeneous skill endowments in both brawn and brain skills, with $E_i = [A_i, B_i]$, and both A_i and B_i are uniformly distributed between 0 and 1 for all i. Each worker i can choose to supply A_i units of brawn labor, B_i units of brain labor, or any convex combination of the two. Define the relative efficiency of individual i at brain skill versus brawn skill as $\eta_i = B_i/A_i$. Our assumptions above imply that $\eta_i \in (0, \infty)$. Let w_A and w_B be the wage per unit of brawn skill and brain skill, respectively. At the labor market equilibrium, the marginal worker with relative efficiency η^* is indifferent between supplying brawn and brain skills when

$$\eta^* = w_A/w_B. \tag{29}$$

Individual i supplies brawn labor if $\eta_i < \eta^*$, and supplies brain labor if $\eta_i > \eta^*$. The total supply of brawn labor is given by $L_A = \int_0^1 \int_0^{\eta^*} A_i f(\eta_i|A_i) d\eta_i dA_i$ and $L_B = \int_0^1 \int_{\eta^*}^{\infty} B_i f(\eta_i|B_i) d\eta_i dB_i$, where $f(\eta_i|A_i)$ and $f(\eta_i|B_i)$ are conditional density functions. It is straightforward to see that L_A is an increasing function of η^* and L_B is a decreasing function of η^*.

Labor demand is determined by the first order conditions for profit maximization:

$$w_A = z\beta L_A^{\rho-1}(R^\rho + L_A^\rho)^{\beta/\rho-1}(C^\theta + L_B^\theta)^{(1-\beta)/\theta}, \tag{30}$$

$$w_B = z(1-\beta)L_B^{\theta-1}(R^\rho + L_A^\rho)^{\beta/\rho}(C^\theta + L_B^\theta)^{(1-\beta)/\theta-1}. \tag{31}$$

The brain skill premium, w_B/w_A, is given by:

$$\frac{1-\beta}{\beta}\left[\frac{\left(\frac{R}{L_A}\right)^\rho + 1}{\left(\frac{C}{L_B}\right)^\theta + 1}\right]\left(\frac{L_A}{L_B}\right) = \frac{1}{\eta^*}, \tag{32}$$

where η^* is an implicit function of R and C. The allocation of labor inputs across skill/task types depends on the levels of robots and computers.

Over time, as the prices of robot and computer capital go down, there is wider adoption of both robots and computers. Next we analyze how wider adoption of robots and computers affects employment and wages. Taking total differentiation on Eq. (32) with respect to R yields

$$\begin{aligned}\frac{\partial\eta^*}{\partial R} &= [-(1-\beta)\rho\eta^* R^{\rho-1}L_B^{\theta-1}]/[(1-\beta)(\theta-1)\eta^* L_B^{\theta-2}(R^\rho + L_A^\rho)\frac{\partial L_B}{\partial\eta^*} - \beta\theta L_A^{\rho-1}L_B^{\theta-1}\frac{\partial L_B}{\partial\eta^*} \\ &\quad + (1-\beta)\rho\eta^* L_B^{\theta-1}L_A^{\rho-1}\frac{\partial L_A}{\partial\eta^*} - \beta(\rho-1)L_A^{\rho-2}(C^\theta + L_B^\theta)\frac{\partial L_A}{\partial\eta^*} + (1-\beta)L_B^{\theta-1}(R^\rho + L_A^\rho)].\end{aligned} \tag{33}$$

Given that $0 < \rho, \theta, \beta < 1$, $\frac{\partial L_A}{\partial\eta^*} > 0$, and $\frac{\partial L_B}{\partial\eta^*} < 0$, we obtain $\frac{\partial\eta^*}{\partial R} < 0$. Similarly we can show that $\frac{\partial\eta^*}{\partial C} > 0$. That is, marginal workers will reallocation their labor input from brawn to brain labor with the rise of robot adoption and from brain to brawn labor with the increase of computers. It is immediate that the brain skill premium ($\pi = 1/\eta^*$) satisfies:

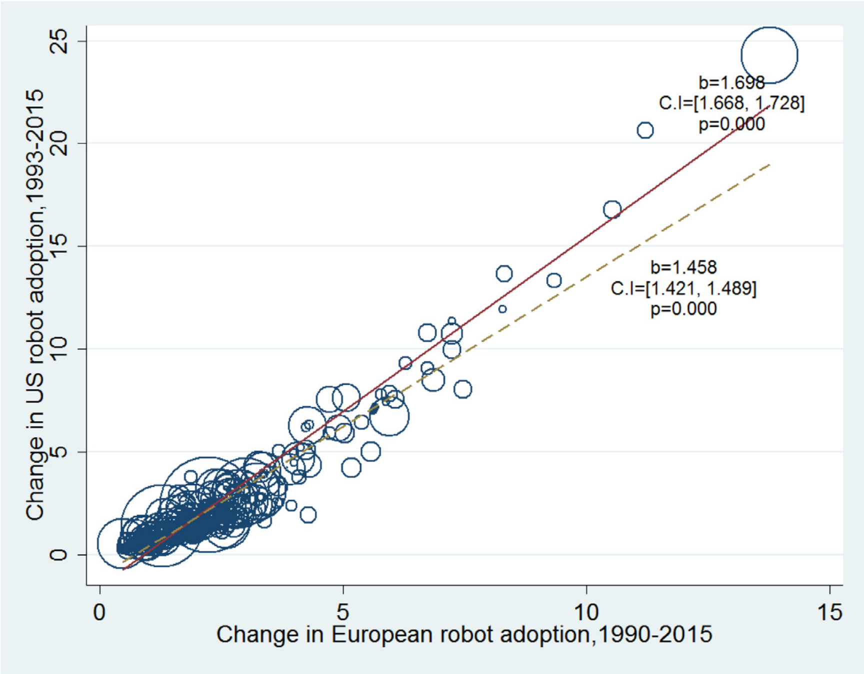
$$\frac{\partial\pi}{\partial R} > 0, \quad \text{and} \quad \frac{\partial\pi}{\partial C} < 0. \tag{34}$$

However, the effects of R and C on brawn and brain wage levels, w_A and w_B, are ambiguous, which can be shown by taking total differentiation on Eqs. (30) and (31).

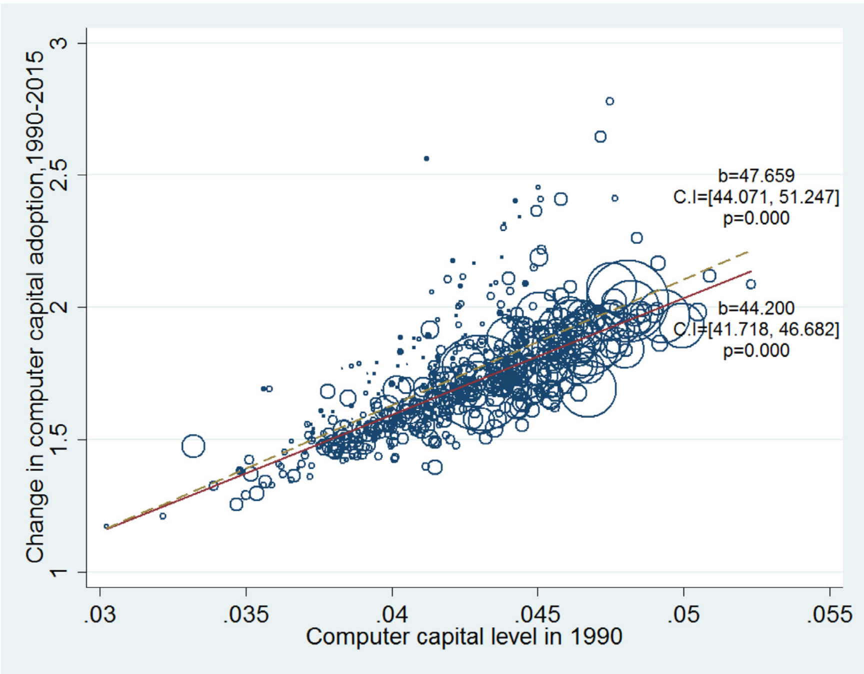
We assume that men have a comparative advantage in brawn skills and women have a comparative advantage in brain skills. For example, let B_i^f, B_i^m, A_i^f all uniformly distributed between 0 and 1, and A_i^m uniformly distributed between ϵ and $1+\epsilon$, where $\epsilon > 0$. Then the average relative efficiency at brain skills versus brawn skills, η_i, is higher for females. That is, more women will choose to supply brain labor at the labor market equilibrium. Therefore, women's relative wage increases with brain skill premium. As a result, women's relative wage increases with growth in robots and decreases with growth in computers.

In summary, workers sort themselves into different tasks according to comparative advantage when they have heterogeneous skill endowments. Robot and computer adoption directly changes the allocation of labor inputs across skill types. We show that the implications for the effects of robots and computers on gender-specific wage levels and gender wage gap would be unchanged in this extended model.

Appendix C. Additional Figures and Tables



(a) Robot Adoption in Europe and the US



(b) Initial Computer Intensity and Computer Adoption

Fig. A.1. First Stage Regressions. *Notes:* The robot data come from the IFR, and the computer capital data come from the EUKLEMS. The solid lines correspond to fitted lines from linear regressions with commuting zone population in 1990 as weights. The dashed lines are for unweighted regressions. Bubble size indicates the 1990 population size in the corresponding commuting zone.

Table A.1
Summary Statistics on Commuting Zone Data.

	Mean	Standard Deviation	Min	Max
Variables in 1990				
Gender wage gap	0.261	0.046	0.143	0.419
Robot capital	0.295	0.350	0.013	3.136
Computer capital	0.042	0.003	0.030	0.052
Total capital	176.057	89.898	90.970	738.875
Exposure to Chinese imports	0.363	0.641	0.000	8.965
Share of routine occupations	0.283	0.034	0.200	0.377
Log population	11.484	1.573	7.166	16.490
Population shares by education				
High school dropout	0.158	0.051	0.066	0.353
High school graduate	0.392	0.055	0.224	0.569
Some college	0.284	0.046	0.166	0.428
College graduate	0.112	0.030	0.043	0.226
Postgraduate	0.053	0.016	0.024	0.159
Population shares by race				
Non-white	0.110	0.111	0.004	0.666
White	0.890	0.111	0.334	0.996
Population shares by gender				
Female	0.500	0.016	0.422	0.537
Male	0.500	0.016	0.463	0.579
Population shares by age				
Age 16 to 34	0.461	0.034	0.331	0.638
Age 35 to 49	0.321	0.021	0.230	0.413
Age 50 to 64	0.218	0.028	0.131	0.307
Employment shares of				
Manufacturing	0.221	0.128	0.007	0.618
Female in manufacturing	0.078	0.050	0.014	0.303
Change between 1990–2015				
Δ Gender wage gap	−0.085	0.072	−0.278	0.205
Δ Robot adoption	1.685	2.138	0.228	24.302
Δ Computer adoption	1.723	0.213	1.172	2.780
Δ Total capital	132.269	22.525	86.105	235.351
Δ Exposure to Chinese imports	2.846	2.917	−1.490	28.375
Δ Share of college male workers	0.047	0.038	0.081	0.217
Δ Share of college female workers	0.119	0.038	0.021	0.285

Notes: See text for variable definitions and data sources. The initial year for variables on robots is 1993.

Table A.2
The Effects of Robots and Computers on Gender Wage Gap, OLS Estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
Robot adoption	−0.003**	−0.003**	−0.003**	−0.003**	−0.003**	−0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Computer adoption	0.040***	0.039**	0.037**	0.038**	0.036**	0.036**
	(0.013)	(0.017)	(0.017)	(0.017)	(0.020)	(0.018)
Total capital		−0.000	−0.000	0.000	−0.000***	−0.000**
		(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Trade exposure			−0.068	0.086	0.058	0.031
			(0.093)	(0.098)	(0.083)	(0.075)
% Routine jobs				−0.004***	−0.004***	−0.004***
				(0.001)	(0.001)	(0.001)
Δ Female college share						−0.974***
						(0.167)
Δ Male college share						0.786***
						(0.168)
Census division dummies	yes	yes	yes	yes	yes	yes
Demographics and industry shares					yes	yes
Observations	722	722	722	722	722	722
R-squared	0.36	0.36	0.36	0.38	0.53	0.54

Notes: The table presents OLS estimates of the impact of robot and computer adoption on gender wage gap for 1990–2015. All estimates are from regressions weighted by population in 1990. Column 1 only includes Census division dummies. Columns 2–4 add change in total capital, the US trade exposure to Chinese imports, and share of employment in routine jobs. Column 5 adds demographic characteristics of commuting zones (log of population, shares of population with high school, some college, college, and postgraduate education, share of whites, and shares of workers between age 35–49 and 50–64) and employment share of manufacturing and share of female workers in manufacturing employment in 1990. Column 6 includes changes in the shares of workers with at least college education for both genders. Robust standard errors are in the parentheses. *** and ** stand for significance at the 1% and 5% level, respectively.

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