Automation, Labor Markets, and Trade

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Abstract

Digital technologies, robotics, and artificial intelligence that substitute tasks performed by labor are bringing back old fears regarding the impact of technology on labor markets and international trade. This paper aims to provide evidence about the causal impact of automation on the labor market outputs and sectoral US imports. I use robots´ penetration, as proxy for new technologies, to study the effect of automation on employment in almost 800 occupations in 246 industries between 2002 and 2016. I use Autor et al. (2003) and Frey and Osborne's (2017) methodologies to define occupations at risk of automation and to study their behavior after the robots' penetration. It was found that employment in occupations at risk of automation has been declining at an annual rate of 1.8–2.2% compared to riskless occupations. This result is primarily driven by a substitution effect within industries defined at the 4-digit NAICS level. Employment at risk grows 1.6-2.1% less per year than riskless occupations in the same sector. In my preferred estimation, robot penetration in the US reduces annual employment growth by 1.7-1.8% in occupations at risk compared to riskless occupations in the same sector. Industries with a higher share of occupations at risk showed a lower rate of employment growth during the period 2002–2016. Moreover, imports of commodities produced in these sectors have been decreasing (3.2%), particularly from countries with lower penetration of automation technologies (-3.6%). This result indicates that automation is changing countries' comparative advantages.

Keywords: automation, industrial robots, labor demand, occupations, trade.

JEL Classification: D2, J23, J24.

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1. Introduction

The last decades have brought remarkable technological changes. First, the reduction in prices of hardware, software, and telephone services has induced the exponential growth rate of computer power and telecommunications capability with an explosive development of the Internet. Furthermore, the twenty-first century brought additional technological accomplishments such as machine learning, along with increased development in the field of robotics and the internet of things. This phenomenon has also been referred to as the "digital age".[1] As pointed out by Acemoglu and Restrepo (2019a), "recent technological change has been biased towards automation" and its implications are a source of controversy. Digital technologies, robotics, and artificial intelligence, substitute tasks performed by labor and are bringing back old fears regarding the impact of technology on labor markets.[2]

Acemoglu and Restrepo (2018a), Frey and Osborne (2017), Arntz et al. (2017), McKensey (2017), Fort (2017), and Boston Consulting Group (2015) along with other studies claim that due to recent developments, a significant fraction of current jobs/tasks are and have been susceptible to automation.[3] Graetz and Michaels (2018), Brynjolfsson and McAfee (2014) and Acemoglu and Restrepo (2018ab,2019a) argue that recent capital and technological innovations will increase productivity in an extensive range of industries. These technologies can automate tasks previously performed by labor and create new tasks and activities in which humans can be more productive. However, it has also been argued that this development might have adverse effects. Automation might reduce labor demand, decline labor share in the national income, and lead to a rise in inequality.[4]

[1] See Nordhaus (2007), Gordon (2016), and MGI (2013; 2017)
[2] Already in 1930, J. Keynes talked about "technological unemployment."
[3] Frey and Osborne (2017), and related studies suggest that 47% of US jobs, 57% of jobs across the OECD, and 77% of jobs in China are susceptible to automation.
[4] Similar to previous technology development, the new digital era also could be behind the increasing wage dispersion reported by the Bureau of Labor Statistics in the USA during the last few years.

This paper uses US employment data with respect to coccupations in 285 sectors to provide evidence of the causal effect of automation on the labor market.[5] First, I provide evidence that on average, occupations at risk of automation (OaRA) grew 1.8–2.2% less than riskless occupations in the entire economy of the US during the 2004–2016 period.[6] I use both Frey and Osborne's (2017) and Autor et al.'s (2003) approach to define OaRA. This result is primarily driven by a substitution effect within 285 industries defined at the 4-digit NAICS level. OaRA has growing 1.61-2.07% less than riskless occupations in the same sector. I use Rajan and Zingalez (1998) approach to provide causal evidence on the role of automation on the decline of OaRA. After controlling for sector-occupation and sector-year fixed effects, I show that the change of robots per worker in the US, instrumented by EU countries' robot penetration, reduces employment by an average annual growth rate of 1.1–1.8% in OaRA compared to riskless occupations in the same sector.[7] Our econometric approach allows us to claim that the employment fall in OaRA cannot be explained by Chinese and Mexican import penetration nor by the international financial crises. Changes in wages reassure the idea that changes in employment are driven by a demand shock on OaRA (the automation process). My results suggest a larger effect than previous estimates that use variation of employment growth within commuting zones in the US during the '80s and '90s (Autor et al. 2013; Acemoglu and Restrepo 2018a). This new evidence indicates that the automation process was more pronounced in the last decade and a half in the US. Furthermore, I also present evidence of a "cleaning effect" during the 2008–2009 great recession.

Second, at the aggregate level, the share of total employment in sectors characterized by a sizeable initial fraction of OaRA also decreased during this period. Controlling for Chinese and Mexican import penetration, sectoral external financial requirement, and aggregate shocks, it was found that a sector with

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[5] The number of occupations used in econometrics exercises varies depending on I am using national, sectoral, and wage bill or employment. For example, my results for occupation at the national level use 791 occupations for wage bill and 795 for employment.
[6] This is the unweighted simple average. The weighted number is minus 1.3%.
[7] These results use US aggregate robots penetrations, instrumented with EU data.

a large share of OaRA (percentile 90^{th}) presented a 1.5–1.6% lower annual growth rate than a sector with a low share of OaRA (percentile 10^{th}) during the period 2002–2016. Using robot penetration and an IV approach, it was found that one standard increase of robots per worker reduced annual employment growth by 0.9-1.1% in the former sector (80^{th}) compared to the latter (20^{th}).

Third, it was found that US imports of goods manufactured by sectors that are characterized by a high share of OaRA falls during the 2004–2016 period. Controlling for initial conditions, country of origin of import-year fixed effects (which also control for aggregate shocks), and sector financial conditions, it was found that imports of goods produced by a sector with a large share of OaRA (percentile 80^{th}) grew 2.0–2.1% less per year than imports of goods produced by a sector with low OaRA (20^{th}). When I separated the exporting countries of the US into leaders (25% of countries with higher robots per worker) and laggards in terms of automation technology adoption (75%), it was revealed that US imports primarily decreased in laggard countries (the decrease is more than twice). To study causation, I employed robots per worker in the US instrumented by EU data. Using robots penetration and an IV approach, it was revealed that imports from a sector with a large share of OaRA (80th) show a 1.9–2.4% lower annual rate of growth relative to a sector with low OaRA (20^{th}) after the aggregate increase in robots per workers in the US and the average aggregate increase in robots penetration in trade partners´ countries. This effect is also more significant, in absolute term, for imports from countries which are lagging behind in the adoption of robots per workers (our proxy for automation technologies). The results suggest that comparative advantages are changing due to automation. Sectors prone to automation have been increasing their comparative advantages in the USA vis-a-vis countries with low robot penetration.

This paper adds to a growing literature that studies the labor market consequences of automation technologies. Centered on workplace computing, Autor and Dorn (2013) argue that new technologies augment human and physical capital and allow firms to automate routine tasks previously performed by humans. Autor and Dorn (2013) and Autor, Dorn, and Hanson (2013; 2015) studied 722 local labor markets' reactions to technological change in the US. They found that commuting zones (CZ) with a large share of jobs in professions characterized by routine tasks adopt more workplace computing and reduce employment in routine task-intensive occupations. Furthermore, CZ at the 80th percentile of 1980 routine occupation share experienced one standard deviation faster computer adoption per decade than a 20th percentile CZ between 1980 and 2005. The same CZ at the 80th percentile experienced a 1.8% higher contraction of the routine occupation share per decade than a 20th percentile CZ.

Although this paper confirms Autor et al.'s (2013) results, it also found that the effects of automation, proxied by robots per workers, on employment in professions prone to automation or characterized by routine tasks (percentile 80% versus 20%) were one order of magnitude higher in the last 12 years compared to Author et al.'s (2013) results for the 80's and 90's. Also, the use of data at the sector-occupation level allows my paper to fully disentangle the effects of import penetration and new technology penetration using sector-year dummies.

In the last few years, there has been a surge in empirical papers studying the effects of automation on the economy. Most of these new works use robots per workers from the International Federation of Robotics (IFR) as a proxy for increased automation (e.g. Acemoglu and Restrepo 2018a and b; 2019a; Graetz and Michaels 2018; Artuc, Bastos and B. Rijkers 2018; Giuntella and Wang 2019; Artuc, Christiaensen, and Winkler 2019). A key element in these papers is the empirical strategy identifying the causal relationship between automation and economic outputs. In most cases, identification comes from the fact that robot penetration varies across sectors within countries. Although this data has been an important input to study automation, it has some limitations at the country-sector level. For most countries, it only started in 2004 at the sector level, and with much of the data unclassified in any sector. For example, for the USA 89% of robots were unclassified in 2004, 44% in 2010, and 10% in 2016. Western Europe had better data.[8]

[8] Unclasified robots in any industry represent 8% of total robots in Austria, Belguim, Switzerland, Germany, Spain, France, Great Britain, Italy, Nederland and Portugal in 2004. For the rest of countries in IFR (42), unclassified data represents 32% of robots in 2004.

Using country-sector data for 17 countries in 14 sectors, Graetz and Michaels (2018) estimated productivity growth as a function of robots' penetration at the country-sector level between 1993 and 2007. They argued that the country-sector fixed effect nature of their models and the use of a sector level measure of "replaceable hours" as an instrument of robots' penetration (they used IFR classification that defines only six general and 29 specific tasks)[9] controls for the reverse causality problem between sector productivity and robots. They found that robot penetration implies an additional 0.37% growth in sector labor productivity. However, they did not find a significant effect on sector employment.

Contrary to Graetz and Michaels (2018), this paper found evidence of a negative effect on sector employment after robots per worker penetration in the US during the last decades. Although my results for the US sectoral imports agree with Graetz and Michaels's findings on productivity, new technologies seem to increase the comparative advantages of sectors that benefit more from automation (a large share of initial employment in OaRA). The primary difference with these authors is the level of disaggregation I have used in my instrumental variable approach (285 sectors versus 17). When I use robots per workers at the sector level (22 aggregate sectors) I also do not find a statistically significant effect on employment at the industry level in the USA. As mentioned previously, the employment behavior of occupation with different levels of risk of automation within the same sector validates our results for employment.

Using US CZ data for 19 sectors, Acemoglu and Restrepo (2018b) estimated employment growth for the period 1993–2007. Due to a lack of information about robots' penetration for the sector-year data in the US as well as penetration at the CZ level, these authors estimated a proxy for robots' penetration at the CZ-sector level. Accordingly, they studied the effects of robots' penetration as a proxy for new technology penetration on local labor markets. To avoid any reverse causality issue between US labor outcomes and robot penetration, they instrumented their sector robots' variable using sector robots' penetration in EU

[9] Handling operations/ Machine tending (9 subdivisions of handling), Welding and soldering (5 subdivisions), Dispensing (3 subdivisions), Processing (4 subdivisions of cutting), Assembling and disassembling (4 subdivisions), others (4 subdivisions).

countries. They found a negative effect of robots' penetration on local labor markets. The replacement effect was higher than the productivity effect on labor demand at the CZ level. An increase in one robot per thousand workers reduced the employment rate by 0.18–0.34%. During this period, US robots per thousand workers went from 0.35 to 1.08 at the aggregate level.

The effect suggested by Acemoglu and Restrepo (2018a) is more prominent than the one by Autor et al. (2013), although lesser than the results we found in this paper for the period 2004-2016. This difference might be due to the use of cross-analysis of CZs instead of cross-analysis of industries and the period covers. Also, the use of sector-occupation-year data allows my paper to fully control for external factors such as Chinese and Mexican import penetration and financial disturbances. These factors should affect the employment in industries and firms and not specific occupations within industries or firms. Although these authors control for some of these factors, in my paper I control for Chinese and Mexican import penetration and sector-year financial shocks using dummies, which allows me to ensure that my results for automation are not capturing these two important effects.

Artuc et al. (2018) studied the impact of automation on trade using country-sector data. As a proxy of automation, they also used robots' penetration. They instrumented it using a triple interaction between pre-determined country-wide labor costs (which they claimed governs the incentives to robotize), the share of workers engaged in replaceable tasks in the industry (they follow Graetz and Michaels's (2018) approach to construct replaceable tasks),[10] and the global stock of robots as a proxy for the price of robots. They found that greater robot intensity in own production leads to a rise in imports in the same sector sourced from less developed countries in the same industry and more exports to the same countries.

[10] Using the 2000 Census three-digit occupations, Artuc et al (2018) assign a replaceability value of one to a three-digit occupation if the name and/or description of at least one of the five-digit occupations included in it contains at least one of the IFR application categories and zero otherwise.

Controlling for sector financial requirements over time, sector-country of origin imports and year-country of origin fixed effects, my results for the US are not in line with Artuc et al. (2018). U.S. imports of commodities from sectors with higher OaRA in the State, and therefore that should benefit more from automation, fall. Mainly from countries that have lower robot penetration. As mentioned previously, we tested this hypothesis by splitting U.S. imports into leader countries with respect to the adoption of automation technologies and laggard economies. The primary difference between my empirical model and theirs is that I only covert the US. Second, the level of disaggregation of sectors they used (16 sectors at 1–2 dig level versus 285 at 2–3dig level), and third, their methodology for identifying the occupations prone to automation.[11] Given the higher level of sector disaggregation (2–3 dig NAICS) implemented in this study, results mainly captured the import substitution effect and not the scale effect induced by higher demand of other subsectors in the same one digit aggregate sector used by Artuc et al. (2018). Finally, at the 1–2 dig level of aggregation, they might have captured the effect of a third exclude variable that was increasing demand of all subsectors.

This paper aims to provide new and detailed evidence about the causal effect of automation on the labor market and sectoral US imports in the last decade and a half. To establish the direction of the causal mechanism, the paper combines two standard approaches. First, following Rajan and Zingales (1998), it focuses on the details of theoretical mechanisms through which automation affects labor demand in different occupations (characterized by different tasks). Specifically, it uses Autor et al.'s (2003; 2013) analysis that routine tasks, either manual or cognitive, are prone to automation. Frey and Osborne (2017) claim that besides these routine tasks, there are certain non-routine tasks that new technology development can automate. Therefore, the development of new technologies should disproportionately reduce labor demand of occupations that predominantly perform tasks prone to automation. This approach is in line

[11] "*They* assign a replaceability value of one to a three-digit occupation if the name and/or description (e.g. welding, haldling operations, etc) of at least one of the five-digit occupations included in it contains at least one of the IFR application categories and zero otherwise".

with Graetz and Michaels's (2018) identification method at the sector level, although this study went one step further and presented evidence of the mechanism, that is, the analysis of the evolution of employment at the sector-occupation level in our dataset. This paper uses Autor et al.'s (2003) tasks analysis, complemented by Frey and Osborne (2017), to define the occupations that are prone to automation or whether the tasks they perform have a higher probability of being automated. These two papers engage in a specific and detailed analysis at the task and occupation level and cover the entire sample of tasks and occupations in O*NET data (702 occupations).[12][13] Following Acemoglu and Restrepo (2018), this paper uses as a broad proxy of automation, robots' penetration per worker instrumented with the average of robots' penetration in 6 EU countries with a similar level of robots per worker in 2016.

Second, the paper utilizes the three-dimensional structure of the data used. Data at the sector-occupation-year level allows us to control for initial conditions and specific shocks at the sector and year frequency. The occupation dimension allows the paper to specifically control for Chinese and Mexican large import penetration in the last decades and for the 2008–2009 great recession and financial distress among other factors. Therefore, these factors are not driving our results.

Finally, the paper provides evidence that the proposed approach can explain variables that should be also affected by automation beyond employment and wage occupations. US imports in sectors that use occupations prone to automation at the beginning of the period examined in this study should be affected by new technologies. The benefit of these technologies should be greater in these sectors, and therefore, comparative advantage should be affected. Imports of commodities manufactured by these sectors should decrease, predominantly from countries that are lagging behind in the adoption of these novel

[12] We expanded the number of Frey and Osborne (2017) occupations to 788.
[13] On the contrary, the IFR application areas are limited to 29 types of tasks in 6 broad categories centered on industrial tasks.

technologies. For trade analysis, I have used imports at the sector-country of origin-year level data which also allows us to control for macro US and country of import origin macro shocks.

To reassure the mechanism behind the fall in employment and wages and, therefore, on the wage bill, I have derived a simple econometric model in which production in sector “j” in period “t” is a function of occupation-services which are produced by the aggregation of the labor of occupation “o” and capital. I assume that there is a different labor-capital elasticity of substitution for each occupation-service. I also assume a different initial labor share in each occupation-service. Under these assumptions, the demand for occupation “o” in sector “j” will fall more after a reduction in the price of the capital-technology if a) the product between the occupation-sector capital share and the elasticity of substitution between occupation “o” and capital is high and if b) the initial occupation-sector share is large. I test these two additional hypotheses in the data and the results indicated that they hold.

The rest of the paper is organized as follows. Section 2 presents the methodology and data used to estimate the impact of automation. Section 3 presents the relevant results—first, for 790 occupations at the country level, second, within sectors, and finally for total employment and imports at the sector level defined at a 4-digit NAICS 2007 level. Section 4 concludes.

2. Data and Methodology

Data

Risk of automation

I use Frey and Osborne (2017) index, from now on *FO RISK Probability*, which extends Autor et al (2003)´s task model, to identify which occupations are prone to automation. The task model suggests that routine tasks, either routine cognitive or routine manual, are prone to automation. On the contrary, non-routine cognitive analytic, non-routine interpersonal, non-routine manual physical or non-routine manual interpersonal tasks are more difficult to be automated. FO claims computerization can be extended to any non-routine task that is not subject to any engineering bottlenecks to computerization.

FO implement a methodology to estimate the probability of computerization for detailed occupations using the BLS data as well as the expert opinion of Machine Learning researchers. Using a subset of specifics occupations, they asked expert participants at the 2010 Oxford University Engineering Sciences Department the engineering bottlenecks to computerization present in tasks realized by these specific occupations. Using this information FO defines several types of bottlenecks which are mainly present in three task categories: perception and manipulation tasks, creative intelligence tasks, and social intelligence tasks.

Then they used an econometric method to assign the risk of automation to 702 occupations defined at the 3- to 6- digit level of OES-2010 BLS definition (OES 2010). I am able to merge 698 of these occupations to the OES employment dataset.[14] They define the ***FO RISK Probability*** and ***FO RISK Index*** which is equal to one is *FO RISK Probability* is equal or higher than 0.7.[15]

For robustness, I construct an alternative proxy for the risk of automation. I borrow Autor et al. (2003) method to classify 796 occupations according to the number of routine tasks and non-routine tasks they have to perform in 2010. These authors identify six types of tasks: Routine cognitive, routine manual, non-routine cognitive analytic, non-routine interpersonal, non-routine manual physical and non-routine manual interpersonal tasks. They argue that routine tasks, either cognitive or manual are prone to be automated.

[14] Frey and Osborne report probability of being susceptible to automation for 702 occupations, but some of them at higher level of aggregation than 6 digits.
[15] We use 70% to follow the literature. See Frey and Osborne (2017).

Using the Autor et al (2003) codes, I construct the previous 6 tasks index using O*NET 23 database and occupation employment data from OES 2010. Indexes are normalized to have mean 0 and variance 1. I construct our alternative automation measure as:

$$PROB_o^b = \sum_{\tau \in routine} T_\tau^o - \sum_{\tau \in Non\ routine} T_\tau^o$$

Where T_τ^o is the index for task τ in occupation "o". There are two routines and four non-routine tasks. $PROB_o^b$ or ***Routine Task Index*** is a proxy for the probability that occupations "o" is at risk of automation.

The first two rows in Table 1 Panel A presents *FO RISK Probability* of automation for all occupations I am able to match with BLS employment data (698), and our extended set (794). The probability of automation goes from 0.03 in "Recreational Therapists" to 0.99 in occupation "Insurance Underwriters" and "Telemarketers". The mean probability is 0.5 and its standard deviation is 0.4. The third row presents FO RISK Index of automation, which equals 1 for occupations with a probability of automation 0.7 or higher. 42% of occupations are at risk of automation under FO RISK proxy. The fourth row presents our alternative probability measure PROBb or *Routine Task Index*. It has a mean -0.31 and a standard deviation of 3.36.[16]

[Table 1 Here]

Figure (1) and Appendix A present the relationship between *FO RISK Probability*, *Routine Task Index*, wages and occupation employment level in 2010, and the 12-year occupation employment growth. Figure (1a) shows there is a strong correlation between *FO RISK Probability* and *Routine Task Index*. The correlation coefficient is 0.74 significant at the 1% level. The *Routine Task Index* explain 54% of the

[16] In econometric exercises I normalized Routine Task Index to have mean 0 and the difference between the 90th and 10th percentile to be equals 1.

variance of *FO RISK Probability.* Appendix A analyzes the correlation between routine and non-routine tasks and *FO RISK Probability*. *I* regress *FO RISK Probability* on routine and non-routine tasks. All four non-routine task indexes have the expected negative sign, although only two of them are significant at standard levels. The coefficients for Routine Cognitive and Manual indexes are positive as expected.

Figures (1b) and (1c) present the occupations mean log wage and log employment for deciles of occupations according to the distribution of the risk of automation defined by FO (2017). Even though there is large volatility, there is a clear negative correlation with wages and no correlation with the level of employment. The correlation coefficient is -0.61 significant at the 1% level for wages and 0.01 significant at the 70% level for employment. One standard deviation increase in FO RISK probability is related with a 24% lower wage. In an unreported table, I also use the "The American Community Survey" to study the correlation between wage and automation risk controlling for worker (Age, Sex and Education) and the firm´s characteristics (Sector). I still find a negative correlation between log wage and the *FO RISK Probability*.

Figure (1d) presents the relationship between the average aggregate annual rate of employment growth for different occupations and the FO RISK Probability (2004-2016).[17] Besides volatility, there is a clear downturn in employment growth in occupations with a higher risk of automation. The correlation coefficient is -0.32 significant at the 1% level. Appendix A shows a steeper decline in wages-bill than in the employment of occupations subject to a higher risk of automation during the same period. I find the same relationship with the Routine Task Index instead of FO RISK Probability.

[Figure 1 Here]

[17] I use the 2004-2016 period because in 2004, OES opened 10 occupations to 6-digit from 5-digit SOC 2000 in 2003.

Table (A1) in Appendix A, regresses wage bill growth on all 6 routines and non-routines task´s indexes and *FO RISK Probability*. Tasks´ indexes, which are statically significant, have the expected sign, but more importantly, the *FO RISK Probability* is significant at standard level, even after controlling for all 6 tasks indexes. This last result shows that beyond routine and non-routine tasks, FO probability has additional predictive power. In the rest of the paper, I use FO RISK Probability as our main index due to this additional predicted power, and because it aggregates the 6-related routine and non-routine tasks into one index in a non-arbitrary way (like my PROBb index does).

Employment and Wages

Employment and wage data at occupation and sector level comes from the Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES). The OES program conducts a semiannual survey designed to produce estimates of employment and wages for specific occupations. The program collects data on wage and salary workers in nonfarm establishments in order to produce employment and wage estimates for about 800 occupations. It does not include data from self-employed workers. The OES program surveys approximately 200,000 establishments per panel every six months. It takes three years to fully collect the sample of 1.2 million establishments. 1997 is the earliest year available for which the OES program produced estimates of cross-industry as well as industry-specific occupational employment and wages. Although only in 1999, the OES survey began using the Office of Management and Budget (OMB) Standard Occupational Classification (SOC) system. For this reason, our occupation results at the economy level use the 2001-2016 period.

Occupations are defined using the Standard Occupational Sector (SOC) system at 6-digit of aggregation. Original data uses SOC 2000 for years before 2010, a mixed classification between SOC 2000 and 2010 for the years 2010 and 2011, and SOC 2010 for years between 2012 and 2016. This data does not include the firms’ owners. For occupation data at the national level, OES includes the Federal, State and Local governments.

In 2004, OES opened 10 occupations to 6-digit from 5-digit SOC 2000 in 2003.[18] I keep the highest level of aggregation for years previous 2004. Since 2004 I only use more disaggregated occupations. I include different dummies for a different level of aggregation.

Since 2002, the BLS uses the North American Industry Classification Standard (NAICS) to define industries/sectors at 4-digit aggregation level. Original data uses 2002 NAICS for years between 2002 and 2007, version 2007 for years between 2008 and 2012, and version 2012 for the rest of our sample.

Using official crosswalks between different revisions of the SOC, I construct a subset of occupations I can follow between 2002 and 2016, as well as a set of industries I can also follow over time.[19] I end up with 795 occupations and 285 sectors. For econometric exercises at the sector/occupation level, I neither include the Federal, State or Local government.[20]

For each sector, I compute the weighted average probability of automation using as weigh occupation-sector employment in 2004. I also compute the weighted risk of automation as the share of employment in occupations with a probability of automation equal to or higher than 0.7. I use 2004 because this is the first year I have data for robots per workers in the US at the industry level and because of this year, OES opened 10 occupations to 6-digit.

Table 1 Panel B presents the evolution of total employment and employment in occupations that I am able to classify at risk of automation and no (FO Index equals to 1 and 0, respectively). The simple average for total wages covered by OES and for wages in occupations at risk of automation, the ratio of percentile 75 and percentile 25 and the ratio of percentile 90 and 10, over the period 2002-2016. Table 1 Panel C presents the summary statistics of employment (ln), average wage (ln), the weighted average probability of

[18] Occupations 113040, 191010,254010,273010, 273020,291020,299010 and 472130 at 5-digit SOC 2000 in 2003, were opened to 6 digits in 2004.

[19] We have three groups of equivalence of sectors across time: a) equivalence one to one, b) equivalence one to m, and c) equivalence n to m equivalent sectors. For case b we aggregate the m sectors, and for case c we aggregate sectors until we get a bijective function.

[20] In some econometric exercises the number of occupations falls to 794 because off collinearity with sector-occupation dummies.

automation and employment at risk of automation at the industry-year level, and at the occupation-industry-year level.

Table 1 Panel B shows that total employment in our sample grew by an average annual rate of 0.7% during 2002 and 2016 (including government). Employment growth for OaRA is 0.5% whereas for riskless occupation this average annual rate is 1.8%. OaRA grew 1.8% less per year than riskless occupation between 2002 and 2008. During the great recession, this difference jumps to 3.7%. Between 2010 and 2016, riskless occupations continue to grow faster than OaRA, although the difference is only 0.13% per year.

Wages, in nominal terms, increased by 39%, and 6% in real terms during the whole period.[21] Real wage growth is 0.4% per year during the whole period. During the great recession, it jumps to 1.7% per year. This jump is mainly driven by a composition effect.[22] Wage inequality increased during the period. The ratio between the mean and the median grew 2% (almost a 7% increase in the variance of wage),[23] and the ratio between the highest 90 percent and the lowest 10 percent increased by 9.7% between 2001 and 2016. The latter index grew only 2.5% within occupations (simple average) although wage dispersion across occupations, measured as the Std.Dev. of (log) occupation mean wage, increased by 12.1%.

Figure (2a) presents the un-weighted evolution of log wage-bill, log employment and wages for occupations at risk of automation (*FO RISK Index=1*) relative to the rest of the economy controlling for year effects (See Table Ba). [24] There is a monotone decline in the relative wage-bill and employment in occupations at risk of automation. As long as the price of labor-replacing capital/technologies falls (proxy

[21] I use the CPI to deflate nominal variables.
22 OaRAs have lower wages and employment in these occupations falls by 4.7% during the great recession.
23 Under the assumption of a log normal distribution, the ratio between the mean and the median is e to the power of 1 plus 2 standard deviations.
24 Figure 2a report the year dummies interacted with the occupation FO RISK Index (β_t^R) estimated in the following econometric model: $Ln(Y_{ot}) = D_o + \sum_t \beta_t^R \ RISK_o D_t + D_t + e_{ot}$, where Yo is either wage bill, employment or wages for occupation “o” in period “t”.

by dummies), employment in an occupation at risk of automation falls relative to riskless. Also, they have a lower rate of wage growth during the period 2002-2016.[25]

Wage bills and employment in occupations at risk grow at an average annual relative rate of minus 2.0% and 2.1%, respectively (Figure 2a). Controlling for initial wages (Initial Occupation Wage (ln) x Agg. Wage (ln) over time), these percentages are -2.1% and -1.8% (Figure 2b). There is a rapid decline pre-2008, a sharp fall in the 2008-2009 financial crises, and a moderate posterior decline (similar to the one presented in Table 1B).

Figure (2c) presents a close up of the evolution of the relative wage of occupations at risk of automation. During the whole period (16 years), relative wages of occupations at risk of automation fall 4.7% (on average -0,3% per year). Employment and wage results suggest that occupations at risk suffer a negative demand shock. Employment and wages decline during the first half of the period, although the fall in wages is one order of magnitude lower. In the second half, wages start a slight recovery and employment in occupations at risk, after a large relative decline during the 2008 crisis, moderate their initial negative trend.

These results are in line with the idea that firms do a cleaning process during recessions. Anticipating a continuous automation process going into the future, firms adjust occupations that will continue to be automated. Wage slight recovery, post-2009, may reflect a change in the composition of workers after this adjustment process.

Figure (2d) reports the log-ratio between wages at the 90th and the 10th quantile for occupations at risk of automation relative to the same ratio for riskless occupations in the economy. Wage dispersion within occupation at risk falls 3.4% during the period 2000 and 2016. It remains relatively constant until 2005, and then it starts to fall. Figures Ba and Bb, in Appendix B, show that at the beginning of the period wages

[25] We report growths between 2002-2016 to compare with sector-occupation results.

fall at the bottom and at the top of the distributions. After 2006, wages at the bottom starts to recover and by the end of the sample, they get their initial level. Wages at the top continue to fall until 2011 and remain at this level until the end of the period. By the end of the period, the lower rate of wage growth at the top explains the compression in wages in occupation at risk of automation. This result suggests that the increase in wage dispersion observed in Table 1, Panel 1b, cannot be explained by an increase in wage dispersion within occupation at risk of automation. Aggregate wage dispersion increases because wages in occupation at risk of automation, which are on average low, fall until 2011 and then they remain almost constant.

In Appendix B, I use alternative proxies for the risk of automation (Routine Tasks Index and FO RISK Probability). With the Routine Task Index instead of the FO RISK Index, I find that annual employment growth in occupation in the percentile 90th is -2.4% lower than occupation in the percentile 10th of the Routine Task Index. This coefficient compares with -2.1% and -1.8% when I use FO RISK Index and I control or not for initial wages, respectively (Figure 2 and Table Ba).

[Figure 2 Here]

Table 1 Panel C presents summary descriptive statistics at the sector level. The sector average share of employment at risk of automation is 0.56. There is heterogeneity across sectors. The standard deviation is 0.56 and the sector in the 90th percentile has a share of employment at risk of automation that equals 0.77, whereas the share for the sector in the 10th percentile is 0.21.

Imports and other data

For trade exercise, I use data from Schott's International Economics Resource Page. This dataset has US imports for each country around the world classified at 4 digit NAICS classification for the period 2001-2016. I also use Schott's dataset to construct our proxy to control for Chinese and Mexican import penetration.

I use the stock of industrial robots by industry, country and year from the International Federation of Robotics (IFR). These data cover about 90 percent of the industrial robots market ("multipurpose manipulating industrial robots" based on the definitions of the International Organization for Standardization) The data are disaggregated in a little more than 20 sectors roughly at the three-digit level for manufacturing and roughly at the two-digit level for non-manufacturing activities. As mentioned in previous studies, this data have some limitations. First, and more important, for most countries, it only started in 2004 at the sector level, and with much of the data unclassified in any sector. For the USA 89% of robots were unclassified in 2004, 44% in 2010, and 10% in 2016. Acemoglu and Restrepo

(2017b) allocate these unclassified robots to industries in the same proportion as observed in the classified data. I assign half of the unclassified robots using this method and half using the share of robots per sector in 2016. Using only Acemoglu and Restrepo method I may over estimate the number of robots in sector that have initial information. IFR data does not cover the same number of countries over time.

Finally, to control for financial events at the sector level *I use External Financial Dependence a la* Rajan and Zingales at the sector level interacted with time dummies. I estimate *External Financial Dependence* following Rajan and Zingales (1998) at the 3 digit ISIC rev 3 code using Compustat data for the 90s.

Empirical Methodology

In this sub-section, I formalize how automation in general, and robotics and AI in particular, affect the demand for labor, and I describe our empirical specifications.

A Simple Framework

Households maximize their utility combining goods from "J" sectors according to a constant elasticity of substitution (σ) aggregator function (we drop time sub-index t). Sector *"j"* output is produced by combining "*O*" types of occupation-services (S_o) according to a constant elasticity of substitution (α)

function. There is no capital as in the traditional neoclassical model. [26] An occupation-service is provided by a specific type of labor (occupation) and labor-replacing capital (R) using a CES technology. In this setup, investment in labor–replacing capital corresponds to the adoption of new technologies that enable capital to be substituted for labor in a range of tasks.[27] There is a specific elasticity of substitution for each occupation-service (ρ_o). These elasticities of substitution may go from zero to infinite ($0 \leq \rho_o < \infty$). Following Acemoglu and Restrepo (2018a), ρ_o maybe lower than one for some occupations, and therefore automation may complement labor (increasing the demand for current tasks or increasing the number of tasks performed by this occupation), or substitute it. The cost of labor-replacing capital, from now on capital, is given for producers and it decreases over time.

There are different wages for each occupation in each sector (*Woj*). And there is a unique price for capital (P_R).[28] All markets are perfectly competitive, and production has constant returns to scale. For simplicity, I assume a closed economy.[29] In a given sector (j) firms minimize the following costs function:

$$\begin{aligned}
&\underset{L_{oj},K_{oj}}{Min} \sum_{o=1}^{O} \left(L_{oj} W_{oj} + R_{oj} P_R \right) \\
&sa: \\
&\left(\sum_{o}^{O} a_{oj}^{1/\alpha} S_{oj}^{(\alpha-1)/\alpha} \right)^{\alpha/(\alpha-1)} = Y_j \\
&where \\
&\left(\lambda_o^{L\,1/\rho_o} L_{oj}^{(\rho_o-1)/\rho_o} + \lambda_o^{R\,1/\rho_o} R_{oj}^{(\rho_o-1)/\rho_o} \right)^{\rho_o/(\rho_o-1)} = S_{oj}
\end{aligned}$$

where L_{oj} and R_{oj} represent labor, from the occupation "o", and capital used to produce the occupation-service (S_{oj}) in sector *"j"*, respectively.

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[26] Results are similar if we include capital in the neoclassical sense using a cobb-douglas aggregator function between regular capital and the aggregate of occupation services. $\left(\sum_{o}^{O} a_{oj}^{1/\alpha} S_{oj}^{(\alpha-1)/\alpha} \right)^{\alpha/(\alpha-1)\Phi} K_j^{1-\Phi} = Y_j$

[27] As pointed by Acemoglu and Restrepo (2019), automation is the adoption of technologies that allows capital to takes over tasks previously performed by labor.

[28] In the empirical part, we allow for multiple prices for capital.

[29] In our econometric analysis external competition is captured by sector year dummies therefore does no affect my main analysis.

There is a continuation of households with mass one which maximizes the following utility function subject to an income constraint (PY).

$$U = \left(\sum_j^J d_j^{1/\sigma} Y_j^{(\sigma-1)/\sigma}\right)^{\sigma/(\sigma-1)}$$

where d_j are demand weight. From first-order conditions for labor I have:

$$\frac{L_{oj}W_{oj}}{PY} = \lambda_o^L \left(\frac{W_{oj}}{P_{oj}^S}\right)^{1-\rho_o} a_{oj} \left(\frac{P_{oj}^S}{P_j}\right)^{1-\alpha} d_j \left(\frac{P_j}{P}\right)^{1-\sigma}, \text{[Eq: 1]}$$

Where

$$P_{oj}^S = \left(\lambda_o^L W_{oj}^{(1-\rho_o)} + \lambda_o^R P_R^{(1-\rho_o)}\right)^{1/(1-\rho_o)},\ P_j = \left(\sum_o a_{oj} P_{oj}^{S(1-\alpha)}\right)^{1/(1-\alpha)} \quad and \quad P = \left(\sum_{oj} d_j P_j^{(1-\sigma)}\right)^{1/(1-\sigma)}$$

As already mentioned, in this simple setup, ρ_o higher that one represents the idea that automation (capital) replace labor in occupation "o" for a given cost share of occupation-service in sector "j". But there may be some occupations which are complement ($\rho_o < 1$).

Using previous results, I estimate the percentage change of the wage bill of occupation "o" after a fall in the price of capital-technology (P_R) in the whole economy. The change in the price of labor-replacing capital works as a demand shifter for the demand for labor, therefore it moves the number of employees and wage in the same direction.

$$\begin{aligned}\frac{d\ln(L_{oj}W_{oj})}{d\ln(P_R)} = &-(1-\rho_o)ShK_{oj}^S \\ &+(1-\alpha)\left(ShK_{oj}^S - \sum_{o'} ShS_{o'j}^J\, ShK_{o'j}^S\right) \\ &+(1-\sigma)\left(\sum_{o'} ShS_{o'j}^J\, ShK_{o'j}^S - \sum_{j'o'} ShJ_{j'}\ ShS_{o'j'}^J\, ShK_{o'j'}^S\right) \quad \text{[Eq: 2]} \\ &+\frac{d\ln(PY)}{d\ln(P_R)},\end{aligned}$$

where $ShK_{oj}^{S} = \lambda_{o}^{R}\left(P_{R} / P_{oj}^{S}\right)^{(1-\rho_{o})}$ is the capital share in the production of occupation-service "o" in sector "j". ShS_{oj}^{J} is the cost share of occupation-service "o" in the production of product "j". Finally, ShJ_{j} is the household expenditure share in product Y_j.

There are three factors behind the demand shifter reported in [Eq:2]. First, the elasticity of substitution between labor and capital at the occupation-service level (1st term in Eq [2]). If the elasticity (ρ_o) is larger than one, a reduction in the price of capital reduces the demand for labor for this occupation given an expenditure share for this occupation service. The larger the elasticity and the capital share are for occupation-service "o", the larger is the wage bill fall. If the elasticity of substitution is lower than one, a reduction in the price PR increases the demand for labor of this occupation. This term represents the replacement effect in Acemoglu and Restrepo (2019).

Second, there are two composition effects. One is at the occupation-sector level. A reduction in the price of capital reduces the cost of production of each occupation-service. The reduction in costs is larger for occupation-services with a large capital share. Under the assumption, there is a low substitution across occupations, i.e. "α" lower than one, so a fall in the price of capital-technology implies a fall in the wage bill of occupations with higher capital-technology share (2nd term in Eq.[2]).

There is an additional and similar composition effect at the household-sector level (3rd term in Eq.[2]). If sector "j" is less capital intensive than the whole economy, the fall in the price of capital increases its relative price. If the demand elasticity of substitution is lower than one (σ<1) there will be a fall in the expenditure share of sector "j"; and therefore, a fall in the demand of all occupations-services in the sector "j", including occupation-service and employment in occupation "o".

Finally, there is the standard "technology effect" at the aggregate level (4th term in Eq.[2]).

Empirical analysis at the sector-occupation-year level

Our main results use occupation-sector-year information. I assume sector specifics production functions. The sector-dimension allows us to study the effect of automation within sectors using fixed-effect model i) at the industry-occupation level, which controls for initial conditions; and ii) at the sector-year level, which controls for the sector and aggregate shocks. These set of dummies control for the 3rd and 4th term in [Eq.2]. I define each industry using the 2007 NAICS classification system at 3-4 digits level (285 Industries).

Grouping coefficients that only varies across sectors, assuming a linear relationship between the risk of automation and the occupation-capital elasticity at the occupation-service level $(\rho_o = r + \beta^R \ Risk_o)$, and using labor share instead of capital share at the occupation-service ($ShK_{oj} = (1 - ShL_{oj})$), [Eq:2] simplifies to:

$$\begin{aligned}\frac{\partial \ln(W_{oj} L_{oj})}{\partial \ln(P_R)} &= \rho_o (1 - ShL^S_{oj}) + \alpha (ShL^S_{oj} - \sum_{o'} ShS^J_{o'j} ShL^S_{o'j}) + D'_j \\ &= \beta^R \ Risk_o - \beta^R \ Risk_o \ ShL^S_{oj} + (\alpha - r) \ ShL^S_{oj} + D_j\end{aligned} \qquad \text{[Eq:3]}$$

The wage bill elasticity with respect to the price of capital is increasing with the elasticity of substitution between labor and capital (ρ^o), and with the capital share at the occupation-service level $(1 - ShL^S_{oj})$.

[Table 2 Here]

There is available data for all variables but the occupation "o" labor share (ShL^S_{oj}). I compute a proxy for labor share using equation [1] in 2004: [30]. For this exercise I assume that labor share for occupations-service "o" is independent of sector j $(ShL^S_{oj} = ShL^S_o)$:[31]

$$\ln(LW_{oj}) = d_o + d_j + e_{oj} \qquad \text{[Eq:4]}$$

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30 $\frac{L_{oj} W_{oj}}{PY} = \lambda^L_{oj} \left(\frac{W_{oj}}{P^S_{oj}} \right)^{1-\rho_o} a_{oj} \left(\frac{P^S_{oj}}{P_j} \right)^{1-\alpha} d_j \left(\frac{P_j}{P} \right)^{1-\sigma} = ShL^S_{oj} * ShS^J_{oj} * ShJ_j$

31 The additional assumption is that wages for each occupation is the same across sectors.

where $e_{oj} := \ln(ShS_{oj}^{J})$, $d_o := \ln(ShL_o^S) + cte1$, $d_j := \ln(ShJ_j) + cte2$, and $cte1 + cte2 = \ln(PY)$

The year 2004 is the base year. As I mentioned before, some occupations at the 5-digit were replaced for occupations at 6-digit SOC 2000 the year 2004. I compute Equation 4 using data from 2003 and 2004. I use dummy d_o to construct a proxy of $\ln(ShL_o^S)$. Using these two years, I obtain values for all occupations no matter the level of aggregation. This is a good proxy as long as labor share in occupation-service "o" is independent of the sector "j". For this reason, in the empirical part, I use either this proxy for labor share at the sector-occupation level or a constant labor share for all sector-occupation services ($ShL_o^S = ShL^S$).

I use the exponential value of dummies "d_o" as our proxy for labor share. I normalize and get rid of outlier dividing our proxy by the exponential value of the dummy term in the percentile 80, and taking the minimum between the previous term and 0.95 ($Sh\hat{L}_o^S = \min(\exp(d_o - d_{o,p80}), 0.95)$). I am assuming that computed dummies in the 80th percentile or higher represent a labor share equals to 0.95.

Table [2] presents the pairwise correlation of the computed "do" dummies and our proxy for labor share for four different base years (2002-2003), (2003-2004), (2004-2005) and (2005-2006)). Pairwise correlations are all above 0.9.

For sector-occupation-year exercises I integrate [Eq:3]. [Eq.5] presents the fixed effect model I use to study the evolution of the wage bill, employment, and wages:

$$\begin{aligned} Ln(X_{ojt}) = \beta^R RISK_o\, P_{R,t} - \beta_t^{RxShL}\, Sh\hat{L}_o^S\, RISK_o P_{Rt} \\ + \gamma^{Sh\hat{L}}\, Sh\hat{L}_o^S\, P_{Rt} + \mu Z_{oj} + D_{oj} + D_{jt} + e_{ojt} \end{aligned} \quad \text{[Eq.5]}$$

where X_{ojt} is either the dependent variable in occupation "o", in sector "j" in period "t". D_{oj} accounts for initial conditions. $RISK_O$ is the proxy for the risk of automation. $Sh\hat{L}_o^S$ is our proxy for the labor share of occupation "o" in occupation-service "o" in sector "j". $P_{R,t}$ is the proxy for the price of labor-replacing capital. In the empirical section, I use either year dummies or robots per worker (at the country or sector level) to account for the evolution of capital price. Z_{oj} is an additional sector-occupation level control (sector-occupation initial wage (ln) x aggregate wage (ln)). D_{jt} accounts for sector-year shocks.

To get rid of any reverse causality between robots and the occupation-sector movement of employment, I follow Acemouglu and Restrepro (2018), and I instrument robots per workers in the USA with the average of robots per workers in 6 EU countries with a similar level of robots penetration in 2016.

If *Routine Task Index, FO RISK Index,* and *FO RISK Prob.* measure the risk of automation, when I use dummies to account for the evolution of capital prices, I should expect a decreasing value for dummy coefficients (year dummies x RISKo).

Following Autor et al (2003), I use the ln ratio between the 90th and 10th quantile as a proxy for wage dispersion within occupations.

Sector Level Approach.

The last set of econometric results studies the effect of automation on employment and imports at the sector level. I use sector import because of its disaggregate data availability (4 digits NAICS level). To study the effect of automation on sector imports, I compute for each industry two measures of automation risk by sector: i) the employment-weighted average of each occupation's probability of automation (FO RISK Probability $_j$), and ii) share of employment in occupations that have a probability of automation higher than 70% in the sector (*FO RISK Index* $_j$). I use employment data from the year 2004 to compute our weighted means.[32]

[32] First year in which I have data for robots in the US at the sector level.

For sector wage bill, employment, and average wage I estimate a sector and year fixed-effect model. I control for a vector of variables that vary at the sector-year level. For example, External Finance Dependence multiplied by the log level of credit to the private sector as a percentage of GDP.[33] The share of imports from China in sector "j" at the beginning of the period (the year 2002) multiplied by the evolution of total Chinese exports during the period 2002-2016. The same for México.[34]

For log imports, I estimate a sector-"country of origin" and "country of origin"-year fixed-effect model. There is a sample of countries that are running behind in the adoption of new technologies. Relative to the latter countries, the automation process in the US should have increased its relative advantage in sectors with a higher probability of automation in the last years. To account for the previous effect I either split the sample in countries with high and low robots per worker penetration, or I control for robots per worker at the "country of origin" interacted with sector risk of automation. This last term should have the opposite sign than our main coefficient of interest sector robots per worker in the US interacted with sector risk of automation.

For imports, I also control for a vector of variables that vary at the sector-year level (financial variables).

3. Results

This section presents my estimation results. The first subsection presents my main results using national occupational employment and wages at the industry level. The second subsection uses employment, wages, and imports at the national industry level for the first two variables, and at the *national-sector-country of origin* for imports.

[33] We follow Chor and Manova (2012) to account for the credit financial crises on trade.
[34] We follow Autor et al (2016) to control for Chinese and Mexican import penetration in the USA:

Occupation employment and wages at the sector-occupation level

Table (1b) and Figure (2) show that wage bills, employment, and wages have been falling in OaRA during the period 2002-2016. Although suggestive, these results may be driven by two composition effects. First, sectors that demand fewer occupations at risk of automation may be driven these results if they have been growing faster during the period 2002-2016. In this section, I control for different trends and sectoral shocks using sector-year dummies. Second, there is an additional composition effect at the occupation-service level within sectors. Occupations at risk of automation may be correlated with occupation-services which are less capital-technology intensive (and therefore with a higher initial labor share - ShL_o^S -). A fall in the price of capital-technology increases the relative price of labor-intensive occupation-services. A sufficiently large elasticity of substitution between occupation-services implies a reduction in the labor demand in these labor-intensive occupation-services (See [Eq:2] and [Eq:3]).[35]

Tables (3a), (3b) and (3c) report our results using [Eq.5] for wage bill, employment and wages at the sector-occupation level. I allow for different sector production functions, and for any composition effect at the sector level -an elasticity of substitution between final goods (sectors) different from one (σ≠1)-. In Table (3b) and (3c) I also allow for different labor share (capital share) at the occupation-services level $\left(ShL_o^S \neq ShL_q^S\right)$, and a positive cross elasticity of occupation-services $\left(0<\alpha\right)$.

For the period 2002-2016, the OES dataset allows us to study employment and wage at the occupation-sector level. I take advantage of this panel structure to control for sector-occupations and sector-year factors using dummies. The former set of dummies captures the initial condition, and the latter set of dummies captures industry/sector composition effects and, sectoral and aggregate shocks (third and fourth term in [Eq:2]). I assume a linear relationship between the occupation risk of automation (or the Routine

[35] The condition to have this effect is α > r (r isthe constant coefficient in the linear relationship between the capital-labor elasticity and the risk of automation-). Without the direct effect of capital-technology price on the occupation "o" wage bill $\left((1-\rho_o)\Delta P^R\right)$, the condition to have this negative composition effect will be (α >1). See [Eq:2].

Task Index) and the elasticity of substitution between capital and labor $\left(\rho_o = r + \beta^R \ RISK_o\right)$. I integrate [Eq: 3] and I obtain [Eq:5].

It is important to note that $\gamma^{S\hat{h}L}$ in [Eq.5] is proportional to "α" minus "r" $\left(\gamma^{S\hat{h}L} \propto (\alpha - r)\right)$, therefore the coefficient could be positive or negative. I am only able to identify dummies term interacted with deep parameters $\left(eg.\ \beta^R \ P_{Rt}\right)$.

Tables (3a) and (3b) and Figures (3) to (6), present my results for wage bill, employment, and wages using dummies to proxy for capital-technology price at the country level (P_{Rt}). In this setup, identification comes from the differential effect of the evolution of the aggregate price of labor-replacing capital on each occupation (788) within each sector (285).

[Figure 3 Here]

To compare results with and without controlling for sector composition effect, Column (1) in Table (3a) presents results for (log) sector-occupation employment imposing a unique labor share across occupation-services $\left(S\hat{h}L_o^S = cte\right)$, and controlling only for sector-occupation and year fixed-effects (which is equivalent to impose $\sigma = 1$).

Columns (2)-(3) also impose a unique labor share but control for sector-year fixed effect for (log) wage bill, (log) employment and (log) wages, respectively $(\sigma \neq 1)$. Results at the aggregate level (Figure 2) hold within industries. Controlling by sector-occupation and sector-year fixed effects, Columns (2) and (3), and Figure (3a) show that wage bill and employment in occupations at risk of automation has been falling, in relative term to riskless occupations within the same sector, at an annual rate of -2.11% and -2,07% per year during the period 2004-2016, respectively. These falls are smaller, in absolute value than the one I get using aggregate data, -2.4% and -2.2% for wage bill and employment during the same period, respectively (Figure 2 and Table Ba).[36] As already mentioned, aggregate data includes Federal, State, and Local government, whereas sector data does not, therefore I have to take with caution this comparison.

To see how results change once I control for sectoral shocks, Figure (3) presents (log) employment results from Column (1) and (3) in Table (3a). Without sector-year fixed effect, sector-occupation (log) employment of occupations at RISK fall -2.3% per year relative to the rest of the economy, whereas when I control for sectoral shocks (sector-year dummies) this fall is -2.1% per year. Figure (3b) shows this difference originates during the 2008-2010 period. Almost all the occupation adjustments happen within sectors.

Figure (3) also **suggests** there is a “cleaning effect” around the 2008 financial recession. Firms in all sectors seem to adjust more occupations that are prone to automation during the period around the financial crisis. But also, it seems that sectors with a high share of jobs in occupation at risk reduce more their total employment during this period. Controlling for sector-year shocks, Figure (4a) and (4b) presents the evolution of wage bills, employment, and wages. Figure (4a) does not control for initial wages interacted with the aggregate wage, whereas (4b) does. In both cases, the wage bill and employment fall during the whole period, whereas the average wage is more stable and it starts to recovers by the end of the period.

Column (4) presents the evolution of relative wages for occupations at risk of automation vis a vis riskless occupations within sectors (Figure (5a)). Their wages fall during the first half of the sample. In 2007, they are 3.4% lower in relative term to riskless occupation vis-a-vis 2002. After 2008, they start to recover. By the end of the sample, they are only 2% lower than in 2002. Aggregate data (Table (Ba) and Figure (2c)), present a similar inverted U pattern, they fall to -5.6% in 2011 and then they recover to -4.7% by the end of the period. The already **suggested** cleaning effect could be behind the average wage recovery in the second half of the period of analysis. Firms reduce employment of low productivity/low wage workers.

[36] Average percentage for aggregate data are calculated for the same period (2004-2016).

[Table 4a Here]

After an initial small jump, wage dispersion in occupations at risk of automation, relative to dispersion in other occupations, has been falling slightly during the whole period (see Column (5)). The initial jump in wage inequality comes from an initial fall in wages at the bottom of the distribution larger than the decline in wages at the top (see Figure (5b)). Since 2006, the relative wage at the bottom of the distribution starts to increase. By 2016, wages at the bottom almost recover their initial level. Wages at the top of the distribution starts to revert only by 2008, and by the end of our sample, they continue to be 2% below their initial position.

[Figure 4 Here]

Results for employment and wages suggest that occupations at risk of automation suffer a demand shock within sectors, and sectors with a higher share of employment at risk of automation also seem to have suffered a demand shock relative to the whole economy during the period covered in this paper.

[Figure 5 Here]

Figure (4b) presents coefficients of regressions (2) to (4) in Table (3a) now controlling for sector-occupation initial wages (initial log wages interacted with log aggregate wage over time).[37] Once I control for initial wages, the wage bill and employment become almost indistinguishable. In both cases, they present a monotonic fall during the whole period (Columns (6) and (7) in Table (3a)). By the end of the period occupations at risk of automation have lost, relative to riskless occupations, 20% of their wage bill and employment (EXP(-.227)-1). This is a 1.65% lower annual rate of growth.

Figure (4c) and (4d) redo the previous model regressions using the continuous *FO RISK Probability* and our index of the importance of routine tasks in each occupation –*Routine Task Index*- (Autor et al (2003) approach) instead of the *FO RISK Index*. Figure (4c) does not control for initial sector-occupation wages

[37] We include initial sector-occuaption wage (log) multiplied by aggregate wage over time (log).

whereas (4d) does. For both sets of exercises, I find that wage bills fall monotonically during the whole period. Without initial wage controls, occupations with *Routine Task Index* in the 90th percentile reduce their relative wage bill by -27% relative to occupations with *Routine Task Index* in the 10th percentile during the whole period (See Column (8) in Table 3a). When I control for initial wages, the contraction on the wage bill is smaller (-17%), in absolute value (See Figure (4d)). Results for *FO RISK Probability* are analogous.

Table (3b), presents previous results allowing for different labor share across occupations-services $\left(S\widehat{h}L_o^S \neq S\widehat{h}L_q^S\right)$. Sub-column (a) reports the coefficient for the risk parameter, sub-column (b) reports the coefficient for the risk parameter interacted with labor share, and sub-column (c) reports the coefficient for the labor share. Assuming a fall in the price of capital-technology, I should expect falling coefficients for the risk parameter and increasing for the interacted term (see [Eq:5]).

Columns (1) and (2), and Figure (6a), (6b) and (6c) use the FO RISK Index; and column (3) and Figure (6d) use the Routine Task Index. The dependent variable is the log wage bill for all models but in Figure (6c) where the dependent variable is the log sector-occupation employment.

As predicted by [Eq:5], after a fall in the price of labor-replacing capital, the black cross in Figure (6a) shows the decreasing and monotonic evolution of the FO RISK Index parameter. I find the same behavior for wage bill when I control or not for the initial sector-occupation wage (Columns (1) and (2), and Figure (6b) and (6a)), and when I use log employment as dependent variable (Figure (6c)). Also, as predicted, the coefficient for RISK interacted with the share of employment at the sector-occupation service level has the opposite sign (positive) and it is increasing. When I use our routine task index instead of the FO RISK, Column (3) in Table (3b) and Figure (6d) show similar results for the evolution of our proxy for risk of automation and its interaction with occupation-service labor share. The main results are similar (Routine Task Index and Routine Task Index x Labor Share).

Finally, using the FO RISK Index as a proxy for the risk of automation, the coefficient for labor share interacted with year dummies has a monotonic fall. Using Routine Task Index as a proxy for the risk of automation the coefficient for labor share increases until 2005 and then it starts to fall. Under the null hypothesis that the price of labor-replacing capital is the only factor changing the occupation share of occupation-services withing sectors, we should expect a monotonic increase ($r>\alpha$) or decrease ($r<\alpha$) of labor share coefficient over time. Therefore these results suggest that the evolution of the price of labor-replace capital is not the only factor that is changing the occupations-service composition withing sectors and its effect is correlated with the initial labor share at the occupation-service level. This result is not surprising because we are using dummies as a proxy for the evolution of the price of capital. These dummies may be capturing other factors. This is not the case for my risk variables, FO RISK Index or Routine Task Index, alone and interacted with the initial labor share, because in these cases the real proxy for the price of capital is the time dummy interacted with the risk proxy which varies across occupation.

[Table 4b Here]

Previous results allow different values for year dummies in each of the three main independent variables: Risk of automation, Risk of automation interacted with sector-occupation labor share, and sector-occupation labor share. If time dummies account for the evolution of the price of capital-technology price, year dummies should be the same for the FO RISK Index coefficient and its interaction with the initial labor share at the occupation-service level. Column (4) presents results for wage bill using as the independent variable the FO RISK Index and controlling for occupation-service labor share interacted with an independent set of year dummies. And Column (5) presents results for wage bill using as independent variable the FO RISK Total Effect, which is the FO RISK Index times one minus the occupation-service labor share (FO RISK Index x (1-ShL)), and also controlling for occupation-service labor share interacted with year dummies. Both independent variables have a monotonic fall that implies an annual rate of growth of minus 1.7% and 3.0% for Column (4) and (5), respectively. When I use the

FO RISK Total Effect as the independent variable, the model has a higher likelihood than the model when I use FO RISK Index instead. Columns (6) and (7) redo the same exercises using Routine Task Index instead of the FO RISK index. Results hold.

[Figure 6 Here]

Table (3c) uses annual data of robots per worker at the aggregate level and at the sector level (Rpw_{jt}) instead of year dummies to proxy for capital-technology prices (inverse proxy). To avoid any reverse causality, and following Acemoglu and Restrepo (2018), I instrument our proxy using the average value of robots per worker in 5 EU countries with similar robots per worker penetration.

I use two approaches to get causation. First, I use the interaction of my measure of the risk of automation and robots per worker instrumented by the simple average of EU robots per worker at the aggregate level. Second, following Acemoglu and Restrepo, I use robots per worker at the industry level in the US instrumented with EU data. For completeness, I use robots per worker at the industry by itself and its interaction with the proxy for occupation risk of automation (in both cases instrumented with EU data). As I mentioned in the introduction, for the U.S. there is a large share of robots that the IFR is not able to assign to a specific sector. Also, it is important to note, that robots per worker at the industry level could be endogenous to the level of occupation at risk of automation in this industry. This endogeneity is positive (high share of employment in occupations at risk more sectoral penetration of robots per worker).[38]

The second approach does not allow to control for sector-year effect, therefore it requires to control for effects at the sector-year level (import penetration and financial crises).

To control for initial conditions I use sector-occupation dummies and I cluster errors at the sector-occupation level.

[38] Autor et al (2003) shows that a sector with an initial high share of employment in routine occupations has a posterious large penetration of computers.

Table (3c) presents my main results. Panel A and B use *FO RISK Index*, and Panel C uses my *Routine Task Index*. The dependent variable is the log wage bill in all columns but in columns (2) and (7) where I study log employment. In all models, I control for initial conditions (sector-occupation dummies). Panel A imposes that labor shares at the occupation-service level are equal $\left(S\hat{h}L_o^S = S\hat{h}L_q^S\right)$. Panel B and C allow for different occupation-service labor shares, and I control for the composition effect at the occupation-services level using my proxy for the initial occupation-service labor share interacted with robots per worker. I use [Eq:5]. Wage bill, employment and wages in occupation at risk of automation should growth less in sectors that adopt more labor replacing capital-technology (First term in [Eq.5]). This negative substitution effect should be lower (in absolute value) in occupation-services which are initially less labor-intensive (second term in [Eq:5]). I also control for the relative change in the occupation-services cost-share due to the fall in the relative price of capital-technology (third term in [Eq.5]).

In columns (1) to (7) in Panel A, I control for financial conditions and Chinese and Mexican import penetration at the sector level, and aggregate shocks using year dummies. Following Rajan and Zingales (1998) I use a measure of sectoral external financial dependence interacted with an index of credit tightness constructed using the FED "Senior Loan Officer Opinion Survey on Bank Lending Practices".[39] Following Autor et al. (2013) and Acemoglu and Restrepo (2018), I use the initial U.S. sectoral imports from China and Mexico times the log annual total Chinese and Mexican exports to the world. I only report the coefficient for sector-year variables in Panel A, although I also control for them in Panel B and C.

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[39] Following Rajan and Zingales (1998) I construct Employment Finantial Dependence for sectors at 3-digit ISIC rev3. Using Compustat data. I construct a proxy for the tightness of the credit market using the variables NIS "Net percentage of domestic banks increasing spreads of loan rates over banks' cost of funds to large and middle-market firms" and NIT "Net percentage of domestic banks tightening standards for C&I loans to large and middle-market firms" from the FED. The index is equal to the last year index plus NIS and NIT divided by 100. In regression I use the demean value of the EFD x Tighness Index divided by its standard deviation.

Columns (8) to (12) control for sector composition effect and sectoral shocks, or sectoral import penetrations using sector-year dummies.

Columns (3) to (12) control for the initial sector-occupation wages interacted with log aggregate wage, whereas (1) and (2) do not.

The third row in Table 3c describes the "robots per worker" variable I use to construct independent variables in the econometric model. It could be at the aggregate level (Columns (1)-(4) and (8)-(9)) or at the sector level (22 IFR sectors).[40]

The "Annual Growth 2016-04 (p90-p10)+" row reports the effect, of the average change in robots per worker times the risk proxy between 2004 and 2016, on the dependent variable annual rate of growth for sector-occupations in the 5th quintile of the risk of automation, relative to the sector-occupations in the 1st quintile ("RISK x Robots/worker"). In some models I use sectoral robot penetration, therefore I cannot take the effect for the sector-occupation in the 90th or 10th percentile, but the average effect around these to percentiles to capture the joint effect of different robots penetrations and risk of automation.

The "Annual Growth 2016-04 (p90-p10)++" row reports the effect, of the average change in robots per worker times the occupation-service labor share between 2004-2016, on the dependent variable annual rate of growth for sectors in the 5th quintile of the risk of automation relative to sectors in the 1st quintile ("ShL x Robots /worker"). And, when I use sectoral robot penetration, it also includes the direct effect of the different changes on robot penetration across occupations with a high risk of automation (5th quintile) and low risk (1st quintile) ("Robots /worker").

Columns (1) to (3), in Panel A, present my empirical approach using aggregate robots per worker. FO RISK Index interacted with aggregate robots per worker is negative and highly significant. Occupation at risk of automation (FO RISK Index=1) reduces their relative wage bill participation by an annual rate of

[40] I use robots per workers at 2 digits for sectors defined at 4 digits NAICS.

2.7% when I control for initial wages or not, between 2004 and 2016 (Columns (1) and (3)). In Column (2), I find the same negative relative rate of growth for employment (-2.6%). In all these cases, control variables have the expected sign. Sectors with higher external financial dependence present a lower rate of growth when the financial condition is tight. Coefficients for Chinese and Mexican import penetrations have the expected negative sign, although only the Chinese import coefficient is significant at standard levels of confidence.

Column (4) use FO RISK Total Effect as proxy for automation risk (FO RISK Index x (1-ShL)). In this specification I also control for ShL times robots per workers. OaRAs have an average wage bill rate of growth 2.2% lower than riskless occupations. When we include the composition effect (ShL x Robots/worker) the lower rate of growth falls, in absolute value, to -2.0% (-2.2%+0.2%). The effect is lower than the one I find using FO RISK Index and I do not control for labor share interacted with robot penetration (Columns (1) to (3)).

Columns (5) and (7) use sectoral data for robots per worker (also instrumented with robots per worker at sector level in 5 EU countries). The coefficient for Robots per worker is negative. In column (5), the average increase in robots penetration in OaRA (FO RISK Index=1) minus the average change in riskless occupation, implies a lower annual rate of growth of -0.1%. In Column (6), I include the interaction term between my risk proxy and robots per worker. The coefficient for the interaction term is negative and statistically significant. It implies a lower wage bill relative rate of growth for OaRA of 1.2%. When I include the direct effect of sectoral robot penetration (“Robots/Worker”) the total effect is -1.3%. As I already mentioned, the data for robots per workers at the sector level is noisier than the aggregate one (at the beginning of the sample only a third of total robots are classified in a specific sector in the US), therefore there could be a downward bias (in absolute value) due to measurement errors in the dependent variable.

Column (7) uses FO RISK Total Effect instead of FO RISK Index, and it also includes the control for occupation-service labor share. The direct effect of robots per worker at the sector level vanish, the interaction term with the FO RISK Index for OaRA remain negative and statistically significant. The latter coefficient implies a 1.0% lower wage bill rate of growth for OaRA.

Columns (8) to (12) redo equations (2) to (7) but (5), including sector-year fixed effects. Computed coefficients are stable. In columns (8) and (9), the main variable is the FO RISK Index interacted with aggregate robots per worker. For wage bill and employment, I find that occupations at risk of automation have an annual rate of growth 2.% lower than riskless occupations during the period 2004-2016. This rate of growth is lower than the one I find when I do not use sector-year fixed effects (Columns (2) and (3)). Column (10) uses FO RISK Total Effect, as in Column (4), I find a lower effect, in absolute value, of robot penetration on OaRAs´ wage bill than I find using FO RISK Index. In Columns (11) and (12) I also got smaller effect, in absolute value, than I only control for year fixed effects, instead of year-sector fixed effect. Controlling for sector-year dummies reduces the negative impact of robot penetration on OaRA in around one ten.

Panel B redoes Panel A allowing for different occupation-service labor shares $\left(S\hat{h}L_o^S \neq S\hat{h}L_q^S\right)$. From [Eq.5] I know that if the coefficient for "RISK x Robots/Worker" is negative (first term in [Eq.5]) the coefficient for its interaction term with occupation-service labor share ("RISK x ShL x Robots /worker") should be positive (second term in [Eq.5]).[41] I find this result in all specifications. The net effect is negative, the sum of the main effect (Risk x Robots/worker) and the interaction term with the sector-occupation labor share (RISK x ShL x Robots/worker). This negative effect remains when I include also the composition effect across sector-occupation withing sectors (ShL x Robots/worker). A higher labor

[41] I am using a robors per worker as a proxy (inverse) for the price of robots, therefore coefficients switch sign from [eq: 5].

share reduces the effect of the price of labor replacing technology on wage bills and employment. These results reinforce our previous results using year dummies as a proxy for the price of capital-technology.

In Column (1), estimated coefficients imply that the average increase of robots per worker induces wage bills of OaRAs to grow 2.7% less per year relative to riskless occupations. The interaction term between my risk proxy and robot penetration is negative and highly significant. The triple interaction term (RISK x ShL x Robots/worker) is positive and statistically significant. The previous two variables imply a reduction in the relative rate of growth of wage bill of 2.8% per year. The interaction term between labor share and robot penetration is negative (ShL x Robots/worker), although its effect on the relative wage bill rate of growth for OaRA is positive (the average of ShL for OaRA is smaller than for riskless occupations).

For Columns (2) to (12) results are similar to the ones I find in Panel A. The effect of robot penetration on the wage bill and employment is stable to allow for the decomposition define in [Eq:5].

Panel C redoes Panel B using our Routine Task Index instead of the FO RISK Index. I find similar results, although their magnitudes are slightly larger in absolute value in most models.[42]

Summing up, data at the sector-occupations level shows that robot penetration reduces the average annual rate of growth of wage bills and employment in OaRA by 2.2-3.5% relative to riskless occupations. This percentage fall, in absolute value, to 2.0-2.9% when I control for sector-year shocks (suing fixed effects) during the period 2004-2016.

Results for risk of automation interacted with labor share at the occupation-service level reassure we are capturing the effect of the price of labor-replacing capital on occupation labor demand.

[42] For robustness, I redo Panel B using three, six and twelve-period changes instead of fixed effect at the sector occupation level (non reported). My independent variable is the change in wage bill or employment. I allow for dynamics using Anderson and Hsiao (1982) model. Results are stable.

Wage Bill, Employment and Wages: Sector Level

The previous results present the relative impact of automation on occupations prone to automation. To focus the impact of automation at the sector level I collapse sector-occupations' data and I construct indexes of risk of automation at the sector level. These are the average of the FO RISK Index of automation for each occupation weighted by the number of employees in this occupation (which is equivalent to the share of workers at risk), and the weighted average of the FO RISK Total Effect -FO RISK (1-ShL) - and the Routine Tasks Index in 2004. I keep 285 sectors defined by the BLS (NAICS 2007 3-4 digit).

Table Ca, in appendix C, shows the results for log sector wage bill, log average wage and log sector employment using year dummies as a proxy for capital-technology prices. Due to the sector and year panel structure of the data, I include sector and year dummy variables which account for initial conditions and aggregate shocks. In all empirical specifications, I control for Chinese and Mexican sectoral exports to the US, and for financial conditions. Some regressions control for initial (log) sectoral wages interacted with the (log) average wage in the economy over time.

Figures (7a) reports the coefficient for the FO RISK Index (in 2004) for (log) sectoral wage bill, (log) employment, and (log) wage, over time (Columns (1) to (3) in Table Ca). FO RISK Index is normalized to have a difference between the 90^{th} and the 10^{th} percentile equals to one. Reassuring previous results, the wage bill in sectors with a large share of employment at risk of automation falls during the first half of our sample. Until 2007 the relative fall is only 9%, but it accelerates between 2008 and 2010. This reassures the “cleaning effect” hypothesis during the financial crises. After 2010 their wage bills remain constant (relative to other sectors). Employment shows a similar pattern than the wage bill. Wages in a sector with a large share of OaRA falls during the whole period relative to wages in a sector with a low share of OaRA. By the end of the period, the relative fall is 6%.

Figure (7b) presents the evolution of employment for different proxy for OaRA, FO RISK Index, FO RISK Total Index -RISK (1-ShL)-, and Routine Task Index (See Table (Ca)). In all cases, employment in sectors with a high share of OaRA presents a similar pattern. They slightly fall during the initial period, during the 2008 crises they show a 10% fall relative to the sector with little employment in OaRA. By the end of the period, they started to recover relative employment.

Table (4a) presents results using robots per worker as a proxy for the capital-technology price during 2004-2016. In some models, I instrument robots per worker in the US using the average robots per worker in EU countries. I control for the initial condition using sector dummies and aggregate shocks using year dummies. In all models, I control for (log) initial wage interacted with the (log) aggregate wage, for external financial dependence interacted with the proxy for Credit Thighness from the FED, and sectoral Chinese and Mexican import penetration.

The second row reports the dependent variable: (log) Wage Bill and (log) Employment. The third row reports the proxy for the risk of automation I use. The fourth row reports the level of aggregation I use to construct the variable robots per worker that I interact with the proxy for risk of automation (Aut.Risk x Robots /worker). The fifth row shows the econometric method I use, OLS or IV.

The “Annual Growth 2016-04 (p90-p10)+” row reports the effect, of the average change in robots per worker times the risk proxy between 2004 and 2016 (“RISK x Robots/workers”), on the dependent variable annual rate of growth for sectors in the 5th quintile of the risk of automation, relative to sectors in the 1st quintile. The “Annual Growth 2016-04 (p90-p10)++” row reports the effect, of the average change in robots per worker times the average occupation-service labor share at the sector level between 2004-2016 (“ShL x Robots/worker”), on the dependent variable annual rate of growth for sectors in the 5th quintile of the risk of automation relative to sectors in the 1st quintile. And, when I use sectoral robot penetration, it also includes the direct effect of the different changes in robot penetration across sectors with a high risk of automation (5th quintile) and with a low risk (1st quintile) (“Robots /worker”).

[Table 4a Here]

Columns (1) and (2) report results for (log) wage bill and (log) employment, using the share of workers at risk of automation at the sector level in 2004 interacted with aggregate robots per worker penetration (instrumented with the average of 5 EU countries). Due to the aggregate robot penetration in the US (during 2004-2016), the (log) Wage Bill of a sector with a high share of employment at risk of automation (in the 5^{th} quantile) grows 2.9% less per year than a sector with a low share of employment at risk (in the 1^{rd} quantile). For (log) employment, the same percentage is 2.7%. In both cases, coefficients are statistically significant at standard levels. For robustness, Columns (3) and (4) redo the same exercises using the weighted average of FO RISK Total Effect index (FO RISK Index * (1-ShL)). The Wage Bill in a sector characterized by a large share of OaRA grows -1.4% less than the other sectors characterized by little OaRA. In this model, I also control for ShL times robot penetration. Results are qualitatively the same for (log) employment (-1.3%).

In Column (5) I follow previous studies, and I redo Column (1) but now I also include robots per worker at the IFR sector level (22 aggregate sectors). The coefficient for robots per worker at the IFR sector level is negative although not statistically significant at standard level. The coefficient for FO RISK Index interacted with aggregate robots per worker is still negative, smaller than in Column (1) and not statistically significant. The Kleibergen-Paap rk Wald F statistic shows I have weak instruments. Column (6) redoes the previous exercise using OLS. The coefficient for sectoral robots per worker is smaller although now it is statistically significant. The average sector robot penetration is related to a fall of 0.1% in the average annual rate of growth of wage bills. FO RISK Index interacted with aggregate robot penetration is negative, similar to the one in Column (1) that implies a reduction in the average annual rate of growth of -2.4%, and it is statistically significant.

In Columns (7) and (8) I regress (log) wage bill and (log) employment on robots per worker at the IFR sector level (22 aggregate sectors) and its interaction term with the average FO RISK index at the sectoral level. I instrumented with EU data. In both cases, the coefficient of interest is not significant at standard levels. The Kleibergen-Paap rk Wald F statistic does not reject weak instruments in the first stage. In columns (9) and (10), I redo the previous two regression without using IV, but OLS. In this case, the coefficient for the interaction term between robot penetration and sector average FO RISK Index is negative and statistically significant. Wage bills and employment fall by a relative annual rate of growth of 0.1% in sectors characterized by a large fraction of OaRA relative to others. The coefficient for robots per worker at the sector level is not statistically significant and switch sign. The last two columns use the average of FO RISK Total Index and sectoral robot per workers at the sector level. The interaction term in both cases is negative and statistically significant if I use OLS, with IV the coefficients estimated have large standard errors (not reported). The Kleibergen-Paap rk Wald F statistic is low.

Summing up, a sector that uses more occupations at risk of automation at the beginning of the period presents a lower rate of the wage bill and employment growth. For employment, this fall is during the first half of the period and mainly during the financial crises. After 2010 it seems to start to recover. There seems to be a recession cleaning effect at the sector level for industries with a higher risk of automation, and then they stabilized. The productivity/income effect does not counteract the displacement effect at the sector level.

I identify weak instruments when I use sectoral data for robots per worker. As I already mentioned, sectoral data has a large share of unclusified sector at the beginning of the sample. When I estimate OLS models, the interaction term between robot penetration at the sector level and the share of OaRA is negative and significant.

Finally, it is important to take into account that these results are subject to the critique that they could be capturing other factors at the sector level beyond financial factors and Chinese and Mexican trade penetration, or these controls may be imperfects.

Automation and Sectoral Imports

Previous models present results for labor market outcomes at the sector level. Tables (5a) to (5c), and Figure 9, present the relationship between automation and US imports from each of its trade partners.

We use the data from the US custom collected by Schott (2008) and posteriors updates until 2016. I find that the US import of commodities in sectors with a large fraction of workers at risk of automation, at the beginning of the period, falls relative to the rest of imports. This reduction is explained by imports from countries with low adoption of automation technology (proxy by robots per worker penetration at the country level).

In Table (5a) and Figure 9, I use year dummies as a proxy for capital-technology prices. I control for initial conditions with trade partner-sector dummies and for aggregate factors with trade partner-year dummies. I control for each country's financial conditions at the sector-year level with sector external financial dependence interacted with log credit to the private sector in the U.S. and in the exporter country.

External financial dependence interacted with log credit to the private sector is not significant at the standard level for exporter countries, although tight financial condition in the US has the expected sign and it is statistically significant for the US. Results show that the US imports more commodities produced by sector that depend more on external financing when the credit market is tight in the US. This result is in line with previous empirical works about the effect of financial distress on trade.[43]

Columns (1) use as a proxy for sector risk of automation the share of employees at risk using FO RISK Index. Figure (9a) presents the sector risk coefficient for Column (1). Imports of commodities fall in sectors with a higher share of jobs at risk of automation. By 2012, relative imports in these sectors are 40% lower than in 2002. After 2012 they remain stable. Column (2) and (3) include only countries that are included in the IFR. Column (3) includes all countries but China and Mexico. Risk coefficients remain

[43] See Chor and Manova (2012).

almost identical. "Annual Growth 2016-04 (p90-p10)" shows that a sector with an initial high share of workers at risk of automation (90th percentile -FO RISK Index-) presents a 2.1%-3.5% lower average annual rate of import growth than a sector with a low initial share of workers at risk (10th percentile).

Columns (4) and (5) redo column (1) using the weighted average of the FO RISK Total Effect and the Routine Tasks Index instead of FO´s RISK, respectively. In both cases, the annual rate of growth of commodities imports from sectors characterized in the US by a large share of workers at risk is 2.9%-4.0% lower.

Firms have been substituting job/occupation with a higher risk of automation. Import results suggest that these firms have also been substituting imports. If automation is behind this increase in import substitution, I should expect that import substitution should be higher from countries that have lower penetration of automation-technologies. In Column (6), I split the sample into two groups of countries by their level of industrial robots per worker in 2002. There are 17 countries with high robot penetration (25% of countries covered by tye IFR).[44]

[Table 7a Here]

[Figure 9 Here]

Figure (9b) presents the evolution of RISK coefficients for each group (Column (6) a and b). Import substitution is twice as larger from countries with lower robot penetration than for countries with high penetration. For the former group, Column (6a) shows that commodity imports from these countries fall 3.7% in sectors characterized by a large share of OaRA, whereas for the latter group of countries, Column (6b) shows that this percentage is -1.4% and not statistically significant. Figure (9b) shows the evolution of the estimated coefficients over time. These suggest that automation is behind imports´ behavior.

[44] Austria, Belgium, Germany, Denmark, Spain, Finland, France, Italy, Japan, South Korea, Netherlands, Singapore, Slovak Republic, Sweden, United Kingdom, Slovenia, and Switzerland.

In Table (7b), I use aggregate robots per worker at the country level divided by total employment in the economy as a proxy for capital-technology price. I control for sector financial requirements in the trade partner country and in the US. I include trade partner-sector and trade partner-year fixed effects. Error terms are clustered at the trade partner-sector level.

For odd columns, the "Annual Growth 2016-04 (p90-p10) a " row reports the effect, of the average change in aggregate robots per worker in the US times the risk proxy between 2004 and 2016 ("RISK x Robots/workers" for the US), on US imports annual rate of growth of commodities produced in sectors with a large share of OaRA (5^{th} quintile), relative to commodities produced with few OaRA (1^{st} quintile). The "Annual Growth 2016-04 (p90-p10) b" row reports the effect, of the average change in robots per worker in the US trade partner times the risk proxy between 2004 and 2016 ("RISK x Robots/workers" for US trade Partner), on US imports annual rate of growth of commodities produced in sectors with a large share of OaRA (5^{th} quintile), relative to commodities produced with few OaRA (1^{st} quintile).

For even columns, the "Annual Growth 2016-04 (p90-p10) a" row reports the effect, of the average change in aggregate robots per worker in the US times the risk proxy between 2004 and 2016 ("RISK x Robots/workers" for the US), on US imports annual rate of growth of commodities produced in sectors with a large share of OaRA (5^{th} quintile) in countries with low robot penetration, relative to commodities produced with few OaRA (1^{st} quintile) in the same set of countries. The "Annual Growth 2016-04 (p90-p10) b" row reports the effect, of the average change in robots per worker in the US trade partner times the risk proxy between 2004 and 2016 ("RISK x Robots/workers" for US trade Partner), on US imports annual rate of growth of commodities produced in sectors with a large share of OaRA (5^{th} quintile) in countries with high robot penetration, relative to commodities produced with few OaRA (1^{st} quintile) in the same set of countries.

Column (1) uses the share of FO RISK Index interacted with aggregate robots per worker. Using OLS, I find that US imports of commodities produced in sectors characterized by a high share of OaRA fall by an annual rate of -2.6%, relative to sectors with a low share of OaRA, due to robot penetration in the US during 2004 and 2016. The average increase in robot penetration in US trade partner countries increases US imports in the same set of commodities, although the increase is small and it is not statistically significant. Column (2) shows that the fall in US imports of commodities produced in sectors with a large share of OaRA is explained mainly by imports coming from countries with a low capital-technology penetration (proxy by robots per worker). For this set of trade partners, US imports fall by 3.2% whereas for countries with high robot penetration this fall is only -0.7% and it is not statistically significant.

Columns (3) and (4) redo the previous two exercises using instrumental variables. The estimated fall in US imports is slightly higher in absolute value. The K-P rk Wald F statistic rejects the presence of weak instruments. Columns (5) and (6) use the Routine Task Index instead of FO RISK Index. Predicted falls in US imports are higher for commodities produced by sectors characterized by a high share of OaRAs. US commodities imports, produced in sectors with a high share of OaRA, from countries characterized by a low robot penetration fall by an annual rate of growth of 5.0%, for countries with high robot penetration this percentage is -.2.1%.

The last two columns use the FO RISK Total Effect (FO RISK Index x (1-ShL)). With this proxy, and controlling for ShL, coefficients fall in absolute value. The estimated impacts are around 2/3 the ones estimated using FO RISK Index.

In all models, the coefficient for external financial dependence interacted with the proxy for Credit Thighness from the FED has the expected positive sign and it is significant at standard levels. Access to credit increase US production and reduces imports. I do not find that US imports vary with the financial condition in trade partner countries.

In Table (7c), I present results using robots per worker at the sector level as a proxy for the capital-technology price in the US.[45] As in even columns in Table (7b), I present results for US imports coming from 25 countries with high robot penetration and from laggard countries. The second row presents the dependent variable and the third row the proxy for the risk of automation I use. The fourth and fifth rows present the variable I instrument in the econometric model (sector robots per worker and/or aggregate robots per worker in the US).

"Annual Growth 2016-04 (p90-p10) a" row reports US import annual rate of growth of commodities, coming from countries with low robot penetration, due to robot penetration in US sectors. "Annual Growth 2016-04 (p90-p10) b" row reports the same annual rate of growth but for countries with high robot penetration. "Annual Growth 2016-04 (p90-p10) c" row reports the effect, of the average change in robots per worker in the US times the risk proxy between 2004 and 2016 ("RISK x Robots/workers", aggregate or sectoral robot per worker in the US), on US imports annual rate of growth of commodities produced in sectors with a large share of OaRA (5^{th} quintile) in countries with low robot penetration, relative to commodities produced with few OaRA (1^{st} quintile) in the same group of countries. "Annual Growth 2016-04 (p90-p10) d" row reports the same previous rate of growth but for countries with high robot penetration (Countries with high Capital-Tech.).

Using IV, Column (1) reports the effect, of US sectoral robot penetration, on US imports coming from countries with low robot penetration and from trade partners with high robot penetration. In both cases, coefficients are negative although they are not statically significant. The model can not reject the null hypothesis of weak instruments. Column (2) redoes the previous model using OLS. Coefficients for robot penetration in the US continue to be not statistically significant.

[45] I am able to countruct robots per worker at the sectorl level for few countries, because of lack of employment at the sector level (STAN dataset).

In Column (3) I include the FO RISK Index multiplied by aggregate robot penetration in the US for imports from low robot penetration countries and for high penetration trade partners. I also control for robot penetration at the sectoral level in the US. Coefficients for previous variables have the expected sign although they are not statistically significant. The model suffers from weak instruments.

Column (4) redoes the previous model using IV only for aggregate robot penetration in the US. With this setup, the model does not report weaks instrument. The coefficient for the RISK variable interacted with aggregate robot penetration in the US is negative and highly significant for imports coming from countries with low robot penetration. Imports of commodities characterized by a high share of OaRA have a 4.3% lower annual rate of growth relative to commities produced in sector with a small share of OaRA. For import coming from countries with high robot penetration the same coefficient is smaller in absolute value, and it is not statistically significant. Column (5) redoes include sectoral robot penetration in the US for import coming for countries with low and high robot penetration. Results do not change.

Column (6) uses FO RISK Total Effect instead of FO RISK Index. Results hold, although the impact on US import of commodities characterized by a large share of OaRA falls, in absolute value, from an annual rate of growth of -4.3% to -3.4%. In column (7) I use the Routine Task Index as proxy for risk of automation. The previous coefficient increase, in absolute value, to -4.4%.

Finally, in Column (8) I include sectoral robots penetration and risk of automation interacted with sectoral robot penetration, for import coming from countries with low and high robots penetration. I use IV for the four previous variables. Al coefficient are not statistically significant, and the the

Results for US imports from different trade partners suggest that the fall in capital-technology price, proxy either by dummies or by robots penetration, substitute occupations prone to automation increasing US comparative advantage in a sector with a large share of workers with high probability to be automated or equivalently that were intensive in routine tasks.

Sectors that substitute more workers (routine tasks performed by humans) were sectors with lower initial wages, therefore automation in the US reduces the comparative advantage of low wages countries.

[Table 7b Here]

[Table 7c Here]

4. Conclusion

The last decades have brought remarkable technological changes. The new century brought new technological attainment, the so-called "digital age". The implications for jobs, occupations, and skills of this technological progress brought back old fears about the impact of technology on labor markets, and its effects are controversial.

The paper presents new and detailed evidence about the causal effect of automation on the US labor market at the sector and occupation level between 2002 and 2016, and its impact on US sectoral trade.

To establish the direction of the causal mechanism, the paper mixes three standard approaches. The paper follows Rajan and Zingales 1998, and it uses previous studies, Autor et al (2003) and Frey and Osborne (2017), that establish which tasks and occupations should be prone to automation. The paper uses as a proxy for automation robots per workers level in the US, instrumented by robots per workers in 5 EU countries, during 2004-2016. Finally, the paper controls for sector-year shocks. Chinese and Mexican import penetration, financial crises, among other events are controlled by sector-year dummies.

New capital technologies are affecting US labor markets at the economy and sector level and within sectors. In the latter case, I am able to provide a causal interpretation. I find that occupations with a higher risk of automation have been declining at an annual rate of -2.7% within sector (280). The fall in the wage bill is even larger, reassuring that occupation prone to automation suffer a demand shock during the period covered by this paper. Robots per worker are also related to a change in the composition of sectors in the economy.

New capital penetration implies a large labor replacement in sectors with initial low wages. At the same time, I observe a reduction in imports of commodities from these sectors. These results suggest that new capital penetration has allowed local firms to compete with foreign production in sectors with a large share of employment prone to automation (and with low wages) at the beginning of our period of analysis. Reassuring this interpretation, I find that imports of commodities produced by these sectors have been falling, in particular from countries with low penetration of automation technologies (proxy by robot per worker). These results suggest that comparative advantages have been changing due to automation. Sectors prone to automation have been increasing their comparative advantage in the USA vis-a-vis countries with low robot penetration.

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Appendix A

The main text describes FO (2017) methodology to estimate the risk of automation to 702 occupations defined at the 3- to 6- digit level of OES-2010 BLS definition (OES 2010).

To construct a measure of the share of employment at risk automation at the industry level, I expand the sample in 97 additional occupations using two assumptions. Firstly, for 50 occupations, defined at the 6-digit level, I use FO assigned risk of automation for occupations aggregated at 3- and 5- digit level. For example, FO computes the risk of automation for occupation OES2010 “25-1000” (aggregate at 3-digit level); I use the same automation risk for 38 sub-level occupations of OES2010 “25-1000”. I also use the same approximation for 12 sub-level occupations of OES2010 “29-1060” and “45-2090”. Secondly, for the remaining 47 occupations, I use the risk of automation of the contiguous SOC occupation with FO information. For example, for OES2010 “27-1029” I use the same risk of automation than OES2010 “27-1027”. Table 2 in the main text presents the summary statistics for the original FO variable and the extended sample I use in the paper.[46]

[46] Results are robust to restricting our occupation set to the initial FO 698 professions.

Table Aa presents the relationship/correlation between FO RISK Prob. and a set of variables: routine and non-routine tasks from Autor et al (2003), wages and occupation employment level in 2010, and the 12-year occupation employment growth.

Column (1) presents the OLS regression between FO´s risk of automation and routine and non-routine tasks. All routine tasks have the expected positive sign, although only the coefficient for routine cognitive tasks is significant at standard levels. All non-routine tasks have the expected negative coefficient, although only non-routine cognitive analytical and non-routine manual interpersonal are significant at standard levels of significance. The lack of statistical significance for some of the routine characteristics is not surprising because of the high correlation existing among them. These six categories of task explain 59% of the variance of *FO RISK probability*.[47] Column (2) presents the correlation between *FO RISK Probability* and our proxy for routine task $PROB_b$. The correlation is highly significant and it explains 54% of FO´s probability variance. Columns (3) and (4) present the simple correlation between FO probability index and the log mean wage and the log employment at the occupation level (in 2010), respectively. The probability of automation is highly correlated with occupation wage at the occupation level, but not with the total level of employment. Figures 1b and 1c in the main text present the occupations mean log wage and log employment for deciles of occupations according to the distribution of the risk of automation defined by FO (2017). In Column (3), one standard deviation increase in FO RISK probability is related with a 24% lower wage.

Columns (5) and (6) present the relationship between the average aggregate annual rate of employment and the wage bill growth for different occupations and the FO RISK Probability (2004-2016).[48] There is a negative relationship between employment growth and risk of automation. The estimated coefficient is

[47] There is no evidence of outliers, but occupation OES code 152091 for the coefficient of non-routine manual interpersonal task. In a non-reported model, we exclude this occupation. All results remain.
[48] We use 2004-2016 because for our main results, at occupation-sector instrumented with robots per workers, we only have data for this period.

-0.28 significant at the 1% level. Column (6) presents a steeper decline in wages-bill than in employment of occupations subject to a higher risk of automation during the same period. In column (7), I redo column (5) using PROBb instead of FO RISK Probability. The PROBb coefficient is negative and highly significant, although it has slightly lower predictive power than FO index.

[Table Aa Here]

Finally, column (8) regresses wage bill growth on all 6 routine and non-routine tasks' indexes and *FO RISK Probability*. Tasks´ indexes, which are statically significant, have the expected sign, but more importantly, the *FO RISK Probability* is significant at standard level, even after controlling for all 6 tasks indexes. This last result shows that beyond routine and non-routine tasks, FO probability has additional predictive power.

A non reported table studies the relationship between log wage and risk of automation using "The American Community Survey (ACS)" (in 2010). This household survey has information for wage incomes, education, occupations, and age, so I can study the differential impacts of automation on workers. I use this dataset with caution because, contrary to the OES dataset, which collects information from business establishments, the ACS is a household survey. The Census Bureau develops estimates of occupational employment with its household-based Current Population (CPS) and ACS, but "it is concerned about the size and dispersion of employment in an occupation in determining if it can collect and report data on that occupation." In addition, the Census Bureau claims that "Household survey respondents tend to give general or informal, rather than specific or technical, occupational titles", It has concerns whether ACS respondents are "likely to report the job titles and job activities associated with an occupation accurately and completely."[49]

[49] See https://www.bls.gov/soc/soc_2010_faqs_and_acknowledgements.pdf.

With the ACS data, I estimate a standard Mincer equation. I find a negative coefficient for FO RISK Index. Wages for OaRA are 27% lower. There is a monotonic negative relationship between education level and occupation risk of automation.

Appendix B

This appendix studies the evolution of employment and wages for 795 occupations at the national level for the period between 2000 and 2016.[50] It assumes there is a unique production function at the aggregate level (not σ), the elasticity of substitution across occupation-services is one ($\alpha=1$) and all capital-technology share at the occupation-service level are the same $\left(ShK_{oj} = 1 - ShL_{oj} = cte\right)$. I assume there is a linear relationship between the risk of automation and the elasticity of substitution between capital and labor $\left(\rho_o = r + \beta^R \; RISK_o\right)$. With these restricted assumptions I estimate [Eq:5] in the main text.

Due to the panel structure of the data, I include occupation (initial conditions) and year dummy variables (aggregate shocks). Columns (1) to (3), in Table (Ba), and Figure (2a) (in the main text) present the evolution of log wage-bill, log employment and log wage without control for initial occupation wages, respectively. I use FO RISK Index as a proxy of risk of automation. This is a binary variable which is equal to one if the FO RISK Probability of automation is equal or higher than 70% for the specific occupation ($RISK_O$). In columns (1) and (2), and Figure (2a), I observe a monotone decline in the relative wage-bill and employment in an occupation at risk of automation. Relative wage bill and employment in these occupations grow at an average annual relative rate of -3.3% and -2.7%, respectively. Results suggest a large and permanent negative shock. Figure (2a) shows a rapid decline pre-2008, a sharp fall in the 2008-2009 financial crises, and a moderate posterior decline.

Column (3) and Figure (2c) present the evolution of relative wage of occupations at risk of automation.

[50] Information of occupations at the national level, using SOC classification, starts in 2000.

During the whole period (16 years), relative wages of occupations at risk of automation fall 5% (on average -0,3% per year).

Column (4) to (6) and Figure (2b) redo the previous exercises controlling for initial occupation wages interacted with year dummies. Not surprising, in this new set of results, wage coefficients move around 0 and their simple variance falls, although they still present a similar pattern than coefficients in Column (3) over time. Wage Bill and employment still present a sharp fall over time, although the log change magnitudes go from -0.41 to -0.31 for wage bill, and from -0.36 to -0.30 for employment.

For robustness check, column (7) redoes column (2) using the *Routine Task Index* instead of *FO RISK Index*. Coefficients present a similar pattern and magnitudes are similar. Between 2000 and 2016, occupations in the percentile 90th of the *Routine Tasks Index* grow 45% less than occupations in the percentile 10th. The same percentage for occupation in percentile 75th and 25th is 24%. For additional robustness checks, I restrict the sample of occupations to those with FO probabilities of automation at the 4-digit level of disaggregation (698 occupations), I use the continuous probability of automation as the independent variable (*FO RISK Probability*), I use a discrete version of the routine index (five quantiles) ; and I estimate the model using employment growth as the dependent variable and I include the initial log level, instrumented with the second lag, as control. I obtain similar results.[51]

The evolution of the relative mean wage across occupation may hide an asymmetric evolution of wages within occupations. If automation replaces routine cognitive tasks that are mainly provided by skilled workers in the upper end of the wage distribution, I should also expect that the average wage in these occupations should fall over time relative to the other occupations.[52] On the contrary, if automation replaces routine tasks of low skilled workers which are at the lower end of the wage distribution, I may

[51] These results are not reported in the paper.
[52] Although we refer to workers with the same occupation, we assume that displaced workers are not perfect substitute for workers which tasks were complemented by new technologies.

have an increase in the average wage in these risky occupations.

The last column in Table Ba and Figure (2d) report the log-ratio between wages at the 90th and the 10th quantile for occupations at risk of automation relative to the same ratio for the rest of the economy. Wage dispersion within occupation at risk falls 3.8% during the whole period. It remains relatively constant until 2005, and then it starts to fall. Figures Ba and Bb show that at the beginning of the period wages fall at the bottom and at the top of the distributions. After 2006, wages at the bottom starts to recover and by the end of the sample, they get their initial level. Wages at the top continue to fall until 2011 and remain at this level until the end of the period. By the end of the period, the lower rate of wage growth at the top explains the compression in wages in occupation at risk of automation.

[Table Ba Here]

These results show that automation within occupations at risk does not explain the observed increase in wage dispersion in OES data reported in Table 1 in the main text. Wage dispersion across occupations increases because wages in occupation at risk of automation, which are on average low, fall until 2011 and then they remain almost constant.

[Figure B Here]

In previous results, I interact our proxy for occupation at risk of automation (RISKo) with year dummies to account for changes in the price of new capital/technologies. As I already mentioned, this is a strong assumption that requires that other factors that affect the demand of occupations are orthogonal to the vector of occupation risks. In Table 3b I use the log robot per workers in the US instead of year dummies to proxy for capital-technology prices.[53] Following Acemougly and Restrepo (2018), I instrument our proxy using the average log value of robots per workers in EU countries to avoid a reverse causality.[54]

[53] Robots at the country level are available since 1993 in the IFR dataset. Information at the sector level starts in 2004.
[54] An in-creasing demand for labor may induce firms to buy labor-replacing capital.

This approach requires that any other factor that affects the demand of occupations have either a different trend than robot per workers in our period, or its impact across occupations is orthogonal to the vector of occupation risks. This is still a strong assumption. This approach becomes convincing, once I use occupation-sector-year data and robot penetration at the sector level (next subsection).

Table Bb presents our results using robot per worker. In all regressions, but the last one, I control for year and occupation fixed effect. Columns (1) to (3) present the results of the level of (log) wage bill, employment and wage without any additional control, respectively. The estimated coefficient for wage bill implies that occupations at risk of automation have a lower annual relative rate of growth of -3.6% with respect to the rest of the economy during 2002-2016. For employment and wages, this relative rate of growth is -3.0 and -0.3%, respectively. Column (4) to (6) present the same set of results controlling for initial occupations wages (ln) interacted with robots per workers (also I instrumented with robots in EU15). As in the case I use dummies as a proxy for capital-technology prices, estimated coefficients for risk of automation falls when I control for initial wages. Column (7) presents our results for the wage bill (column 4) using Routine Task Index instead of FO RISK Probability as a proxy for risk of automation. Occupations in the percentile 90^{th} in the routine index decrease -1.9% more than occupations in the percentile 10^{th}. For employment, this percentage is -1.7%. Finally, column (8) present a growth model for the wage bill between 2001 and 2016.[55] The estimated annual rate of growth difference between occupations at risk and riskless is -3.1%.

Summing up, aggregate results are in line with the displacement effect of automation. Employment and wages fall in occupations at risk due to an increase in the use of labor replacing capital-technologies. The largest effect is for the employment level, which falls during the whole period. For wages, the negative effect is concentrated in the first half of our sample. Wages at the bottom of the distribution fall in the first

[55] We use the year 2000 to instrument the dependent variable in 2001.

half of the sample and them they almost recover. For wages in the top, the effect remains until the end of our sample (2016).

[Table Ba Here]

We find that wage dispersion decreases within occupation at risk of automation relative to other occupations. There are three alternative explanations for the heterogeneous evolution of wages at different quantiles of the wage distribution. First, following Autor (2013) new technologies automate “more complex” tasks in which high skill workers, with higher wages, are more productive than low skill workers. Demand for high skill workers falls and therefore wages in the top of the distributions fall too. Second, new technologies require new skills, knowledge and/or expertise of workers. If adaptability to these new requirements is easier for younger workers, there is a new incentive for firms to replace older workers which, due to experience, have higher wages. This change in composition implies a reduction in wages at the top of the wage distribution. Third, a sector with higher wages in occupations at risk of automation reduces their relative importance during the period of analysis.

Appendix C

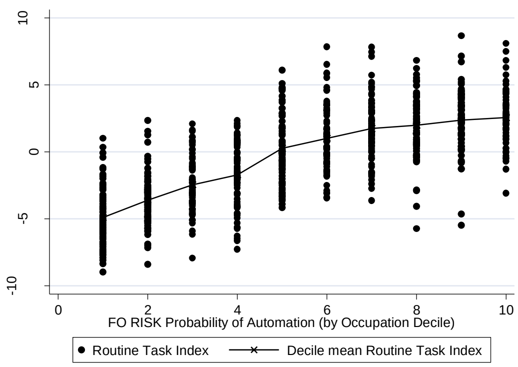
This Appendix studies wage bills, employment and wages at the sector level using year dummies as proxy for the price of capital-technologies.

[Table Ca Here]

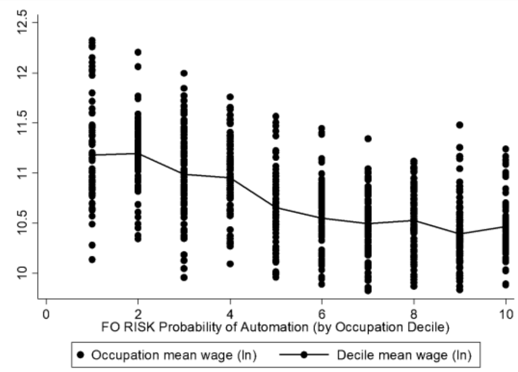
Figures and Tables

Figure 1: Routine Task Index, Wages, and Employment and *FO RISK Prob.* of automation

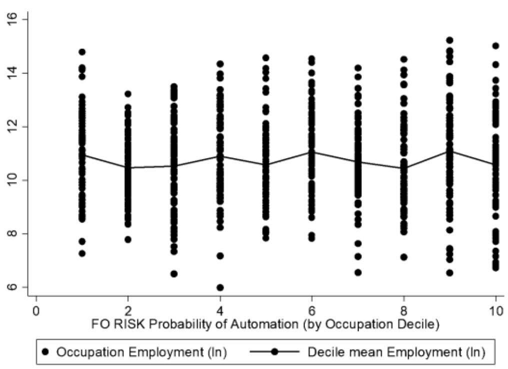
1a: FO RISK Prob. and Routine Task Index
754 Occupations in 2010



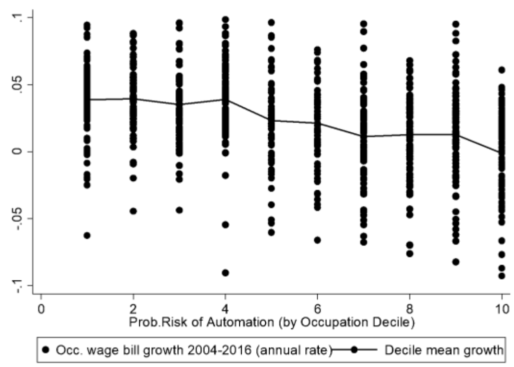
1b: FO RISK Probability and wages (log)
795 Occupations in 2010



1c: FO RISK Probability and Emp. (log)
795 Occupations in 2010



1d: FO RISK Probability and average annual growth rate of Emp. (2004-2016)

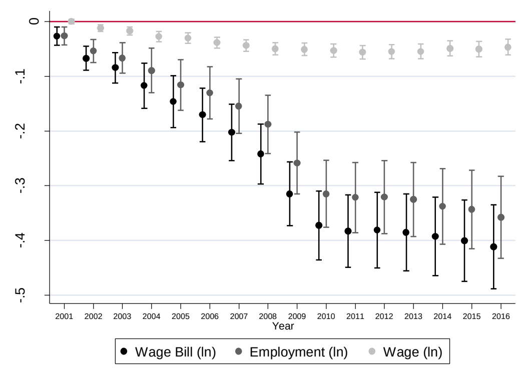


Notes: I split the 795 occupations, defined at 6 digits SOC 2010, into deciles by FO RISK Index of automation. Figure (1a) shows the relationship between FO RISK Index and the Routine Task Index for 754 occupations. Figure (1b) and (1c) show the 795 log average wages and log employment in 2010. Figure (1d) presents the log change of employment divided by 12 for the period 2004-2016.

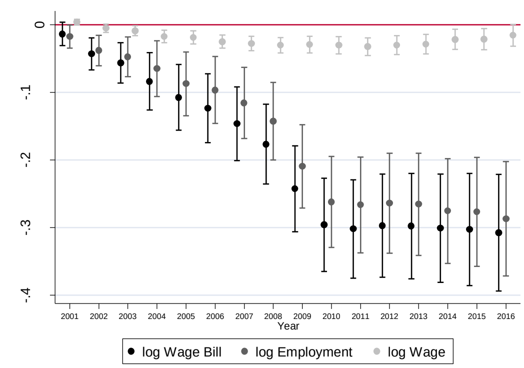
Source: Author's calculations.

Figure 2: Wage Bill, Employment, Wages (ln) and *FO RISK Index*
Aggregate Data (Period 2000-2016)

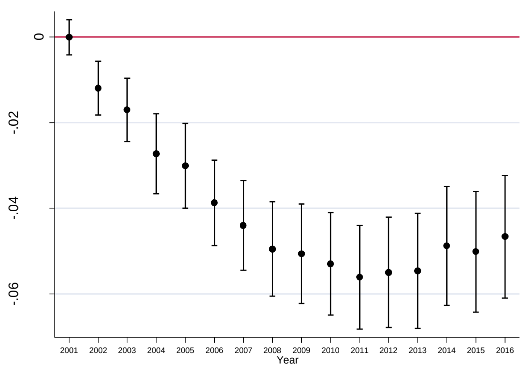
2a: All variables w/o control



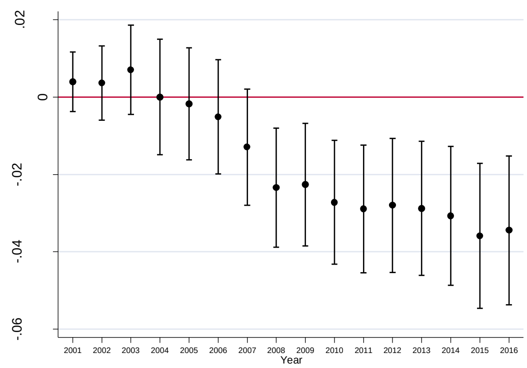
2b: All variables controlling for initial wage



2c: Average Wage w/o control



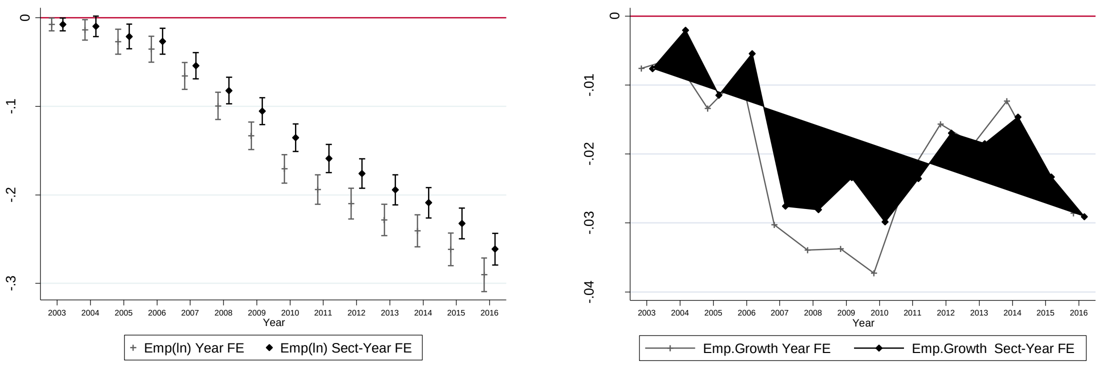
2d: Wage Dispersion (Q90/Q10) w/o control



Source: Author´s construction. Appendix B, Table Ba.

Figure 3: Employment (ln), and *FO RISK Index*
Sector-Occupation (Period 2002-2016)

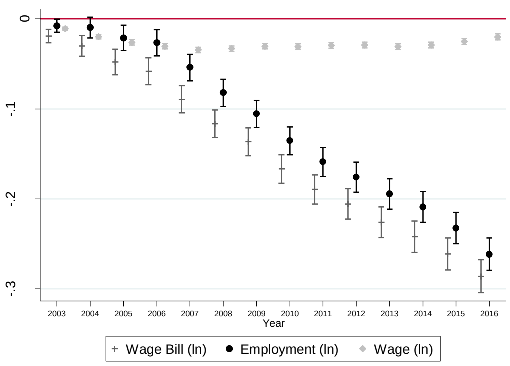
3a: Employment (ln) 3b: Employment Change (ln)



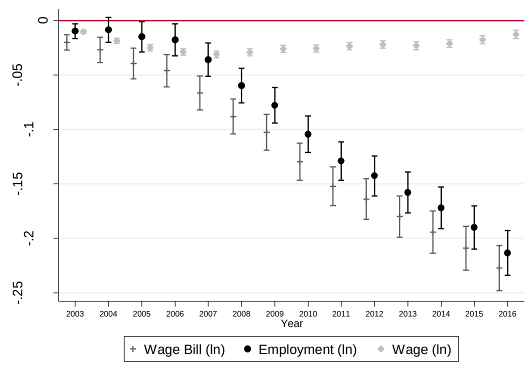
Source: Author´s construction. Table (3a), Columns (1) and (3).

Figure 4: Sector-Occupation Wage Bill and Employment, and Risk of Automation Sector-Occupation (Period 2002-2016)

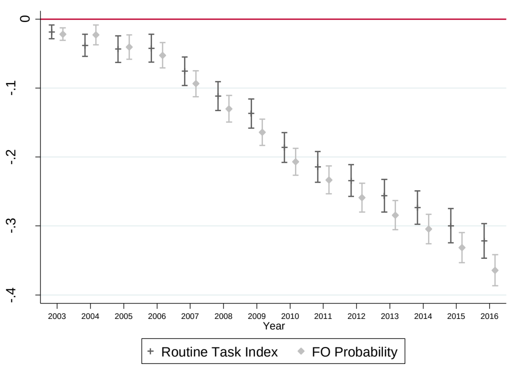
4a: Results using FO RISK index w/o control



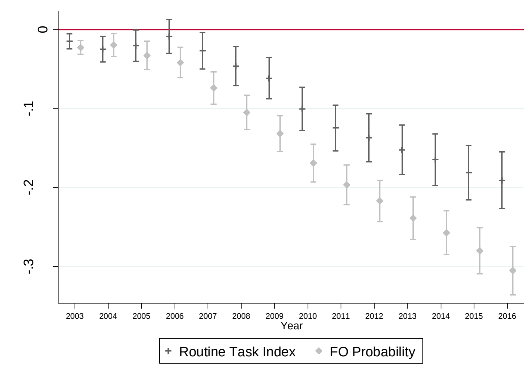
4b: Results using FO RISK index controlling for initial wage



4c: Wage-Bill using different risk proxies w/o control



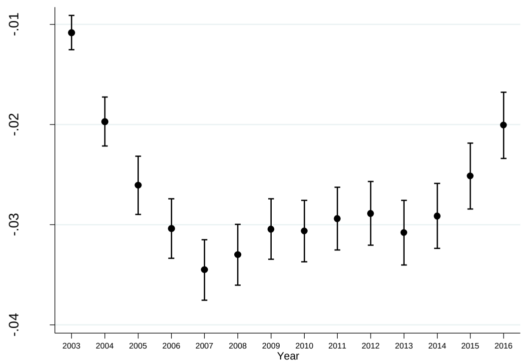
4d Wage-Bill using different risk proxies controlling for initial wage



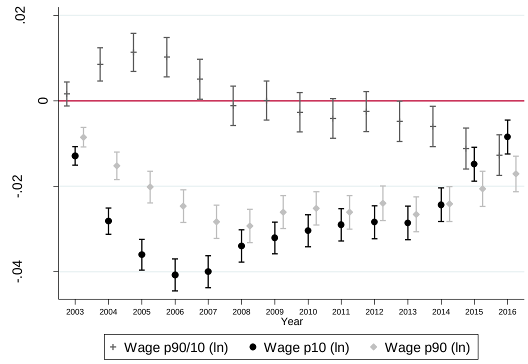
Note: Figures (4a) and (4b) report the evolution of Wage Bills (ln), Employment (ln) and Wages (ln), controlling and not for initial wages interacted with aggregate wages (ln), respectively. Figures 4c and 4d report results using Routine Tasks Index, Quantile of Routine Tasks Index and FO RISK Prob. as a proxy for automation risk.
Source: Author´s estimation. Table (3a).

Figure 5: Occupation-Wage and Risk of Automation
Sector-Occupation (Period 2002-2016)

5a: Average Wage (ln)



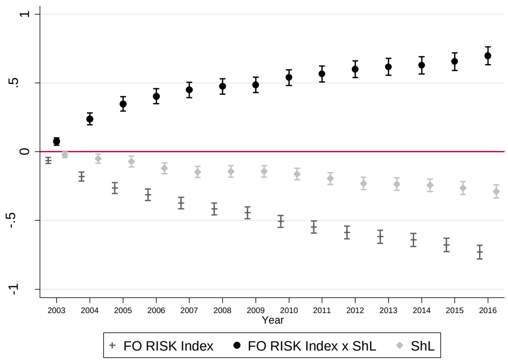
5b: Wage Dispersion (Q90/Q10) (ln)



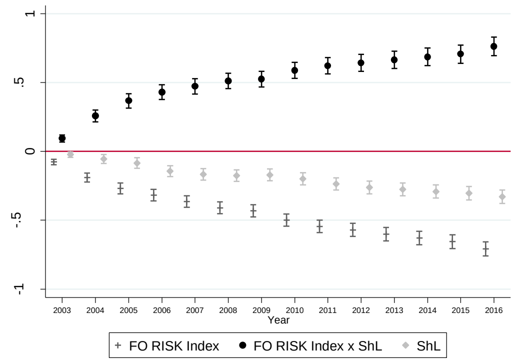
Source: Author´s estimation. Table (3a) and unreported regressions

Figure 6: Wage Bill, Employment, and Risk of Automation and Occupation-Service Labor Share Sector-Occupation (Period 2002-2016)

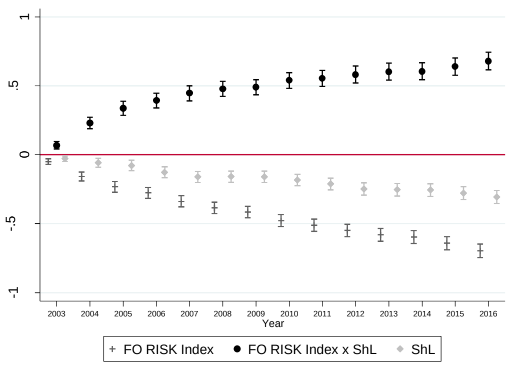
6a: Wage-Bill, FO RISK, and O-S L.Share w/o Control



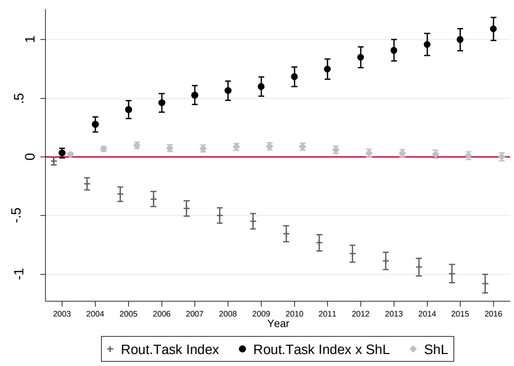
6b: Wage-Bill, FO RISK, and O-S L.Share Controlling for initial wage



6c: Emp., FO RISK and O-S L.Share w/o control



6d: Wage-Bill, Rout.Index and O-S L.Share w/o control

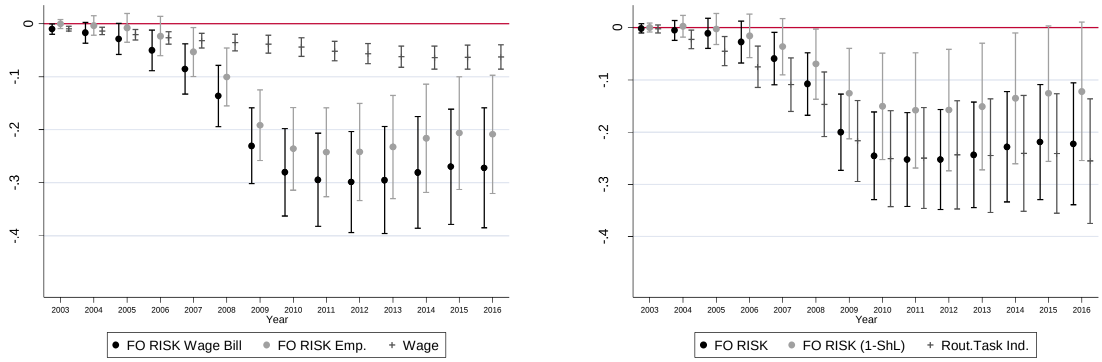


Source: Author´s construction. Table (3b)

Figure 7: Sector Wage Bill, Employment and Wages, and Risk of Automation
Sector Data 3-4 dig NAICS (Period 2002-2016)

7a: Results using FO RISK index
Without controlling for initial wage

7b: Results for Employment
Controlling for initial wage



Note: The share of employment at risk is normalized for each proxy is normalized to have the difference between the percentile 90th and 10th equals to one.

Source: Author's construction. Table (Ca)

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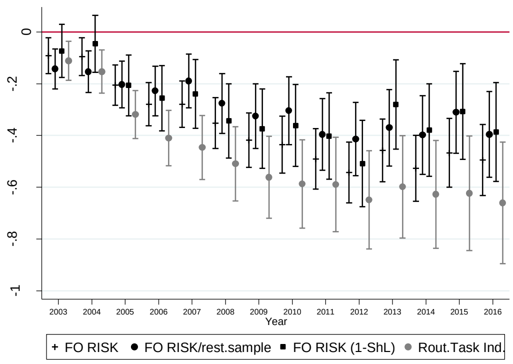
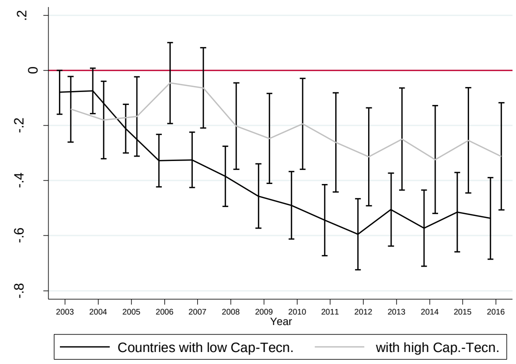
Figure 8: US Imports and Risk of Automation

Sector-Country of Origin (Period 2002-2016)

9a: Imports (ln) and Risk Indexes
Controlling for Initial wage



9b: Imports (ln) and Mean FO RISK Index
Trade Partners with diff. Robots Penetration



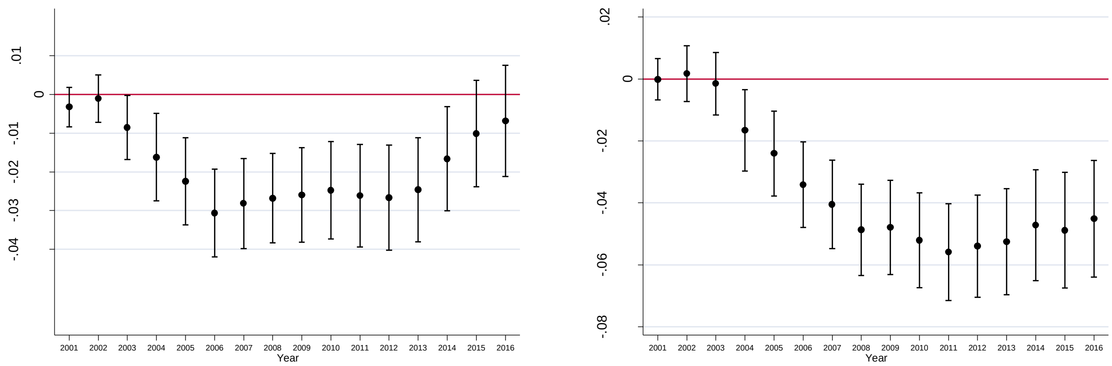
Source: Author´s calculation. Table (9a)

Figure B: Occupation-Wages and Risk of Automation

Aggregate Data (Period 2000-2016)

Ba: Wage Percentile 10th

Bb: Wage Percentile 90th



Source Author´s estimation. The econometric model not reported.

Table 1: Summary Statistics

Panel 1a: Probability and Risk of Automation at the occupation level.

Occupations	Obsv.	Mean	Std.Dev.	Min.	Max
FO RISK probability	698	0.54	0.37	0.00	0.99
FO RISK probability extended	795	0.51	0.38	0.00	0.99
FO RISK Index	795	0.42	0.49	0.00	1.00
PROBb or *Routine Task Index*	754	-0.30	3.41	-8.97	8.68

Panel 1b: Employment and Wage for occupation at the Aggregate Level

	Employment	Employment (a)		Wages: Individual level [2002$]				Within occup.	Betwen occup.
YEAR	Total	Not at Risk	At Risk	Avg.Total	Avg.at Risk	pc75/pc25	pc90/pc10	pc90/pc10	Std.dev.(ln)
2002	127,523,760	57,413,040	62,206,590	49,442	30,548	2.33	4.49	2.67	0.44
2003	127,567,910	57,521,220	62,670,690	49,364	30,328	2.33	4.54	2.66	0.44
2004	128,127,360	63,487,230	64,640,150	49,888	30,313	2.33	4.60	2.67	0.46
2005	130,307,840	64,451,920	65,814,943	49,581	30,120	2.35	4.64	2.66	0.46
2006	132,604,980	65,773,740	66,788,867	49,839	29,991	2.36	4.71	2.67	0.46
2007	134,354,250	67,190,890	67,163,380	50,283	30,057	2.37	4.73	2.65	0.46
2008	135,185,230	68,468,210	66,717,190	50,282	29,775	2.39	4.74	2.66	0.46
2009	130,647,610	67,575,360	63,072,300	51,697	30,523	2.41	4.74	2.64	0.47
2010	127,097,160	67,186,340	60,621,050	51,967	30,574	2.45	4.70	2.65	0.47
2011	128,278,550	68,062,590	61,043,960	51,342	30,114	2.48	4.74	2.66	0.47
2012	130,287,700	68,266,810	62,020,970	50,798	29,858	2.50	4.80	2.67	0.47
2013	132,588,810	69,386,340	63,202,560	50,734	29,870	2.51	4.86	2.70	0.48
2014	135,128,260	70,787,130	64,341,010	50,713	30,066	2.52	4.91	2.71	0.47
2015	137,896,660	72,410,910	65,485,780	51,911	30,684	2.51	4.88	2.73	0.47
2016	140,400,040	74,081,890	66,318,060	52,509	31,102	2.49	4.90	2.74	0.47
Annual gr.									
2002/16	0.7%	1.8%	0.5%	0.4%	0.1%	6.8%	9.1%	2.7%	8.0%
2002/08	1.0%	3.0%	1.2%	0.3%	-0.4%				
2008/10	-3.0%	-0.9%	-4.7%	1.7%	1.3%				
2010/16	1.7%	1.6%	1.5%	0.2%	0.3%				

Panel 1c: Employment, wage, and Risk of automation. Occupation-Sector (2002-16)

Sector: 3-4-dig NAICS [1]	Obsv.	Mean	Std.Dev.	Min.	Max
Employment (ln)	3,690	12.22	1.24	8.52	16.15
Wage (ln)	3,690	10.63	0.31	9.77	11.64
FO RISK Probability (2016)	*264*	0.64	0.14	0.19	0.86
FO RISK Index (2016)	*264*	0.56	0.18	0.08	0.89

Sector-Occupation 6-dig SOC [2]	Obsv.	Mean	Std.Dev.	Min.	Max
Employment (ln)	532,524	6.04	1.73	3.40	14.83
Wage (ln)	526,873	10.69	0.49	9.41	12.55
FO RISK Probability	*532,524*	0.53	0.38	0.00	0.99
FO RISK Index	*532,524*	0.44	0.50	0.00	1.00

Note: In Panel 1a) FO RISK probability represents Frey and Osborne (2017) estimated probability of automation for occupations that I am able to merge with OES data. FO RISK probability extended represents the probability used in the paper (Frey and Osborne probabilities plus 97 proxies - see main text). FO Risk Index is a dummy variable equals to one if the FO RISK probability is equal or higher than 0.7. PROBb is the sum of Autor et al (2003) routine tasks´ indexes minus the sum of the non-routine task indexes.

In Panel 1b) Total represents total employment covered by the OES permanent statistics. It includes Federal, State, and Local Government. Within occup. pc90/pc10 is the average across occupations of the ratio of wage percentile 90th and 10th. Between occup. Std.dev (ln wage) is the standard deviation of the log mean wage at the occupation level.

In Panel 1c), 1: data only includes sector that has information for External Financial Dependence (265). FO RISK Prob. and FO RISK Index are the average of automation proxy weighted by employment in each occupation. 2: variables include all sectors for which I have data (285). For sectoral and sector-occupation exercises, I do not use the years 2000 and 2001 because of they use SIC industry classification.

Source: OES BLS, Autor et al (2003) and Frey and Osborne (2017).

Table 2: Pairwise Correlation between Labor Share at the Occupation Service Level Estimated in different periods

Period		(2002-2003)	(2003-2004)	(2004-2005)
(2002-2003)	Proxy ShL	1.00		
	Obs.	696		
(2003-2004)	Proxy ShL	0.96	1.00	
	Obs.	696	794	
(2004-2005)	Proxy ShL	0.92	0.96	1.00
	Obs.	688	786	787

Note: The row Proxy ShL presents the pairwise correlation of ShL estimated using two different periods. The row Obs. presents the number of observations used to estimate the pairwise correlation.
Source Author´s estimation.

Table 3a: Sector-Occupation Employment and Risk of Automation
Sector 3-4dig NAICS and Occupation 6dig SOC (Period 2002-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Depended Var.	Emp (ln)	Wage Bill (ln)	Emp.(ln)	Wage (ln)	Wage Q90/Q10(ln)	Wage Bill (ln)	Emp.	Wage Bill (ln)	Wage Bill (ln)	Emp. (ln)
Independed Var.	*FO RISK Ind.*	*FO RISK Ind.*	*FO RISK Ind.*	*FO RISK Ind.*	*FO RISK Ind.*	*FO RISK Ind.*	*FO RISK Ind.*	*Rout.Task*	*Rout.Task*	*Rout.Task*
Ind. Var. X 2003	-0.008	-0.019	-0.008	-0.011	0.002	-0.020	-0.010	-0.018	-0.015	0.008
	(0.004)*	(0.004)**	(0.004)*	(0.001)**	(0.001)	(0.004)**	(0.004)**	(0.005)**	(0.005)**	(0.005)
Ind. Var. X 2004	-0.014	-0.030	-0.010	-0.020	0.009	-0.027	-0.008	-0.038	-0.025	0.010
	(0.006)*	(0.006)**	(0.006)	(0.001)**	(0.002)**	(0.006)**	(0.006)	(0.008)**	(0.008)**	(0.008)
Ind. Var. X 2005	-0.027	-0.048	-0.021	-0.026	0.011	-0.039	-0.015	-0.043	-0.020	0.025
	(0.007)**	(0.007)**	(0.007)**	(0.001)**	(0.002)**	(0.007)**	(0.007)*	(0.010)**	(0.010)*	(0.010)*
Ind. Var. X 2006	-0.035	-0.058	-0.027	-0.030	0.010	-0.046	-0.017	-0.042	-0.009	0.048
	(0.007)**	(0.008)**	(0.007)**	(0.002)**	(0.002)**	(0.008)**	(0.008)*	(0.010)**	(0.011)	(0.011)**
Ind. Var. X 2007	-0.066	-0.089	-0.054	-0.035	0.005	-0.066	-0.036	-0.075	-0.027	0.038
	(0.008)**	(0.008)**	(0.008)**	(0.002)**	(0.002)*	(0.008)**	(0.008)**	(0.011)**	(0.012)*	(0.012)**
Ind. Var. X 2008	-0.100	-0.116	-0.082	-0.033	-0.001	-0.088	-0.060	-0.111	-0.046	0.020
	(0.008)**	(0.008)**	(0.008)**	(0.002)**	(0.002)	(0.008)**	(0.008)**	(0.011)**	(0.013)**	(0.013)
Ind. Var. X 2009	-0.133	-0.136	-0.106	-0.030	0.000	-0.103	-0.078	-0.137	-0.061	-0.002
	(0.008)**	(0.008)**	(0.008)**	(0.002)**	(0.002)	(0.008)**	(0.008)**	(0.011)**	(0.013)**	(0.013)
Ind. Var. X 2010	-0.171	-0.167	-0.135	-0.031	-0.003	-0.130	-0.104	-0.186	-0.100	-0.035
	(0.008)**	(0.008)**	(0.008)**	(0.002)**	(0.002)	(0.009)**	(0.009)**	(0.011)**	(0.014)**	(0.014)*
Ind. Var. X 2011	-0.194	-0.189	-0.159	-0.029	-0.004	-0.152	-0.129	-0.214	-0.125	-0.060
	(0.008)**	(0.008)**	(0.008)**	(0.002)**	(0.002)	(0.009)**	(0.009)**	(0.011)**	(0.015)**	(0.015)**
Ind. Var. X 2012	-0.210	-0.206	-0.176	-0.029	-0.002	-0.164	-0.143	-0.234	-0.137	-0.072
	(0.009)**	(0.009)**	(0.009)**	(0.002)**	(0.002)	(0.010)**	(0.009)**	(0.012)**	(0.015)**	(0.015)**
Ind. Var. X 2013	-0.228	-0.226	-0.194	-0.031	-0.005	-0.180	-0.158	-0.256	-0.152	-0.084
	(0.009)**	(0.009)**	(0.009)**	(0.002)**	(0.002)*	(0.010)**	(0.010)**	(0.012)**	(0.016)**	(0.016)**
Ind. Var. X 2014	-0.241	-0.242	-0.209	-0.029	-0.006	-0.194	-0.172	-0.273	-0.165	-0.097
	(0.009)**	(0.009)**	(0.009)**	(0.002)**	(0.002)*	(0.010)**	(0.010)**	(0.012)**	(0.017)**	(0.017)**
Ind. Var. X 2015	-0.262	-0.261	-0.232	-0.025	-0.011	-0.209	-0.190	-0.300	-0.181	-0.115
	(0.009)**	(0.009)**	(0.009)**	(0.002)**	(0.002)**	(0.010)**	(0.010)**	(0.013)**	(0.018)**	(0.017)**
Ind. Var. X 2016	-0.290	-0.286	-0.261	-0.020	-0.013	-0.227	-0.213	-0.322	-0.191	-0.129
	(0.010)**	(0.009)**	(0.009)**	(0.002)**	(0.002)**	(0.011)**	(0.011)**	(0.013)**	(0.018)**	(0.018)**
Fixed effects	Sect-Occ & Year	Sect-Occ & Sect-Year			Sect-Occ & Sect-Year			Sect-Occ & Sect-Year		
Occ.Init.Wage (ln) x Ag.Wage (ln)	No	No	No	No	No	Yes	Yes	No	Yes	Yes
Annual Growth 2016-04 (p90-p10)	-2.27%	-2.11%	-2.07%	0.00%	-0.18%	-1.65%	-1.69%	-2.34%	-1.37%	-1.15%
OBS	528,304	522,616	528,304	522,616	496,577	482737	486374	505,796	469,495	473,021
Max.Likelihood	-269415	-250761	-246217	567010	318608	-226026	-220999	-240,150	-217,968	-213,288

Standard errors allow for within sector-occupation correlation * $p<0.05$; ** $p<0.01$

Note: The second row describes the dependent variable and the third row describes the proxy I use for the risk of automation. RISK>0.7 is a dummy variable equals to one if the FO RISK Prob. is higher than 0.7. Regressions (4) to (6) controls for initial (log) sector-occupation wage interacted with a year dummy. Regressions (8) and (9) use the *Routine Task Index* which follows Autor et al (2003) approach. The row "Mag.Eff.2016-04 Risk (p90-p10)" presents the estimated annual rate of growth difference between occupations in the percentile 90th and 10th of the risk proxy between 2004 and 2016. When I use FO RISK Index, I use occupations with index equals to 1 and 0, respectively (for Column (1): $(Exp(-0.290-0.14)^{1/12} -1)$. Wage Q90/Q10 (ln) refers to the log ratio of the wage at the 9th decile divided by the 1st decile.

Table 3b: Wage Bill, Employment, Risk of Automation and Occ.-Service Labor Share
Sector 3-4dig NAICS and Occupation 6dig SOC (Period 2002-2016)

	(1)			(2)			(3)			(4)	(5)	(6)	(7)
Depended Var.	Wage Bill (ln)			Wage Bill (ln)			Wage Bill (ln)			Wage Bill (ln)	Wage Bill (ln)	Wage Bill (ln)	Wage Bill (ln)
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)				
Independed Var.	*FO RISK*	*FO RISK x ShL*	*ShL*	*FO RISK*	*FO RISK x ShL*	*ShL*	*Rout.Task*	*Rout.Task x ShL*	*ShL*	*FO RISK*	*RISK T.Effet*	*Rout.Task*	*Rout.Task T.Effet*
Ind. Var. X 2003	-0.063	0.075	-0.022	-0.077	0.094	-0.023	-0.035	0.034	0.022	-0.017	-0.064	-0.014	-0.049
	(0.011)**	(0.014)**	(0.011)*	(0.010)**	(0.013)**	(0.010)*	(0.017)*	(0.021)	(0.007)**	(0.004)**	(0.009)**	(0.005)**	(0.015)**
Ind. Var. X 2004	-0.18	0.239	-0.05	-0.19	0.259	-0.054	-0.229	0.277	0.068	-0.017	-0.139	-0.022	-0.191
	(0.017)**	(0.022)**	(0.017)**	(0.017)**	(0.022)**	(0.017)**	(0.027)**	(0.033)**	(0.011)**	(0.006)**	(0.015)**	(0.008)**	(0.025)**
Ind. Var. X 2005	-0.265	0.348	-0.071	-0.268	0.368	-0.084	-0.317	0.403	0.098	-0.028	-0.195	-0.024	-0.232
	(0.020)**	(0.027)**	(0.020)**	(0.020)**	(0.027)**	(0.020)**	(0.032)**	(0.039)**	(0.014)**	(0.007)**	(0.018)**	(0.010)*	(0.029)**
Ind. Var. X 2006	-0.313	0.404	-0.12	-0.317	0.431	-0.143	-0.359	0.461	0.074	-0.037	-0.233	-0.025	-0.253
	(0.021)**	(0.028)**	(0.020)**	(0.021)**	(0.028)**	(0.021)**	(0.033)**	(0.040)**	(0.014)**	(0.008)**	(0.019)**	(0.010)*	(0.031)**
Ind. Var. X 2007	-0.373	0.45	-0.147	-0.364	0.473	-0.167	-0.438	0.527	0.071	-0.058	-0.283	-0.058	-0.319
	(0.021)**	(0.028)**	(0.021)**	(0.022)**	(0.028)**	(0.021)**	(0.033)**	(0.041)**	(0.015)**	(0.008)**	(0.020)**	(0.011)**	(0.031)**
Ind. Var. X 2008	-0.416	0.476	-0.144	-0.409	0.513	-0.176	-0.499	0.564	0.086	-0.079	-0.334	-0.092	-0.373
	(0.022)**	(0.029)**	(0.021)**	(0.022)**	(0.029)**	(0.022)**	(0.034)**	(0.042)**	(0.015)**	(0.008)**	(0.020)**	(0.011)**	(0.032)**
Ind. Var. X 2009	-0.443	0.488	-0.144	-0.431	0.526	-0.17	-0.548	0.599	0.091	-0.093	-0.362	-0.117	-0.419
	(0.022)**	(0.029)**	(0.021)**	(0.022)**	(0.029)**	(0.022)**	(0.034)**	(0.042)**	(0.015)**	(0.008)**	(0.020)**	(0.011)**	(0.033)**
Ind. Var. X 2010	-0.507	0.54	-0.161	-0.499	0.59	-0.199	-0.655	0.683	0.086	-0.119	-0.433	-0.166	-0.538
	(0.022)**	(0.029)**	(0.022)**	(0.023)**	(0.030)**	(0.022)**	(0.035)**	(0.043)**	(0.015)**	(0.009)**	(0.021)**	(0.011)**	(0.033)**
Ind. Var. X 2011	-0.548	0.566	-0.195	-0.544	0.623	-0.236	-0.731	0.747	0.060	-0.144	-0.487	-0.197	-0.621
	(0.023)**	(0.030)**	(0.022)**	(0.023)**	(0.031)**	(0.023)**	(0.035)**	(0.044)**	(0.016)**	(0.009)**	(0.021)**	(0.012)**	(0.034)**
Ind. Var. X 2012	-0.587	0.601	-0.23	-0.570	0.644	-0.262	-0.823	0.848	0.032	-0.157	-0.517	-0.219	-0.690
	(0.024)**	(0.031)**	(0.023)**	(0.024)**	(0.032)**	(0.024)**	(0.037)**	(0.045)**	(0.016)	(0.010)**	(0.022)**	(0.012)**	(0.036)**
Ind. Var. X 2013	-0.618	0.618	-0.235	-0.601	0.666	-0.275	-0.887	0.908	0.030	-0.173	-0.554	-0.241	-0.748
	(0.024)**	(0.032)**	(0.023)**	(0.025)**	(0.032)**	(0.024)**	(0.037)**	(0.046)**	(0.017)	(0.010)**	(0.023)**	(0.012)**	(0.037)**
Ind. Var. X 2014	-0.641	0.628	-0.244	-0.629	0.688	-0.291	-0.938	0.958	0.023	-0.188	-0.586	-0.259	-0.806
	(0.024)**	(0.032)**	(0.023)**	(0.025)**	(0.033)**	(0.024)**	(0.038)**	(0.047)**	(0.017)	(0.010)**	(0.023)**	(0.012)**	(0.038)**
Ind. Var. X 2015	-0.678	0.656	-0.265	-0.656	0.707	-0.304	-0.994	0.999	0.011	-0.203	-0.619	-0.286	-0.855
	(0.025)**	(0.033)**	(0.024)**	(0.026)**	(0.033)**	(0.025)**	(0.039)**	(0.048)**	(0.017)	(0.010)**	(0.024)**	(0.013)**	(0.039)**
Ind. Var. X 2016	-0.73	0.699	-0.289	-0.709	0.763	-0.328	-1.078	1.089	0.002	-0.221	-0.671	-0.309	-0.915
	(0.025)**	(0.034)**	(0.024)**	(0.026)**	(0.034)**	(0.025)**	(0.040)**	(0.050)**	(0.018)	(0.011)**	(0.024)**	(0.013)**	(0.040)**
Fixed effects	Sect-Occ & Sect-Year			Sect-Occ & Sect-Year			Sect-Occ & Sect-Year			Sect-Occ & Sect-Year		Sect-Occ & Sect-Year	
ShL x D.Year	-			-			-			Yes	Yes	Yes	Yes
Occ.Init.Wage (ln) x Ag.Wage (ln)	No			Yes			No			Yes	Yes	Yes	Yes
Annual Growth 2016-04 (p90-p10)	-2.35%			-1.90%			-3.63%			-1.69%	-3.00%	-3.00%	-2.36%
OBS	522594			482737			505774			482737	482737	505,774	469,495
Max.Likelihood	-249490			-224618			-238500			-225920	-224756	-239,953	-216,278

Standard errors allow for within sector-occupation correlation * p<0.05; ** p<0.01

Note: The second row describes the dependent variable. The third row describes the letter of each sub-column of a particular model, and the fourth row presents the independent variable which is interacted with year dummies. In subcolumns (a), (b), and (c), Ind. Var represents the RISK Index, RISK x ShL, and ShL, respectively. RISK x ShL is the RISK Index interacted with our proxy for the labor share at the occupation-service level. Each of the dependent variables interacts with year dummies. Column (2) controls for initial sector-occupation initial wages (ln) interacted with the aggregate wage (ln). Regression (3) uses the Routine Task Index which follows Autor et al (2003) approach. Columns (4) and (5) estimate the model using as proxy for the RISK the FO RISK Index and FO RISK Total Effect (FO RISK (1-ShL)) controlling for ShL (estimated sector-occupation labor share times year dummies). Columns (6) and (7) redo Columns (4) and (5) using the Routine Task Index instead of FO RISK Index. The row "Mag.Eff.2016-04 Risk (p90-p10)" presents the log difference between the dependent variable for occupations in the percentile 90th and 10th of RISK variable between 2016 and 2004. In case I use FO RISK Index, the difference is between occupations at risk and riskless (FO RISK=1 or 0). Wage Q90/Q10 (ln) refers to the log ratio of the wage at the 9th decile divided by the wage at the 1st decil.

Table 3c: Wage Bill, Employment, Risk of Automation and Robots per Workers
Sector 3-4dig NAICS and Occupation 6dig SOC (Period 2002-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Var.	Wage Bill (ln)	Emp. (ln)	Wage Bill (ln)	Wage Bill (ln)	Wage Bill (ln)	Wage Bill (ln)	Wage Bill (ln)	Wage Bill (ln)	Emp. (ln)	Wage Bill (ln)	Wage Bill (ln)	Wage Bill (ln)
Robots / worker	*Aggregate*	*Aggregate*	*Aggregate*	*Aggregate (a)*	***Sectoral***	***Sectoral***	***Sectoral (a)***	*Aggregate*	*Aggregate*	*Aggregate (a)*	***Sectoral***	***Sectoral (a)***
Model	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
Panel A: Risk proxy = FO RISK Index						***Homogeneous Initial Labor Share at the occupation-service Level***						
Robots /worker					-0.048	-0.041	-0.0070					
					(0.014)**	(0.014)**	(0.014)					
RISK x Robots /worker (a)	-0.437	-0.425	-0.441	-1.029		-0.064	-0.182	-0.3900	-0.3850	-0.924	-0.062	-0.180
	(0.014)**	(0.013)**	(0.014)**	(0.033)**		(0.009)**	(0.023)**	(0.012)**	(0.012)**	(0.030)**	(0.008)**	(0.021)**
ShL x Robots /worker				-0.583			-0.105			-0.401		-0.109
				(0.031)**			(0.022)**			(0.028)**		(0.020)**
External Fin. Dependence	-0.042	-0.038	-0.041	-0.041	-0.033	-0.032	-0.033					
x Credit Tightness	(0.005)**	(0.005)**	(0.005)**	(0.005)**	(0.006)**	(0.006)**	(0.006)**					
Sect. Chinese Expt. 2002	-1.373	-1.332	-1.354	-1.356	-0.296	-0.509	-0.566					
x Tot.Chinese Export	(0.087)**	(0.085)**	(0.088)**	(0.089)**	-0.325	-0.324	-0.327					
Sect. Mexican Expt. 2002	-0.171	-0.089	-0.04	-0.063	2.556	2.087	1.859					
x Tot.Mexican Export	-0.197	-0.182	-0.207	-0.207	(0.762)**	(0.782)**	(0.759)*					
Marg.Eff. RISK ΔRob/Worker +	-2.7%	-2.6%	-2.7%	-2.2%		-1.2%	-1.0%	-2.4%	-2.4%	-2.0%	-1.0%	-0.9%
Marg.Eff. RISK ΔRob/Worker ++				0.2%	-0.1%	-0.1%	0.0%			0.1%		0.0%
OBS	403,693	408,500	370,107	370,107	370,107	370,107	370,107	415,436	419,083	415,436	415,436	415,436
Panel B: Risk proxy = FO RISK Index						***Controlling for Labor Share at the occupation-service level***						
Robots /worker					-0.048	-0.035	-0.007					
					(0.014)**	(0.014)*	(0.014)					
RISK x Robots /worker (a)	-0.441	-0.429	-0.447	-1.029		-0.069	-0.182	-0.386	-0.383	-0.924	-0.068	-0.179
	(0.014)**	(0.013)**	(0.014)**	(0.033)**		(0.017)	(0.023)**	(0.012)**	(0.012)**	(0.030)**	(0.008)**	(0.021)**
RISK x ShL x Robots /worker	0.632	0.628	0.659			0.156		0.667	0.656		0.159	
	(0.049)**	(0.048)**	(0.050)**			(0.033)**		(0.044)**	(0.044)**		(0.029)**	
ShL x Robots /worker	-0.158	-0.170	-0.137	-0.583	0.002	-0.025	-0.105	-0.002	-0.024	-0.401	-0.030	-0.109
	(0.024)**	(0.024)**	(0.025)**	(0.031)**	(0.017)	(0.018)	(0.022)**	-0.023	-0.022	(0.028)**	(0.015)*	(0.020)**
Marg.Eff. RISK ΔRob/Worker +	-2.8%	-2.7%	-2.8%	-2.2%		-1.2%	-1.0%	-2.4%	-2.4%	-2.0%	-1.0%	-0.9%
Marg.Eff. RISK ΔRob/Worker ++	0.1%	0.1%	0.1%	0.2%	-0.1%	0.0%	0.0%	0.0%	0.0%	0.2%	0.0%	0.0%
OBS	403,674	408,480	370,107	370,107	370,107	370,107	370,107	415,436	419,083	415,436	415,436	415,436
Panel C: Risk proxy = Routine Task IndexFO RISK Index						***Controlling for Labor Share at the occupation-service level***						
Robots /worker					-0.048	-0.029	-0.031					
					(0.014)**	(0.014)*	(0.014)*					
RISK x Robots /worker (a)	-0.574	-0.528	-0.576	-0.164		-0.118	-0.035	-0.488	-0.455	-0.145	-0.107	-0.032
	(0.019)**	(0.019)**	(0.019)**	(0.006)**		(0.017)	(0.005)**	(0.017)**	(0.017)**	(0.005)**	(0.014)**	(0.005)**
RISK x ShL x Robots /worker	1.119	1.147	1.138			0.276		1.130	1.157		0.249	
	(0.068)**	(0.068)**	(0.070)**			(0.065)**		(0.062)**	(0.062)**		(0.059)**	
ShL x Robots /worker	-0.195	-0.207	-0.174	-0.147	0.002	-0.041	-0.038	-0.042	-0.061	-0.016	-0.044	-0.039
	(0.025)**	(0.025)**	(0.026)**	(0.026)**	(0.017)	(0.018)*	(0.018)*	(0.023)+	(0.023)**	(0.023)	(0.016)**	(0.016)*
Marg.Eff. RISK ΔRob/Worker +	-3.5%	-3.2%	-3.4%	-2.6%		-2.0%	-1.6%	-2.9%	-2.7%	-2.4%	-1.6%	-1.3%
Marg.Eff. RISK ΔRob/Worker ++	0.1%	0.1%	0.1%	0.0%	-0.5%	-0.3%	-0.3%	0.0%	0.0%	0.0%	0.0%	0.0%
OBS	389,870	394,252	359,460	359,460	370,107	359,460	359,460	403,066	406,602	403,066	403,066	403,066
Fixed effects: Sector-Occupation &	Year	Year	Year	Year	Year	Year	Year	Sector-Year	Sector-Year	Sector-Year	Sector-Year	Sector-Year
Occ.Init.Wage (ln) x Ag.Wage (ln)	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors allow for within sector-occupation correlation * p<0.05; ** p<0.01.

Note: The second and third rows describe the dependent variable and the independent variables I use for as proxy for the risk of automation, respectively. The fourth row describes the econometric model I use. I instrument robots per worker in the US using the simple average of robots per worker in 5 EU countries. All regression has sector-occupation and sector-year fixed effects. FO RISK Index is one when the FO RISK Probability is equal to or higher than 0.7. In Panel A, I impose the same occupation-service labor share, therefore the variable RISK x ShL x Robots/worker collapses to Aut.RISK x Robots/Worker. The variable RISK x ShL collapses to the fixed effect. Panel B and C, allow for different values of labor shares across sector-occupations. In all regression, the mean value of Aut.Risk and ShL are equals to zero. Rout.Task is our Routine Task Index that uses Autor et al (2003) approach. "Annual Growth 2016-04 (p90-p10)+" reports the effect, of the average change in robots per worker times the risk proxy between 2004 and 2016, on the dependent variable annual rate of growth for sector-occupations in the 5th quintile of the risk of automation, relative to the sector-occupations in the 1st quintile ("RISK x Robots/worker"). "Annual Growth 2016-04 (p90-p10)++" reports the effect, of the average change in robots per worker times the occupation-service labor share between 2004-2016, on the dependent variable annual rate of growth for sectors in the 5th quintile of the risk of automation relative to sectors in the 1st quintile ("ShL x Robots /worker"). And, when I use sectoral robot penetration, it also includes the direct effect of the different changes on robot penetration across occupations with a high risk of automation (5th quintile) and low risk (1st quintile) ("Robots /worker").

Table 4a: Sector Employment and Wage Growth and Risk of Automation
At 3-4 NAICS dig. Level (Period 2004-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Var.	Wage Bill (ln)	Emp. (ln)	Wage Bill (ln)	Emp. (ln)	Wage Bill (ln)	Wage Bill (ln)	Wage Bill (ln)	Emp. (ln)	Wage Bill (ln)	Emp. (ln)	Wage Bill (ln)	Emp (ln)
Proxy for Automation Risk.	*FO RISK*	*FO RISK*	*FO RISK(1-ShL)*	*FO RISK(1-ShL)*	*FO RISK*	*FO RISK*	*FO RISK*	*FO RISK*	*FO RISK*	*FO RISK*	*FO RISK(1-ShL)*	*FO RISK(1-ShL)*
Aut.Risk x Robots /worker	*Aggregate*	*Aggregate*	*Aggregate*	*Aggregate*	*Aggregate*	*Aggregate*	*Sectoral*	*Sectoral*	*Sectoral*	*Sectoral*	*Sectoral*	*Sectoral*
Method	IV	IV	IV	IV	IV	OLS	IV	IV	OLS	OLS	OLS	OLS
Sectoral Robots /worker					-0.081	-0.008	-0.367	0.008	-0.343	0.007	0.086	0.086
					(0.123)	(0.002)**	(0.315)	(0.005)	(0.312)	(0.005)	(0.043)*	(0.041)*
RISK x Robots /worker (b)	-0.466	-0.429	-0.252	-0.255	-0.260	-0.383	0.275	0.262	-0.013	-0.011	-0.031	-0.030
	(0.082)**	(0.082)**	(0.102)*	(0.100)*	(0.348)	(0.077)**	(0.254)	(0.252)	(0.004)**	(0.005)*	(0.008)**	(0.008)**
ShL x Robots /worker (b)			-1.534	-1.286							-1.253	-1.571
			(0.486)**	(0.466)**							(0.194)**	(0.234)**
External Financial Dependence	-0.382	-0.135	-0.630	-0.385	-0.008	-0.022	-0.062	-0.061	-0.031	-0.031	-0.031	-0.030
x Credit Tightness	(1.014)	(0.699)	(1.047)	(0.731)	(0.030)	(0.018)	(0.037)	(0.036)+	(0.008)**	(0.008)**	(0.008)**	(0.008)**
Sect. Mexican Expt. 2002	-0.021	-0.021	-0.023	-0.024	4.990	0.052	-0.483	-0.630	-0.243	-0.080	-0.301	-0.178
x Tot.Mexican Export	(0.018)	(0.016)	(0.017)	(0.015)+	(8.206)	(0.975)	(2.658)	(2.532)	(0.422)	(0.334)	(0.464)	(0.369)
Sect. Chinese Expt. 2002	-1.239	-1.537	-1.263	-1.554	0.356	-1.105	1.689	1.128	-1.298	-1.598	-1.253	-1.571
x Tot.Chinese Export	(0.455)**	(0.518)**	(0.469)**	(0.531)**	(2.537)	(0.409)**	(2.620)	(2.554)	(0.203)**	(0.243)**	(0.194)**	(0.234)**
Fixed effects	Sector & Yea	Sector & Yea	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year
Sect.Init.Wage (ln) x Ag.Wage (ln)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Annual Growth 2016-04 (p90-p10)+	-2.9%	-2.7%	-1.4%	-1.3%	-1.6%	-2.4%	3.0%	2.9%	-0.1%	-0.1%	-0.5%	-0.5%
Annual Growth 2016-04 (p90-p10)++			0.0%	0.0%	-1.4%	-0.1%	-6.3%	-5.9%	0.1%	0.1%	1.5%	1.5%
OBS	3,198	3,198	3,198	3,198	3,198	3,198	3,198	3,198	3,198	3,198	3,198	3,198
Kleibergen-Paap rk Wald F test. Ho Weak Instr.	Rejected	Rejected	Rejected	Rejected	Not Rejected	.	Not Rejected	Not Rejected	.	.	.	.

Standard errors allow for correlation within sectors at 3-4 digits NAICS when "Aut.Risk x Robots/worker" is Aggregate and within IFR sector-year when is Sectoral.. + p<0.10; * p<0.05; ** p<0.01

Note: The second and third rows describe the dependent variable and the proxy I use for the risk of automation. FO RISK is the share of employees at risk of automation using FO probability higher than 0.7 in 2004 (equivalent to the mean weighted FO RISK Index). Rout.Task is the weighted average of the Routine Task Index in 2004. FO RISK (1-ShL) is the weighted average of FO RISK Index times one minus the sector-occupation labor share. The fourth row reports the level of aggregation I use to compute the variable Robots per Worker that I interact with my proxy for risk of automation (Aut.Risk x Robots /worker). External Fin. Dependence is Rajan and Zingales' external financial dependence constructed using Compustat data for the 90s. Credit Tightness is an index equal to $CTindex_t = CTindex_{t-1} + 5(\text{NIT}_t + \text{NIS}_t\ ))$, where NIT and NIS is the fraction of domestics banks that increase credit tightness and spread during the quarter to large and medium firms (Source FED). I use the annual average. "Annual Growth 2016-04 (p90-p10)+" row reports the effect, of the average change in robots per worker times the risk proxy between 2004 and 2016 ("RISK x Robots/workers"), on the dependent variable annual rate of growth for sectors in the 5th quintile of the risk of automation, relative to sectors in the 1st quintile. The "Annual Growth 2016-04 (p90-p10)++" row reports the effect, of the average change in robots per worker times the average occupation-service labor share at the sector level between 2004-2016 ("ShL x Robots/worker"), on the dependent variable annual rate of growth for sectors in the 5th quintile of the risk of automation relative to sectors in the 1st quintile. And, when I use sectoral robot penetration, it also includes the direct effect of the different changes in robot penetration across sectors with a high risk of automation (5th quintile) and with a low risk (1st quintile) ("Robots /worker").

Table 5a: US imports and Risk of Automation

	(1)	(2)	(3)	(4)	(5)	(6)		
Dependent Var.	Import (ln)	Import (ln)	Import (ln)	Import (ln)	Import (ln)	Import (ln)		
						(a)	(b)	(c)
						Low Cap-tech.	High Cap-tech.	Dif.
Independent Var	*FO RISK*	*FO RISK*	*FO RISK*	*FO RISK (1-ShL)*	*Rout.Task*	*FO RISK*	*FO RISK*	*[p value]*
Ind. Var. X 2003	-0.339	-0.529	-0.341	-0.683	-0.045	-0.079	-0.140	0.061
	(0.157)*	(0.174)**	(0.160)*	(0.582)	(0.019)*	(0.048)	(0.073)+	[0.482]
Ind. Var. X 2004	-0.354	-0.568	-0.362	-0.426	-0.062	-0.074	-0.180	0.106
	(0.165)*	(0.182)**	(0.169)*	(0.621)	(0.021)**	(0.050)	(0.085)*	[0.285]
Ind. Var. X 2005	-0.762	-0.754	-0.781	-1.924	-0.130	-0.211	-0.167	-0.044
	(0.176)**	(0.204)**	(0.180)**	(0.667)**	(0.023)**	(0.054)**	(0.088)+	[0.648]
Ind. Var. X 2006	-1.036	-0.847	-1.072	-2.386	-0.167	-0.327	-0.045	-0.282
	(0.190)**	(0.216)**	(0.194)**	(0.714)**	(0.026)**	(0.058)**	(0.089)	[0.007]
Ind. Var. X 2007	-1.037	-0.703	-1.065	-2.235	-0.182	-0.325	-0.063	-0.262
	(0.203)**	(0.235)**	(0.207)**	(0.755)**	(0.031)**	(0.061)**	(0.089)	[0.011]
Ind. Var. X 2008	-1.308	-1.025	-1.337	-3.204	-0.207	-0.385	-0.202	-0.183
	(0.222)**	(0.261)**	(0.227)**	(0.814)**	(0.035)**	(0.067)**	(0.096)*	[0.095]
Ind. Var. X 2009	-1.552	-1.209	-1.583	-3.484	-0.228	-0.456	-0.247	-0.209
	(0.237)**	(0.281)**	(0.243)**	(0.870)**	(0.039)**	(0.071)**	(0.099)*	[0.067]
Ind. Var. X 2010	-1.616	-1.129	-1.637	-3.368	-0.239	-0.490	-0.194	-0.296
	(0.249)**	(0.296)**	(0.255)**	(0.894)**	(0.042)**	(0.074)**	(0.100)+	[0.01]
Ind. Var. X 2011	-1.821	-1.468	-1.846	-3.750	-0.240	-0.543	-0.261	-0.282
	(0.264)**	(0.313)**	(0.270)**	(0.946)**	(0.045)**	(0.078)**	(0.110)*	[0.023]
Ind. Var. X 2012	-2.016	-1.536	-2.055	-4.739	-0.264	-0.595	-0.314	-0.281
	(0.265)**	(0.319)**	(0.271)**	(0.949)**	(0.047)**	(0.078)**	(0.108)**	[0.021]
Ind. Var. X 2013	-1.698	-1.375	-1.730	-2.610	-0.244	-0.505	-0.249	-0.256
	(0.274)**	(0.334)**	(0.281)**	(0.980)**	(0.049)**	(0.081)**	(0.113)*	[0.037]
Ind. Var. X 2014	-1.957	-1.478	-1.988	-3.537	-0.255	-0.573	-0.323	-0.25
	(0.287)**	(0.344)**	(0.294)**	(1.012)**	(0.052)**	(0.084)**	(0.119)**	[0.053]
Ind. Var. X 2015	-1.734	-1.153	-1.765	-2.866	-0.253	-0.514	-0.254	-0.26
	(0.299)**	(0.356)**	(0.306)**	(1.047)**	(0.055)**	(0.088)**	(0.116)*	[0.042]
Ind. Var. X 2016	-1.837	-1.470	-1.875	-3.606	-0.269	-0.537	-0.312	-0.225
	(0.310)**	(0.373)**	(0.317)**	(1.082)**	(0.058)**	(0.090)**	(0.118)**	[0.074]
External Fin. Dependence	-0.072	0.015	-0.061	-0.041	-0.077	-0.075		
x Cred.Private Sector (ln) Exporter	(0.073)	(0.084)	(0.073)	(0.072)	(0.072)	(0.073)		
External Fin. Dependence	0.055	0.043	0.052	0.042	0.063	0.054		
x Credit Tightness US	(0.025)*	(0.029)	(0.026)*	(0.025)+	(0.026)*	(0.025)*		
Fixed effects					Exp.Cty.-Sect & Exp.Cty.-Year			
Control ShL x Robots/Worker US & US partne	No	No	No	Yes	No	No		
Sect.Init.Wage (ln) x Ag.Wage in the US (ln)	Yes	Yes	Yes	Yes	Yes	Yes		
Annual Growth 2016-04 (p90-p10) +	-3.5%	-2.1%	-3.5%	-2.9%	-4.0%	-3.7%	-1.4%	
Annual Growth 2016-04 (p90-p10) ++				0.5%				
Sample	All Countries	IFR Countries	w/o CHN & MEX	All Countries	All Countries	All Countries		
OBS	122,237	72,318	119,551	122,237	122,237	122,237		
Max.Likelihood	-178,625	-95,065	-175,781	-178,487	-178,654	-178,604		

Standard errors allow for within Trade Partner-Sector correlation * p<0.05; ** p<0.01

Note: The first row presents the regression number; the second row describes the dependent variable; the third row describes the proxy I use for the risk of automation (in all cases they are weighted average by employment of the risk index at the US sector level). Fin. External Dependence is Rajan and Zingales' external financial dependence constructed using Compustat data for the 90s. Credit to the private (ln) is the log WDI index of credit over GDP in 2004. Countries with high robot penetration are Austria, Belgium, Germany, Denmark, Spain, Finland, France, Italy, Japan, South Korea, Netherlands, Singapore, Slovak Republic, Sweden, United Kingdom, Slovenia, and Switzerland.

Table 7b: US imports and Aggregate Robots per Workers in the US and abroad.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.		Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)
Independent Var.		*FO RISK*		*FO RISK*		*Rout.Task*		*FO RISK (1-ShL)*	
Ind.Var x Robots / worker (+)		*Aggregate*	*Aggregate*	*Aggregate*	*Aggregate*	*Aggregate*	*Aggregate*	*Aggregate*	*Aggregate*
Method		OLS	OLS	IV	IV	IV	IV	IV	IV
RISK x Robots/worker	a	-1.429		-1.727		-0.282		-3.616	
US		(0.460)**		(0.498)**		(0.092)**		(1.689)*	
RISK x Robots/worker	b	0.091		0.133		0.011		0.203	
US trade Partner		(0.178)		(0.177)		(0.022)		(0.630)	
RISK x Robots/worker	a		-1.817		-2.185		-0.327		-5.191
US x Countries with Low Capital-Tech.			(0.486)**		(0.527)**		(0.094)**		(1.748)**
RISK x Robots/worker	b		-0.39		-0.466		-0.137		0.576
US x Countries with High Capital-Tech.			(0.545)		(0.576)		(0.094)		(1.997)
External Financial Dependence		0.018	-0.014	0.014	-0.020	0.015	-0.018	0.035	0.025
x Cred.Private Sector (ln)	Exporter	(0.092)	(0.090)	(0.092)	(0.090)	(0.092)	(0.090)	(0.092)	(0.091)
External Financial Dependence		0.074	0.077	0.078	0.082	0.088	0.091	0.06	0.06
x Credit Tightness US		(0.029)*	(0.029)**	(0.030)**	(0.029)**	(0.031)**	(0.030)**	(0.030)*	(0.030)*
Fixed effects		Trade Partner-Sector & Trade Partner-Year							
Control Initial Wages (ln)		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control ShL x Robots/Worker US & US partner								Yes	Yes
Annual Growth 2016-04 (p90-p10)	a	-2.6%	-3.2%	-3.1%	-3.9%	-4.3%	-5.0%	-1.8%	-2.4%
Annual Growth 2016-04 (p90-p10)	b	0.1%	-0.7%	0.1%	-0.8%	0.1%	-2.1%	0.1%	-0.1%
OBS		73125	74558	73125	74558	73125	74558	73125	73125
Max.Likelihood		-96665	-97950	-96666	-97952	-96692	-97977	-96561	-96627
Kleibergen-Paap rk Wald F statistic		.	.	Rejected	Rejected	Rejected	Rejected	Rejected	Rejected

Standard errors allow for within Trade Partner-Sector correlation * p<0.05; ** p<0.01

Note: The first row presents the regression number; the second row describes the dependent variable; the third row describes the proxy I use for the risk of automation (in all cases they are weighted average by employment of the risk index at the US sector level). Fin. External Dependence is Rajan and Zingales' external financial dependence constructed using Compustat data for the 90s. Credit to the private (ln) is the log WDI index of credit over GDP in 2004. Countries with high robot penetration are Austria, Belgium, Germany, Denmark, Spain, Finland, France, Italy, Japan, South Korea, Netherlands, Singapore, Slovak Republic, Sweden, United Kingdom, Slovenia, and Switzerland.

Table 7c: US imports, Sectoral Robots and US Partness with high and low Robot Penetration

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.		Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)
Independent Var.		*FO RISK*	*FO RISK*	*FO RISK*	*FO RISK*	*FO RISK*	*FO RISK (1-ShL)*	*Rout.Task*	*FO RISK*
Instrumented Variables: Sectoral Robots		Yes	No	Yes	No	No	No	No	Yes
Aggregate Robots		-	-	Yes	Yes	Yes	Yes	Yes	-
Sectoral Robots /worker	a			-0.008	0.004				
US				(0.097)	(0.003)				
Sectoral Robots /worker	a	-0.009	0.006			0.007	0.004	0.005	0.003
US x Countries with Low Capital-Tech.		(0.080)	(0.004)			(0.003)+	(0.003)	(0.003)	(0.026)
Sectoral Robots /worker	b	-0.080	-0.003			-0.001	-0.003	-0.001	-0.021
US x Countries with High Capital-Tech.		(0.101)	(0.004)			(0.005)	(0.005)	(0.005)	(0.025)
RISK x Sectoral Robots/worker	c								1.353
US x Countries with Low Capital-Tech.									(1.806)
RISK x Sectoral Robots/worker	d								0.576
US x Countries with High Capital-Tech.									(0.700)
RISK x Aggregate Robots/worker	c			-2.028	-2.455	-2.430	-7.256	-0.292	
US x Countries with Low Capital-Tech.				(3.546)	(0.609)**	(0.610)**	(2.124)**	(0.110)**	
RISK x Aggregate Robots/worker	d			-0.520	-0.998	-1.026	-1.560	-0.112	
US x Countries with High Capital-Tech.				(3.958)	(0.679)	(0.681)	(2.461)	(0.113)	
ShL x Aggregate Robots /worker (b)	c						-0.531		
US x Countries with Low Capital-Tech.							(1.925)		
ShL x Aggregate Robots /worker (b)	d						2.577		
US x Countries with High Capital-Tech.							(2.197)		
External Financial Dependence		-0.060	-0.044	-0.067	-0.067	-0.067	-0.053	-0.061	-0.100
x Cred.Private Sector (ln) Exporter		(0.081)	(0.072)	(0.080)	(0.080)	(0.080)	(0.079)	(0.080)	(0.096)
External Financial Dependence		0.058	0.069	0.086	0.096	0.096	0.084	0.097	-0.046
x Credit Tightness US		(0.045)	(0.033)*	(0.084)	(0.032)**	(0.032)**	(0.032)**	(0.033)**	(0.159)
Fixed effects		Trade Partner-Sector & Trade Partner-Year							
Sect.Init.Wage (ln) x Ag.Wage (ln)		Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Annual Growth 2016-04 (p90-p10)	a	-0.4%	0.3%	-0.4%	0.2%	0.3%	0.2%	0.2%	0.2%
Annual Growth 2016-04 (p90-p10)	b	-3.9%	-0.2%			0.0%	-0.1%	-0.1%	-1.1%
Annual Growth 2016-04 (p90-p10)	c			-.0359	-.0432	-.0428	-.0339	-.0449	.1957
Annual Growth 2016-04 (p90-p10)	d			-.0094	-.018	-.0185	-.0091	-.0174	.0739
OBS		65,308	65,308	65,308	65,308	65,308	65,308	65,308	65,308
Max.Likelihood		-84395	-83861	-83873	-83836	-83832	-83731	-83855	-89,263
Kleibergen-Paap rk Wald F test. Ho Weak Instr.		Not Rejected	.	Not Rejected	Reject	Reject	Reject	Reject	Not Rejected

Standard errors allow for within Trade IFR Sector-Year correlation * p<0.05; ** p<0.01

Note: The first row presents the regression number; the second row describes the dependent variable; the third row describes the proxy I use for the risk of automation (in all cases they are weighted average by employment of the risk index at the US sector level).

Fin. External Dependence is Rajan and Zingales' external financial dependence constructed using Compustat data for the 90s. Credit to the private (ln) is the log WDI index of credit over GDP in 2004. Countries with high robot penetration are Austria, Belgium, Germany, Denmark, Spain, Finland, France, Italy, Japan, South Korea, Netherlands, Singapore, Slovak Republic, Sweden, United Kingdom, Slovenia, and Switzerland.

Table Aa: Probability of Automation, Routine Tasks, Occupation Employment, and Wages.

OES Occupation Employment and Wages 2010, Change period 2004-2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.	*FO RISK Prob.*	*FO RISK Prob.*	Wage (ln)	Emp. (ln)	Ch. Emp.(ln)	Ch.Wage Bill (ln)	Ch.Wage Bill (ln)	Ch.Wage Bill (ln)
Model	*OLS*	*OLS*	*OLS*	*OLS*	*IV*	*IV*	*IV*	*IV*
non-routine	-0.153							0.005
cognitive analytic	(0.012)**							(0.002)*
non-routine	-0.022							-0.001
interpersonal	(0.014)							(0.002)
non-routine	-0.007							0.004
manual physical	(0.014)							(0.002)*
non-routine	-0.117							0.004
manual interpersonal	(0.014)**							(0.002)
routine	0.069							0.000
cognitive	(0.010)**							(0.001)
routine	0.006							-0.004
manual	(0.015)							(0.002)*
PROBb or *Routine Task Index*		0.081					-0.029	
		(0.003)**					(0.003)**	
FO RISK Index			-0.760	0.051	-0.028	-0.031		-0.014
			(0.035)**	(0.151)	(0.003)**	(0.003)**		(0.005)**
Dependent var. 2004 (ln)					0.001	0.000	0.001	0.001
					(0.001)	(0.000)	(0.001)	(0.001)
Observations	755	755	791	795	700	695	699	699
R2	0.59	0.54	0.37	0.00	0.11	0.12	0.11	0.14

Robust Standard errors, * p<0.05; ** p<0.01.

Note: The first row presents the regression number; the second row describes the dependent variable; the third row describes the model used. FO Probability is the FO probability of automation for different occupations. Employment and Wage (ln) are OES log level of national employment and average log wage for occupations in 2010. OES dataset does not have data for all occupations in all years. Change Employment and Wage Bill are the log change between 2004 and 2016. Dependent var. 2004 is the log dependent variable in level in 2004, instrumented with its value in 2003.

Table Ba: Wage Bill, Employment, Wages, and Risk of Automation
Aggregate Data (Period 2000-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.	Wage Bill (ln)	Emp. (ln)	Wage (ln)	Wage Bill (ln)	Emp. (ln)	Wage (ln)	Emp. (ln)	Wage Q90/Q10 (ln)
Independeent Var.	*RISK>0.7*	*RISK>0.7*	*RISK>0.7*	*RISK>0.7*	*RISK>0.7*	*RISK>0.7*	*Routine Tasks* [1]	*RISK>0.7*
Ind. Var. X 2001	-0.027	-0.026	-0.000	-0.013	-0.017	0.004	-0.045	0.004
	(0.009)**	(0.008)**	(0.002)	(0.009)	(0.009)*	(0.002)	(0.011)**	(0.004)
Ind. Var. X 2002	-0.067	-0.054	-0.012	-0.043	-0.038	-0.005	-0.092	0.004
	(0.011)**	(0.011)**	(0.003)**	(0.012)**	(0.011)**	(0.003)	(0.016)**	(0.005)
Ind. Var. X 2003	-0.084	-0.066	-0.017	-0.056	-0.047	-0.009	-0.102	0.007
	(0.014)**	(0.014)**	(0.004)**	(0.015)**	(0.015)**	(0.004)*	(0.020)**	(0.006)
Ind. Var. X 2004	-0.117	-0.089	-0.027	-0.084	-0.065	-0.017	-0.141	0.000
	(0.021)**	(0.021)**	(0.005)**	(0.022)**	(0.021)**	(0.005)**	(0.027)**	(0.008)
Ind. Var. X 2005	-0.146	-0.116	-0.030	-0.107	-0.087	-0.019	-0.163	-0.002
	(0.024)**	(0.024)**	(0.005)**	(0.025)**	(0.024)**	(0.005)**	(0.031)**	(0.007)
Ind. Var. X 2006	-0.171	-0.130	-0.039	-0.124	-0.096	-0.025	-0.178	-0.005
	(0.025)**	(0.024)**	(0.005)**	(0.026)**	(0.025)**	(0.005)**	(0.033)**	(0.008)
Ind. Var. X 2007	-0.203	-0.154	-0.044	-0.146	-0.115	-0.028	-0.200	-0.013
	(0.026)**	(0.025)**	(0.005)**	(0.028)**	(0.027)**	(0.005)**	(0.036)**	(0.008)
Ind. Var. X 2008	-0.242	-0.188	-0.050	-0.177	-0.143	-0.030	-0.223	-0.023
	(0.028)**	(0.027)**	(0.006)**	(0.030)**	(0.029)**	(0.006)**	(0.040)**	(0.008)**
Ind. Var. X 2009	-0.315	-0.259	-0.051	-0.243	-0.209	-0.029	-0.306	-0.023
	(0.030)**	(0.029)**	(0.006)**	(0.032)**	(0.031)**	(0.006)**	(0.043)**	(0.008)**
Ind. Var. X 2010	-0.373	-0.315	-0.053	-0.296	-0.262	-0.030	-0.392	-0.027
	(0.032)**	(0.031)**	(0.006)**	(0.035)**	(0.034)**	(0.007)**	(0.046)**	(0.008)**
Ind. Var. X 2011	-0.383	-0.322	-0.056	-0.302	-0.267	-0.032	-0.398	-0.029
	(0.034)**	(0.033)**	(0.006)**	(0.037)**	(0.036)**	(0.007)**	(0.048)**	(0.008)**
Ind. Var. X 2012	-0.381	-0.321	-0.055	-0.297	-0.264	-0.030	-0.388	-0.028
	(0.035)**	(0.034)**	(0.007)**	(0.039)**	(0.038)**	(0.007)**	(0.051)**	(0.009)**
Ind. Var. X 2013	-0.386	-0.325	-0.055	-0.298	-0.266	-0.029	-0.383	-0.029
	(0.036)**	(0.034)**	(0.007)**	(0.040)**	(0.039)**	(0.007)**	(0.052)**	(0.009)**
Ind. Var. X 2014	-0.393	-0.338	-0.049	-0.301	-0.276	-0.022	-0.391	-0.031
	(0.037)**	(0.035)**	(0.007)**	(0.041)**	(0.040)**	(0.008)**	(0.054)**	(0.009)**
Ind. Var. X 2015	-0.401	-0.343	-0.050	-0.303	-0.277	-0.021	-0.398	-0.036
	(0.038)**	(0.037)**	(0.007)**	(0.042)**	(0.041)**	(0.008)**	(0.057)**	(0.010)**
Ind. Var. X 2016	-0.412	-0.358	-0.047	-0.308	-0.287	-0.016	-0.425	-0.034
	(0.039)**	(0.038)**	(0.007)**	(0.044)**	(0.043)**	(0.008)	(0.059)**	(0.010)**
Fixed Effects	Occ.& Year	Occ.& Year	Occ.& Year	Occ.& Year	Occ.& Year	Occ.& Year	Occ.& Year	Occ.& Year
Occ.Init.Wage (ln) x Ag.Wage (ln)	No	No	No	Yes	Yes	Yes	No	No
Annual Growth 2016-04 (p90-p10)	-2.4%	-2.2%	-0.2%	-1.8%	-1.8%	0.0%	-2.3%	-0.3%
OBS	13,098	13,164	13,098	13,078	13,117	13078.00	12,563	12,533
Within R2 Adj.	0.116	0.094	0.041	0.133	0.106	0.074	0.106	0.013
Max.Likelihood	3,127	3,489	22,795	3,244	3,594	22,993	3,571	17,439

Standard errors allow for within occupation correlation * $p<0.05$; ** $p<0.01$

Note: The first row presents the regression number; the second row describes the dependent variable; the third row describes the proxy I use for risk of automation. RISK>0.7 is a dummy variable equals to one if the FO probability is higher than 0.7. Regressions (1) to (3) use only the set of RISKs independent variables. Regressions (4) to (6) use the set of Risk dummies and (ln) Initial Wage interacted with year dummies as independent variables. Initial *Wage* is the log wage of occupation "o" in the year 2004. I use the year 2004 because is the year with the highest number of occupations in OES data. Regression (7) use our proxy of routine tasks index. This index uses Autor et al (2003) approach to construct an index of the relative importance of routine tasks in each occupation (*Routine Task Index* in Section 1). The row Mag.Eff.2016-02 (p90-p10) presents the estimated annual rate of growth difference between occupations in the percentile 90th and 10th of the risk proxy between 2002 and 2016. When I use FO RISK Index, I use occupations with index equals to 1 and 0, respectively (for Column (1): $(Exp(-0.412+0.67)^{1/14}-1)$. I use 2002 for comparability reason –sector data starts in 2002-). The 2016 year coefficient represents the same percentage for occupation in the percentile 90 and10. Regressions use wage bill, employment and wages (ln) for 795 occupations defined by the BLS **Occupational Employment Statistics** (OES) program. Wage (ln) refers to the average wage for employees with a particular occupation at the country level (ln) in a given year. Wage Q90/Q10 (ln) refers to the ratio of the wage at the decile 9 divided by the wage at the decile 1 (ln).

Table Bb: Employment and Wages and Robot per Workers
Aggregate Data (Period 2000-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Var.	Wage Bill (ln)	Emp.(ln)	Wage (ln)	Wage Bill (ln)	Emp.(ln)	Wage (ln)	Wage Bill(ln)	Emp.(ln)	Wage Bill(ln)
Model	*IV*	*IV*	*IV*	*IV*	*IV*	*IV*	*IV*	*IV*	*Growth / IV*
FO RISK Index	-0.410	-0.354	-0.048	-0.316	-0.290	-0.021			-0.324
x Robots/worker	(0.042)**	(0.041)**	(0.008)**	(0.047)**	(0.046)**	(0.009)**			(0.037)**
Routine Task Index							-0.411	-0.391	
x Robots/worker							(0.065)**	(0.062)**	
Lag Dependent Var. 2001 (ln)									0.015
									(0.012)
Fixed effects	Occ.&Year		Occ.&Year		Occ.&Year		Occ.&Year	Occ.&Year	No
Occ.Init.Wage (ln) x Ag.Wage (ln)	No	No	No	Yes	Yes	Yes	No	No	No
Annual Growth 2016-01 (p90-p10)	-2.9%	-2.5%	-0.3%	-2.2%	-2.0%	-0.1%	-2.9%	-2.8%	-2.3%
OBS	13098	13164	13098	13078	13117	13078	12524	12563	694
Within R2 Adj.	0.107	0.087	0.030	0.126	0.100	0.065	0.123	0.100	0.137
Max.Likelihood	3058.0	3435.0	22719.0	3187.0	3546.0	22930.0	3155.0	3524.0	-462.0

Standard errors allow for within occupation correlation. * $p<0.05$; ** $p<0.01$

Note: The first column presents the regression number; the second row describes the dependent variable, the third row describes the estimation method. IV stands for an instrumental variable model. Robots/worker is the number of robots per thousand workers at the country level. In the US, "robots per worker" goes from .706 in 2002 to 1.567 in 2019. I use as IV the simple average of robot/workers in EU countries. RISK>0.7 is a dummy variable equals to one if the FO probability is higher than 0.7. Regression (7) use our proxy of routine tasks index. This index uses Autor et al (2003) approach to construct an index of the relative importance of routine tasks in each occupation (PROBb in Section 1). The row Annual growth 2016-02 (p90-p10) presents the estimated annual rate growth difference between occupations in the percentile 90^{th} and 10^{th} of the risk proxy between 2002 and 2016. When I use FO RISK Index, I use occupations with index equals to 1 and 0, respectively (for Column (1): $(\text{Exp}(-0.421*(\text{Rob\_pw2016}- \text{Rob\_pw2002}))^{1/14} -1)$.

Table Ca: Sector Wage Bill, Employment and Wages, and Risk of Automation At 3-4 NAICS dig. Level (Period 2002-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dependent Var.	Wage Bill (ln)	Employment (ln)	Wage (ln)	Wage Bill (ln)	Employment (ln)	Wage Bill (ln)	Employment (ln)	Wage Bill (ln)	Employment (ln)	Wage Bill (ln)	Employment (ln)
Independent Var.	*Mean RISK*	*Mean RISK*	*Mean RISK*	*Mean RISK*	*Mean RISK*	*Mean RISK(1-ShL)*	*Mean RISK(1-ShL)*	*Rout.Task*	*Rout.Task*	*Rout.Task(1-ShL)*	*Rout.Task(1-ShL)*
Ind. Var. X 2003	-0.010	-0.001	-0.010	-0.010	-0.001	-0.003	0.000	-0.011	-0.009	-0.005	-0.002
	(0.005)*	(0.004)	(0.002)**	(0.005)+	(0.005)	(0.005)	(0.004)	(0.004)*	(0.004)*	(0.004)	(0.004)
Ind. Var. X 2004	-0.017	-0.004	-0.014	-0.016	-0.005	0.002	0.003	-0.036	-0.035	-0.024	-0.022
	(0.010)+	(0.009)	(0.004)**	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)**	(0.009)**	(0.010)*	(0.009)*
Ind. Var. X 2005	-0.029	-0.008	-0.021	-0.027	-0.011	-0.003	-0.003	-0.068	-0.059	-0.052	-0.045
	(0.015)+	(0.014)	(0.005)**	(0.016)+	(0.015)	(0.016)	(0.015)	(0.015)**	(0.014)**	(0.015)**	(0.014)**
Ind. Var. X 2006	-0.050	-0.024	-0.027	-0.047	-0.027	-0.017	-0.016	-0.108	-0.093	-0.087	-0.075
	(0.019)*	(0.019)	(0.006)**	(0.021)*	(0.020)	(0.022)	(0.021)	(0.021)**	(0.020)**	(0.021)**	(0.020)**
Ind. Var. X 2007	-0.086	-0.053	-0.032	-0.081	-0.059	-0.036	-0.036	-0.152	-0.134	-0.123	-0.109
	(0.024)**	(0.023)*	(0.007)**	(0.026)**	(0.026)*	(0.028)	(0.027)	(0.027)**	(0.026)**	(0.026)**	(0.026)**
Ind. Var. X 2008	-0.136	-0.101	-0.036	-0.130	-0.108	-0.066	-0.070	-0.196	-0.177	-0.160	-0.147
	(0.029)**	(0.028)**	(0.008)**	(0.031)**	(0.030)**	(0.035)+	(0.034)*	(0.031)**	(0.031)**	(0.031)**	(0.031)**
Ind. Var. X 2009	-0.231	-0.192	-0.039	-0.223	-0.200	-0.119	-0.126	-0.281	-0.264	-0.226	-0.217
	(0.036)**	(0.034)**	(0.009)**	(0.038)**	(0.037)**	(0.046)*	(0.044)**	(0.036)**	(0.037)**	(0.040)**	(0.039)**
Ind. Var. X 2010	-0.280	-0.236	-0.044	-0.272	-0.245	-0.143	-0.151	-0.325	-0.312	-0.256	-0.251
	(0.042)**	(0.040)**	(0.009)**	(0.044)**	(0.043)**	(0.054)**	(0.052)**	(0.041)**	(0.042)**	(0.047)**	(0.047)**
Ind. Var. X 2011	-0.294	-0.242	-0.052	-0.285	-0.253	-0.158	-0.159	-0.323	-0.309	-0.256	-0.250
	(0.044)**	(0.043)**	(0.009)**	(0.047)**	(0.046)**	(0.058)**	(0.056)**	(0.044)**	(0.045)**	(0.050)**	(0.049)**
Ind. Var. X 2012	-0.299	-0.242	-0.057	-0.289	-0.252	-0.162	-0.158	-0.317	-0.303	-0.252	-0.244
	(0.048)**	(0.047)**	(0.010)**	(0.050)**	(0.049)**	(0.061)**	(0.059)**	(0.050)**	(0.049)**	(0.053)**	(0.053)**
Ind. Var. X 2013	-0.295	-0.233	-0.062	-0.285	-0.244	-0.159	-0.151	-0.325	-0.303	-0.261	-0.245
	(0.051)**	(0.049)**	(0.010)**	(0.052)**	(0.051)**	(0.063)*	(0.062)*	(0.053)**	(0.053)**	(0.056)**	(0.055)**
Ind. Var. X 2014	-0.281	-0.216	-0.064	-0.270	-0.228	-0.143	-0.135	-0.321	-0.298	-0.257	-0.240
	(0.053)**	(0.052)**	(0.011)**	(0.054)**	(0.054)**	(0.066)*	(0.064)*	(0.054)**	(0.054)**	(0.057)**	(0.056)**
Ind. Var. X 2015	-0.270	-0.207	-0.063	-0.259	-0.219	-0.130	-0.126	-0.317	-0.297	-0.256	-0.241
	(0.055)**	(0.054)**	(0.011)**	(0.056)**	(0.056)**	(0.068)+	(0.066)+	(0.056)**	(0.056)**	(0.058)**	(0.058)**
Ind. Var. X 2016	-0.272	-0.209	-0.063	-0.260	-0.223	-0.121	-0.122	-0.335	-0.316	-0.268	-0.255
	(0.057)**	(0.057)**	(0.012)**	(0.059)**	(0.059)**	(0.069)+	(0.067)+	(0.058)**	(0.059)**	(0.061)**	(0.061)**
External Fin. Dependence	-0.059	-0.056	-0.003	-0.058	-0.057	-0.054	-0.054	-0.043	-0.043	-0.041	-0.044
x Credit Tightness	(0.026)*	(0.024)*	(0.006)	(0.026)*	(0.024)*	(0.026)*	(0.023)*	(0.026)+	(0.023)+	(0.024)+	(0.022)+
Sect. Chinese Expt. 2002	-0.974	-1.296	0.322	-0.976	-1.294	-0.995	-1.306	-0.698	-1.027	-0.732	-1.056
x Tot.Chinese Export	(0.364)**	(0.435)**	(0.123)**	(0.364)**	(0.436)**	(0.377)**	(0.446)**	(0.303)*	(0.367)**	(0.320)*	(0.385)**
Sect. Mexican Expt. 2002	-0.570	-0.459	-0.111	-0.622	-0.400	-0.865	-0.629	-0.506	-0.260	-0.695	-0.470
x Tot.Mexican Export	(0.912)	(0.663)	(0.325)	(0.910)	(0.669)	(0.942)	(0.697)	(0.849)	(0.606)	(0.930)	(0.680)
Fixed effects	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year
Sect.Init.Wage (ln) x Ag.Wage (ln)	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ShL x YEAR dummy	No	No	No	No	No	No	No	No	No	No	No
Annual Growth 2016-04 (p90-p10)+	-2.3%	-1.8%	-0.5%	-2.2%	-1.9%	-1.8%	-1.4%	-2.7%	-2.6%	-1.6%	-1.1%
Annual Growth 2016-04 (p90-p10)++						-1.1%	-1.2%			-2.2%	-2.1%
OBS	3,690	3,690	3,690	3,690	3,690	3,690	3,690	3,690	3,690	3,690	3,690
Max.Likelihood	2,430	2,593	7,571	2,431	2,594	2,340	2,511	2,534	2,717	2,455	2,626

Standard errors allow for within sector correlation * $p<0.05$; ** $p<0.01$

Note: The second and third rows describe the dependent variable and the proxy I use for risk of automation. Mean RISK is the share of employees at risk of automation using FO probability higher than 0.7 (equivalent to the mean weighted FO RISK index) in 2004. Mean Rout.Task is the weighted by employment average of the Routine Task Index in 2004. External Fin. Dependence is Rajan and Zingales external financial dependence constructed using Compustat data for the 90s. Liquidity Need is labor share from the BEA in 2004. Credit Tightness is an index equal to $CTindex_t = CTindex_{t-1} + 5(\mathrm{NIT}_t + \mathrm{NIS}_t))$, where NIT and NIS is the fraction of domestics banks that increase credit tightness and spread during the quarter to large and medium firms (Source FED). I use the annual average. Cred. Private Sector (ln) is the WDI index of credit to the private sector over GDP. The row Mag.Eff. p90-p10 presents the effect to increase the sector risk of automation from the percentile 10th to 90th on the dependent variable in 2016 relative to 2002. The “Annual Growth 2016-04 (p90-p10)+” row reports the effect, of the average increase in robots per worker during 2004 and 2016, on the dependent variable annual rate of growth for the sector in the percentile 90 of the risk of automation relative to the sector in the percentile 10%. The “Annual Growth 2016-04 (p90-p10)++” row reports the same relative rate of growth for the sector in the percentile 90th of the occupation-service labor share relative to the sector in the percentile 10th.