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Automation, Labor Markets, and Trade

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Abstract

Digital technologies, robotics, and artificial intelligence substitute tasks performed by labor are bringing back old fears about the impact of technology on labor markets and international trade. The aim of this paper is to provide evidence about the causal effect of automation on the labor market and sectoral US imports. We use robots per workers, instrumented by robot penetration in Europe, to study employment in almost 800 occupations in 285 industries in the US during 2002-2016. We use Autor et al (2003) and Frey and Osborne (2017) methodologies to define occupations at risk of automation and to study their behavior after robots´ penetration. We find that employment in occupations at risk has been declining at an annual rate of 2.0-2.5%, relative to other occupations. This result is mainly driven by a substitution effect within industries defined at the 4-digit NAICS level. One standard deviation increase in robots per worker reduces employment growth by 1.25-1.45% in occupations at risk compared to the other professions in the same sector. Industries with a higher share of occupation at risk have a lower rate of employment growth during the period 2002-2016. Also, imports of commodities produced by these sectors have been falling, in particular from countries with lower penetration of automation technologies. This result suggests that automation is changing countries´ comparative advantage.

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

JEL Classification: J23, J24.

1. Introduction

The last decades have brought remarkable technological changes. First, the fall in prices of hardware, software, and telephone services, has induced acceleration of the exponential growth rate of computer power and telecommunications capability with an explosive development of the Internet. Working together, the twenty-first century brought new technological attainments: Machine Learning, along with a stronger development in robotics and the internet of things. This phenomenon has been also known 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 are bringing back old fears about the impact of technology on labor markets.[2]

Acemoglu and Restrepo (2018a), Frey and Osborne (2017), Arntz et al (2017), McKensey (2017), Fort (2017), Boston Consulting Group (2015), along others studies, claim that as a result of recent developments a significant fraction of current jobs/tasks are and have been susceptible to automation.[3] Graetz, Georg, and Guy Michaels (2018), Brynjolfsson and McAfee (2014) and Acemoglu and Restrepo (2018ab,2019a) argue that recent capital and technological innovations will increase productivity in a wide range of industries. They can automate tasks previously performed by labor or create new tasks and activities in which humans can be more productive, but they also argue that this development may also have

[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 percent of US jobs, 57 percent of jobs across the OECD, and 77 percent of jobs in China, are susceptible to automation.

adverse effects. Automation may reduce labor demand, decline labor share in the national income and rise inequality.[4]

This paper uses US data of employment in 788 occupations in 285 sectors to provides evidence of the causal effect of automation on the labor market. After one standard deviation increase in robots per worker, employment falls by an average annual rate of growth of 1.25-1.45% in occupations at risk of automation compared to other professions in the same sector in the last 12 years. At the aggregate level, the share of employment in sectors characterized by a large fraction of employee in occupation at risk also falls during this period. These are low wage sectors. The paper presents evidence that the diffusion of automation technologies reduces US imports of products produced by sectors characterized by a large share of employment at risk. Reassuring this causal interpretation, US imports of these merchandise falls mainly from countries with low adoption of new technologies (proxy by robots per worker). 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 robots´ penetration.

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 done by humans. Autor and Dorn (2013) and Autor, Dorn, and Hanson (2013,2015) study US 722 local labor-market reaction to technological change. They find that commuting zone (CZ) with a large share of jobs in occupation characterized by routine task adopt more workplace computing and reduce employment in routine task-intensive occupations. CZ at

[4] As 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 years.

the 80th percentile of 1980 routine occupation share experienced a 1.8% points larger contraction of the routine occupation share per decade between 1980 and 2005 than did a 20th percentile CZ.

Although this paper reassures Autor et al (2013) results, the effects of automation, proxy by robots per workers, on employment in occupation prone to automation, or characterized by routine tasks (percentile 80% versus 20%), is one order of magnitude larger in the last 12 years, than Author et al (2013) results.[5] These authors use occupation data in commuting zones, instead of occupation data in sectors, and workplace-computing penetration, instead of robots per worker, as a proxy for labor-replacing technologies in the 80s and 90s.

In the last couple of years, there has been a surge in empirical papers about the effects of automation in the economy. Contrary to previous studies, most papers use robots per workers from the International Federation of Robotics IFR as a proxy for increased automation (e.g. Acemoglu and Restrepo (2018a,b, and 2019a), Graetz and Michaels (2018), Artuc, Bastos and B. Rijkers (2018), and Artuc, Christiaensen and Winkler (2019)). A key element in these papers is the empirical strategy to identify the causal relationship between automation and economic outputs.

Using country-sector data for 17 countries in 14 sectors, Graetz et al (2018) estimate productivity growth as a function of robots´ penetration at the country-sector level between 1993 and 2007. They argue 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´

[5] The results that use robots per workers at the sector level are restricted to the period 2004-2016.

penetration (they use IFR classification that defines only 6 general and 29 specific tasks), [6] controls for the reverse causality problem between sector productivity and robots. They find robot penetration implies an additional 0.37% in sector labor productivity growth. They find no significant effect on sector employment.

Controlling for external financial dependence, Chinese and Mexican imports, and year and sector effects, this paper shows that US sectors with a larger share of employment in occupation at risks of automation (percentile 80th), that faced one standard deviation higher robots per worker penetration, are correlated with annual employment growth that is 1.1% lower than in sectors with a low share of occupations at risk (percentile 20th) during the whole period 2004-2016.[7]

Using US CZ data for 19 sectors, Acemoglu and Restrepo (2018b) estimate employment growth for the period 1993-2007. Due to lack of information about robots´ penetration at the sector-year data in the US as well as penetration at the CZ level, these authors estimate a proxy for robots´ penetration at the CZ-sector level. With this measure, they study the effects of robots´ penetration, as a proxy for new technology penetration, on local labor markets. To avoid any reverse causality problem between US labor outcomes and robots penetration, they instrument their sector robots´ variable using sector robots´ penetration in EU countries. They find a negative effect of robots´ penetration on local labor markets. The replacement effect is higher than the productivity effect on labor demand at the CZ level. One more robot per

[6] 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).

[7] To imply causation, this results requires that sectors with a higher share of employment at risks of automation in EU countries did not stimulate the supply of labor-replacing technologies.

thousand workers reduces the employment rate by 0.18-0.34%. During this period, US robots per thousand workers go from 0.35 to 1.08.

The effect suggested by Acemoglu and Restrepo is larger than the one by Autor et al (2013), although lower than the one presented in this paper for the last 12 years.

Artuc et al (2018) study the impact of automation on trade using country-sector data. As a proxy of automation, they also use robots´ penetration, and they instrument it using a triple interaction between pre-determined country-wide labor costs (which they claim governs the incentives to robotize), the share of workers engaged in replaceable tasks in the industry (They follow Graetz and Michaels (2018) approach to construct replaceable tasks),[8] and the global stock of robots (as a proxy for the price of robots). They find that greater robot intensity in own production leads to a rise in imports sourced from less developed countries in the same industry and more exports to the same countries.

Controlling for sector financial requirements over time, and sector-country of origin imports and year-country of origin fixed effects, results for the US does not reassure Graetz and Michaels (2018) outcomes. Greater robot intensity in US sector production reduces imports sourced from countries which have lower robot penetration in the same sectors.

The aim of this paper is 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. It uses robots per workers, instrumented by robot penetration in Europe, to study employment in around 800 occupations in 285 industries during 2002-2016. To establish the direction of the

[8] 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.

causal mechanism, the paper mixes three standard approaches. First, it focusses 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 (2003 and 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 some non-routine tasks that new technology development is able to automate. So new technologies development should disproportionately reduce labor demand of occupations that mainly perform tasks prone to automation. This approach is in line with Graetz et al (2018) identification method at the sector level, although we are able to go one step further and present evidence of the mechanism its works through: the analysis of the evolution of employment at the sector-occupation level in our dataset. We use Autor et al (2003) tasks analysis, complemented by Frey and Osborne (2017), to define which occupations are prone to automation, or if the tasks they perform have a higher probability of being automated. These two papers do a specific and detail analysis at the tasks and occupation level, and they cover the whole sample of tasks and occupation in ONET data (702 occupations).[9][10]

Second, following Acemoglu and Restrepo (2018), the paper uses as a broad proxy of automation penetration robots per workers at the sector level, instrumented with the average of robots´ penetration in 15 EU countries.

Third, the paper takes advantage of the three-dimension structure of the data used. Data at the sector-occupation-year level allows us to control for initial conditions, and for specific shocks at the sector and year frequency. The occupation dimension allows the paper to

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

specifically control for Chinese and Mexican large import penetration in the last decades, and for the 2008-2009 great depression and financial distress, among other factors. So these factors are not driving our results.

Finally, the paper provides evidence that the proposed approach is able to explain variables that should be affected also by automation beyond employment and wage occupations. US imports in sectors that use occupations prone to automation at the beginning of the period should be affected by new technologies. The benefit of these technologies should be larger in these sectors and therefore comparative advantage should be affected. Imports of commodities produced by these sectors should fall, mainly from countries that are falling behind in the adoption of these new technologies.

To understand the mechanism behind the fall in employment and wages, and therefore on the wage bill, we derive a simple model where production in sector "j" in period "t" is a function of occupations-services which are produced by the aggregation of labor of occupation "o" and capital. We assume there is a different labor-capital elasticity of substitution for each occupation-service. We 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 on the price of 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 b) the initial labor share is large. We test these two additional hypotheses in the data. They hold.

For wage bill, employment and wage, we use data at the occupation-sector-year level. For trade analysis, we use imports at the sector-country of origin-year level data, which also allow us to control for macro and sector effects.

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 our main 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 4-digit NAICS 2007 level. Section 4 concludes.

2. Data and Methodology

Data

Risk of automation

We 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 specifics 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). We are able to merge 698 of these occupations to the OES employment dataset. [11] 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. [12]

For robustness, we construct an alternative proxy for risk of automation. We 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 task, either cognitive or manual are prone to be automated.

Using the Autor et al (2003) codes, we 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. We 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. All tasks are routine cognitive, routine manual, non-routine cognitive analytic, non-routine interpersonal, non-routine manual physical and non-routine manual

[11] 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.
[12] We use 70% to follow the literature. See Frey and Osborne (2017).

interpersonal 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 1a present *FO RISK Probability* of automation for all occupations we are able to match with BLS employment data (698), and our extended set (795). 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 to 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 mean -0.31 and a standard deviation of 3.35.

Table 1a: Summary Statistics: Probability and Risk of Automation at the occupation level.
Frey & Osborne (2017) Probability of Automation and Occupation Routine Task Index

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*	795	-0.31	3.36	-9.13	8.75

Note: *FO RISK probability* represents Frey and Osborne (2017) estimated probability of automation for occupations which we are able to merge with OES data. *FO RISK probability* extended represents the probability used in the paper, which is the probabilities computed by Frey-Osborne and the proxies we used for 97 occupations (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. PROB b is the sum of Autor et al (2003) routine tasks´ indexes minus the sum of the non-routine task indexes.
Source: Authors´ construction using Autor et al (2003) and Frey and Osborne (2017).

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 0.7355 significant at the

1% level. The *Routine Task Index* explain 54% of the variance of *FO RISK Probability.* In Appendix A analyzes the correlation between routine and non-routine task and *FO RISK Probability*. We regress *FO RISK Prob.* on routine and non-routine tasks. All four non-routine tasks indexes have the expected negative sign, although only two of them are significant at standard levels. The coefficients for Routine Cognitive and Manual indexes task are positive as expected.

Figures (1d) 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 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 appendix A, we 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). We still find a negative correlation between log wage and the *FO RISK Probability*.

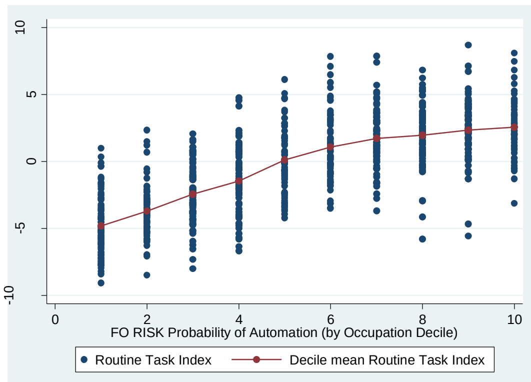
Figure (1d) presents the relationship between the average aggregate annual rate of employment growth for different occupations and the FO RISK Probability (2004-2016).[13] Besides volatility, there is a clear downturn in employment growth in occupations with a higher risk of automation. The correlation coefficient is -0.32 significant at the 1% level.

[13] We use 2004-2016 because for our main results, at occupation-sector instrumented with robots per workers, we only have data for this period.

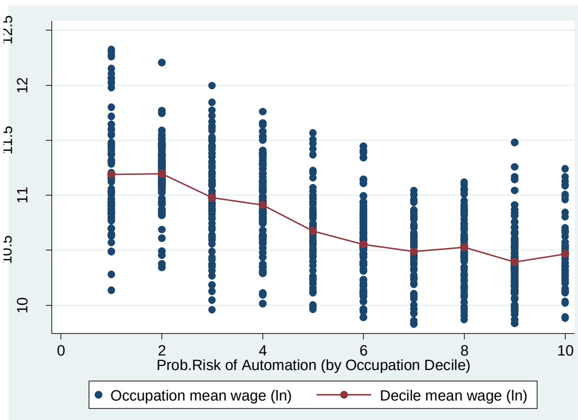
Appendix A shows a steeper decline in wages-bill than in employment of occupations subject to a higher risk of automation during the same period. We find the same relationship with Routine Task Index instead of FO RISK Probability.

Figure 1: Routine Task Index, wages and employment and FO RISK Prob. of automation

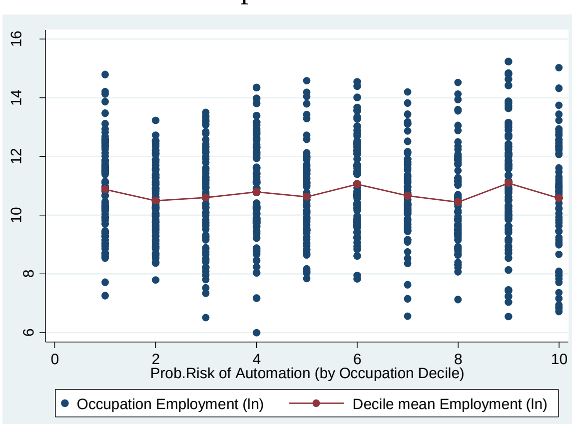
1a: FO RISK Prob. and Routine Task Index
754 Occupations in 2010



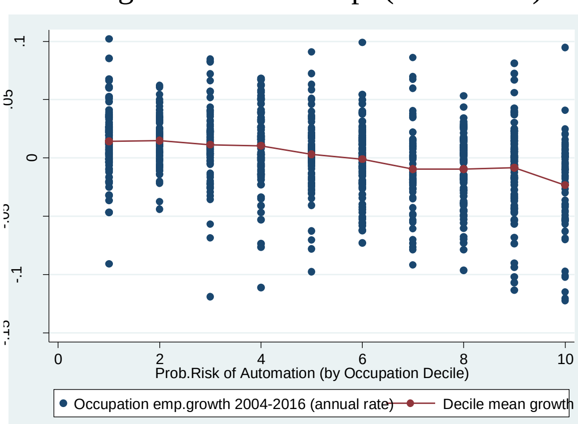
1b: FO RISK Probability and wages (log)
795 Occupations in 2010



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: We split the 795 occupations, defined at 6 digits SOC 2010, into deciles by FO risk of automation. Figure (1a) show the Routine Task Index for 754 occupations. Figure (1b) and (1c) show the 795 log average wages and log employment in 2010. Figure (1d) present the log change of employment divided by 14 for the period 2004-2010.
Source: Authors' calculations.

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, we 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 PROBb).

Employment and Wages

Employment and wage data at occupation and sector level comes from the Bureau of Labor Statistic (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 2000-2016 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 year 2010 and 2011, and SOC 2010 for years between 2012 and 2016. This data does not include the firms' owner. For occupation data at the national level, OES includes the Federal, State and Local government.

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 we construct a subset of occupations we can follow between 2002 and 2016, as well as a set of industries we can also follow over time.[14] We end up with 795 occupations and 285 sectors. We neither include the Federal, State nor Local government.

For each sector, we compute the weighted average probability of automation using as weigh occupation-sector employment in 2004. We 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. We use 2004 because this is the first year we have data for robots per workers in the US at the industry level.

Table 1b presents the evolution of total employment and the simple average for wages covered by OES, the ratio of the mean and median wage, the ratio of percentile 75 and

[14] 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.

percentile 25 and the ratio of percentile 90 and 10, over the period 2000-2016. Table 1c presents the summary statistics of employment (ln), average wage (ln), the weighted average probability of automation and employment at risk of automation at the industry-year level, and at the occupation-industry-year level.

Table 1b: Summary Statistics for Occupation at the Aggregate Level: Total Employment, Average Wage and measures of dispersion by Year

	Employment	Wages					
		At the individual level				Within occup.	Betwen occup.
YEAR	Total	Average	Mean/Median	pc75/pc25	pc90/pc10	pc90/pc10	Std.dev.(ln wage)
2000	129,738,980	32,176				2.70	0.42
2001	127,980,410	34,020	1.26	2.33	4.47	2.68	0.42
2002	127,523,760	35,560	1.28	2.33	4.49	2.67	0.44
2003	127,567,910	36,210	1.29	2.33	4.54	2.66	0.44
2004	128,127,360	37,020	1.29	2.33	4.60	2.67	0.46
2005	130,307,840	37,870	1.29	2.35	4.64	2.67	0.46
2006	132,604,980	39,190	1.29	2.36	4.71	2.67	0.46
2007	134,354,250	40,690	1.30	2.37	4.73	2.65	0.46
2008	135,185,230	42,270	1.31	2.39	4.74	2.66	0.46
2009	130,647,610	43,460	1.31	2.41	4.74	2.64	0.47
2010	127,097,160	44,410	1.31	2.45	4.70	2.65	0.47
2011	128,278,550	45,230	1.31	2.48	4.74	2.66	0.47
2012	130,287,700	45,790	1.32	2.50	4.80	2.67	0.47
2013	132,588,810	46,440	1.32	2.51	4.86	2.70	0.48
2014	135,128,260	47,230	1.33	2.52	4.91	2.71	0.47
2015	137,896,660	48,320	1.33	2.51	4.88	2.73	0.47
2016	140,400,040	49,630	1.34	2.49	4.90	2.74	0.47
Growth 2001/16	9.7%	45.9%	6.6%	7.0%	9.7%	2.5%	12.1%

Notes: Total represents total employment covered by the OES permanent statistics. It includes Federal, State, and Local Government. Only in 2011, OES covered the mining sector. For comparability reason, mining it is not included in this summary statistics. 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. For the year 2010, there is only data at the occupation level, therefore there is not possible to compute percentiles. Source: OES BLS

Table 1b shows that employment in our sample grew by 9.7% during 2001 and 2016. Wages, in nominal terms, increased by 39.8%, and 3% in real terms.[15] At the beginning of the sample real wage fall, and it starts to grow since 2005 (wage growth between 2005 and 2016 is 6.6%).

[15] We use the CPI to deflate nominal variables.

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),[16] 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%.

The increase in aggregate wage dispersion is mainly explained by changes in wages across occupations.

Table 1c presents summary descriptive statistics at the sector level. The sector average share of employment at risk of automation is 0.53. There is heterogeneity across sectors. The standard deviation is 0.20, 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.

Table 1c: Employment, wage, and risk of automation at Occupation and Sectoral level
Occupations at 6-dig SOC system / Sectors 3-4 NAICS dig. (Period 2003-2016)

Occupation-Level	Obsv.	Mean	Std.Dev.	Min.	Max
Employment (ln)	540,143	6.03	1.73	0.67	14.83
Wage (ln)	535,543	10.69	0.49	9.41	12.55
FO RISK Probability	540,143	0.53	0.38	0.00	0.99
FO RISK Index	540,143	0.44	0.50	0.00	1.00

Sector-Level	Obsv.	Mean	Std.Dev.	Min.	Max
Employment (ln)	2,912	12.06	1.39	7.55	16.15
Wage (ln)	2,912	10.65	0.29	9.79	11.53
FO RISK Probability	2,912	0.62	0.15	0.19	0.87
FO RISK Index	2,912	0.53	0.20	0.08	0.90

Note: For occupation-industry-year exercise, we only use data between 2002 and 2016 because years 2000 and 2001 use SIC industry classification instead of NAICS.

[16] 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 deviantions.

Imports and other data

For trade exercise, we 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. We also use Schott's dataset to construct our proxy to control for Chinese and Mexican import penetration.

Finally, to control for financial events at the sector level we use *External Financial Dependence a la* Rajan and Zingales at the sector level interacted with time dummies. We 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, we formalize how automation in general, and robotics and AI in particular, affect the demand for labor, and we 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.[17] 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–

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

replacing capital corresponds to the adoption of new technologies that enable capital to be substituted for labor in a range of tasks.[18] 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 may be 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. Total labor-replacing capital, from now on capital, is given in the economy and it increases over time.

There are different wages for each occupation in each sector (*Woj*). And there is a unique price for capital (P_R).[19] All markets are perfectly competitive, and production has constant returns to scale. In a given sector (j) firms minimize the following costs function:

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

where L_{oj} and R_{oj} represent labor, from occupation "o", and capital used to produce the occupation-service (S_{oj}) in sector *"j"*, respectively. We assume that $a_{oj}=a_o + a_j$. There is a continuous of households with mass one which maximizes the following utility function subject to an income constraint (PY).

[18] As pointed by Acemoglu and Restrepo (2019), automation is the adoption of technologies that allows capital to takes over tasks previously performed by labor.
[19] In the empirical part, we allow for multiple prices for capital.

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

where dj are demand weight. From first-order conditions for labor we have:

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

where

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

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, we 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.

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

where $ShK_{oj} = \lambda_{oj}^{R}\left(P_R / P_{oj}^{S}\right)^{(1-\rho_o)}$ is the capital share in the production of occupation-service "o" in sector "j". ShS_{oj} is the cost share of occupation-service "o" in the production of product "j". Finally, ShY_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 a expenditure share for this occpation 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, "α" lower than one, 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]). Table 2 suggests that the elasticity of substitution across occupation is around 0.3-0.4.

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 ($\sigma<1$) 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. We assume sector specifics production functions. The sector-dimension allows us to study the effect of automation within sectors using a fixed effect model i) at the industry-occupation level, which controls for initial conditions; and ii) at the sector-year level, which controls for 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:

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

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 $(1 - ShL_{oj})$.

Occupation-services with a small labor share increase their relative price after a fall in the price of capital-technology. This reduces the wage bill at the occupation-services level. This fall is larger, the larger is the elasticity of substitution between occupation-services (α).

Table 2: Sector Employment and Wages: Labor Share at the Sector-Occupation Service

	(1)	(2)	(3)	(4)	(5)
Depended Var.	Employment (ln)				
Model	*OLS*	*OLS*	*OLS*	*OLS*	*IV*
Wage (ln)	-0.31	-0.34	-0.40	-0.43	-0.45
	(7.43)**	(7.99)**	(8.94)**	(9.13)**	(9.78)**
IV					Lag wage (ln)
R2	0.10	0.10	0.09	0.10	0.08
OBS	38,093	34137	38093	35762	32,046
FE	Sector	Sector	Sector	Sector	Sector
Sample	2002	2003	2004	2005	2004
Pairwise Correlation errors with 2004	0.95	0.97	1.00	0.94	0.98

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

Note: The first row presents the regression number; the second row describes the model used; the third row describes the independent variable. The "Pairwise Correlation errors with 2004" row present the pairwise correlation between the error term (a proxy for $ln(ShL_{oj})$) and the error for the year 2004.

There are available data for all variable but the occupation "o" labor share (ShL_{oj}). Without loss of generality $ShL_{oj} = \lambda_{oj}^{L}$ for a base year: 2004.[20] [21] I estimate a proxy for λ_{oj}^{L} using equation [1] for labor in occupation "o" in sectors "j" in 2004:[22]

$$\ln\left(L_{oj}\right) = -\alpha \ln(W_{oj}) + D_j + e_{oj} \qquad \text{[Eq:4]}$$

Where $\ln(\lambda_{oj}^{L})$ is the error term e_{oj}. I use the exponential value of the error term to construct our proxy for the labor share. I normalize and get rid of outlier dividing our proxy by the

[20] Lambda and input prices are such that in time 0: $L_{oj}W_{oj} / P_{oj}^{S} S_{oj} = \lambda_{oj}^{L}\left(W_{oj} / P_{oj}^{S}\right)^{1-\rho_o} = \lambda_{oj}^{L}$.

[21] 2004 is both the first year with data for robots at the sector level, and with the most most sector-occupation observations.

[22] $L_{oj}W_{oj} = \lambda_{oj}\left(P_{oj}^{S} / W_{oj}\right)^{\rho_o-\alpha} W_{oj}^{1-\alpha} a_j d_j \left(P_j\right)^{\alpha-\sigma} PY$

exponential value of the error term in the percentile 90, and taking the minimum between the previous term and one ($Sh\hat{L}_{oj} = \min(\exp(e_{oj}) / \exp(e_{p90}),1)$). For robustness, I redo all exercise using only the exponential value of the error term. Results hold. The previous result uses the assumption $(a_{oj} = a_o \ a_j)$, without it, I recover $\ln(\lambda_{oj}^{L} \ a'_{oj})$ which is still a good proxy for $Sh\hat{L}_{oj}$ unless the two technology parameters λ_{oj}^{L} *and* a'_{oj} are correlated.

Table [2] presents our results for [Eq:4] using four different base years (2002-2005). The elasticity of substitution across occupation-services (α) is between -0.31 and -0.45. The pairwise correlations between error terms in 2004 and the other three years are above 0.94.

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

$$\begin{aligned} Ln(X_{ojt}) = D_{oj} + \beta^{R} RISK_o \ P_{R,t} - \beta_t^{RxShL} \ Sh\hat{L}_{oj} \ RISK_o P_{Rt} \\ + \gamma^{Sh\hat{L}} \ Sh\hat{L}_{oj} \ P_{Rt} + \sum_{t=to}^{2016} \mu_t \ Z_o D_t^{Z} + D_{jt} + e_{ojt} \end{aligned} \qquad \text{[Eq.5]}$$

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 risk of automation. $Sh\hat{L}_{oj}$ is our proxy for the labor share of occupation “o” in occupation-service “o” in sector “j”. $P_{R,t}$ is the proxy for labor-replacing capital. In the empirical section, we use either year dummies or robots per workers at the sector level to account for the evolution of capital price. Z_o are additional occupation level controls. D_{jt} accounts for sector-year shocks.

To get rid of any reverse causality between robots and occupation-sector movement of employment, we follow Acemouglu and Restrepro (2018), and we instrument robots per workers at the sector level in the USA with the average of robots per workers in 15 EU countries.

If *Routine Task Index*, *FO RISK Index*, and *FO RISK Prob.* measure the risk of automation, when we use dummies to account to the evolution of capital prices, we should expect a decreasing value for dummy coefficients (year dummies x RISKo). Under the framework presented in [Eq.1], the wage in different quantiles of the distribution should have the same pattern, and therefore wage dispersion within occupations should remain constant. Following Autor et al (2003), we use the ln ratio between the 90th and 10th quantile as a proxy for wage dispersion within occupations.

We control for initial wage level interacted with year dummies. As we show in Figure 1 there is a clear negative correlation between risk of automation and occupation wages, so our $RISK_o$ variable (interacted with year dummies or robots per workers) could capture a specific trend of low wages occupations in the whole economy. For example, migration may have increased the supply of low wage occupations and therefore it may have reduced wages in these occupations.

Sector Level Approach.

The last set of econometric results study the effect of automation on employment and imports at the sector level. We use sector import because of its disaggregate data availability (4 digits NAICS level). To study the effect of automation on sector imports, we 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* $_j$). To be able to compute automation variables for sectors in the mining industry, we use employment data from the year 2011 to compute our weighted means.[23]

For sector wage bill, employment, and average wage we estimate a sector and year fixed effect model. We 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.[24] 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.[25]

For log imports, we estimate a sector-“country of origin” and “country of origin”-year fixed effect model. There is a sample of countries which 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 we either split the sample in countries with high and low robots per worker penetration, or we 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, we also control for a vector of variables that vary at the sector-year level (financial variables).

3. Results

[23] The BLS OES data covers more sector in 2011. This is the only year with data for the mining industry.
[24] We follow Chor and Manova (2012) to account for the credit financial crises on trade.
[25] We follow Autor et al (2016) to control for Chinese and Mexican import penetration in the USA:

This section presents our estimation results. The first subsection presents a first aggregate set of results using national occupational employment and wage data from the OES program. The second subsection presents our main results using national occupational employment and wages at the industry level. The last 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.

National Occupational Results

In this subsection, we present a broad description of the evolution of occupations at risk of automation. We study the evolution of employment and wages for 795 occupations at the national level for the period between 2000 and 2016.[26] Aggregate data, at the national level, includes Federal, State, and Local government. [27]

To describe wage bill, employment and wages, at the occupation-year level, we estimate the following model:

$$Ln(Y_{ot}) = D_o + \beta^R \; RISK_o \; P_{R,t} + \sum_{t=to}^{2016} \mu \;\; Z_o D_t^Z + D_t + e_{ot}$$

where Y_{ot} is either the wage bill, the average wage or employment in occupation “o” in period “t”. D_o accounts for initial conditions. $RISK_o$ is the proxy for occupation risk of automation. $P_{R,t}$ is our proxy for the evolution of capital-technology price. In the main text, we use a set of time dummies, and in some regressions in Appendix B, we use the aggregate ratio of robots per workers in the US over time instead of the dummies variables. Zo are additional controls.

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

[27] It include the Federal Executive Branch and United States Postal Service, State Government and Local Government.

In particular, for employment, we control for the initial average wage at occupation level interacted with year dummies (D_t^Z). D_t accounts for year level shocks.

This econometric model is equivalent to assume there is an aggregate production function, the elasticity of substitution between occupation-services is equal to one (α=1), the capital share in the production of occupation-services is the same for all occupations (ShK_o=cte), and there is a linear relationship between the risk of automation and the elasticity of substitution between occupation-labor "o" and capital-technology $(\rho_o = r + \beta^R \; Risk_o)$.

With these restricted assumptions we find that occupations at risk of automation present a lower rate of employment growth (minus 1.91-2.56% per year) and also a lower rate of wage growth (-0.3% per year) during the period 2002-2016.[28] Wages in the upper part of the distributions drive this fall in average wages. Appendix B presents a complete analysis of aggregate occupation data. This analysis is mainly descriptive because it requires strong assumptions to prove a causal effect.[29]

Figure (2a) presents the 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 (Table Ba). We observe 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 by dummies), relative employment of occupation at risk of automation falls. Relative wage bill and employment grow at an average annual relative rate of -2.98% and -

[28] We report growths between 2002-2016 to compare with sector-occupation results.
[29] To have a causal effect, we require that other factors that affect the demand of occupations are orthogonal to the vector of occupation risks.

2.56%, respectively. There is a rapid decline pre-2008, a sharp fall in the 2008-2009 financial crises, and a moderate posterior decline.

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% (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) 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 period 2002 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 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.

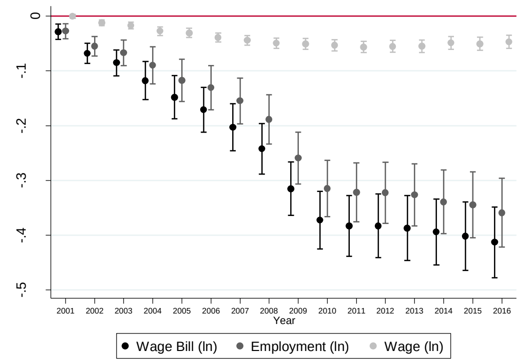
Appendix B presents robustness checks. We use alternative proxies for risk of automation (Routine Tasks Index and FO RISK Probability). With Routine Task Index instead of FO RISK Index, we find that annual employment growth in occupation in the percentile 80th is -1.91% lower than occupation in the percentile 20th of the Routine Task Index. This coefficient compares with -2.10% and -2.56% when we use FO RISK Index and we control or not for initial wages, respectively (Figure 2 and Table B). Appendix B also uses robots per workers as a proxy of labor-replacing capital price instead of year dummies. We instrument robots per workers at the aggregate level in the US with the simple average of the same variable for 15 EU countries (Table Bb). With robots per workers, we find that employment growth in occupations at RISK of automation is -1.9%/3.2% lower relative to other occupations. Appendix B also present growth models for wage bill and employment. In all cases, results hold.

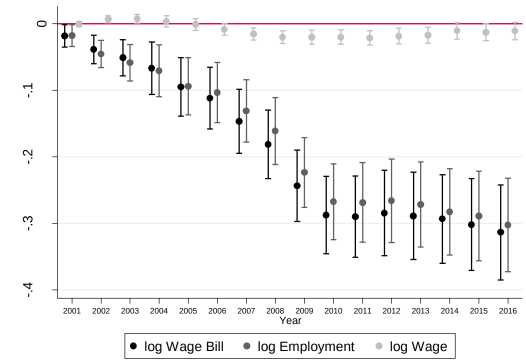
These results show that automation within occupations at risk does not explain the observed increase in wage dispersion in OES data reported in Table 1. Wage dispersion across occupations increases because wages in occupation at risk of automation, which are on average low, fall until 2011 and then they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

Figure 2: Wage Bill, Employment, Wages and Occupation Risk of Automation
Aggregate Data (Period 2000-2016)
Coefficient from Table Ba

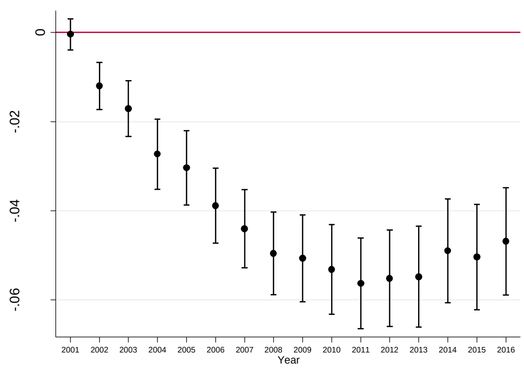
2a: All variables w/o control

2b: All variables w/control initial wage

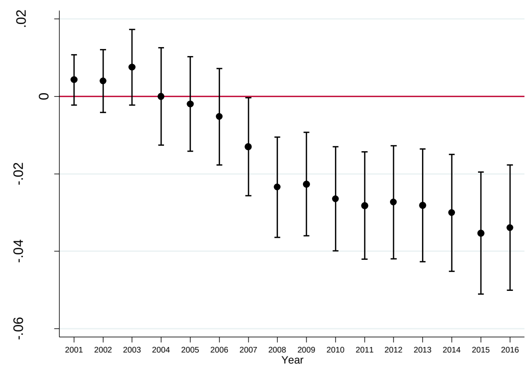




2c: Average Wage w/o control



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



Source: Authors´ construction.

Occupation employment and wages at the sector-occupation level

Previous 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 2000-2016. In this section, we control for different trend and sectoral shocks. 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 more capital-technology intensive (and therefore with a higher capital share -ShK_o-). A fall in the price of capital-technology reduces the relative price of capital intensive occupation-services. An elasticity of substitution between occupation-services larger than r (r<α) –the constant coefficient in the linear relationship between the capital-labor elasticity and the risk of automation- implies a reduction in the labor demand in these capital intensive occupation-services (See [Eq:3]).[30]

Tables (4a), (4b) and (4c) report our results using [Eq.5] for wage bill, employment and wages at the sector-occupation level. We allow for different sector production functions elasticity of substitution between sectors different from one (σ≠1). In Table (4b) and (4c) we also allow for different capital share (or equivalent labor share) at the occupation-services level $\left(ShL_{oj} \neq ShL_{qh}\right)$, and positive cross elasticity of occupation-services different from one $\left(0 < \alpha \neq 1\right)$.

For the period 2002-2016 the OES dataset allows us to study employment and wage at the occupation-sector level. We 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 composition effects and aggregate technology shocks (third and fourth term in [Eq:2]). We assume there is a linear relationship between the risk of automation/routine tasks and the elasticity of substitution between capital and labor $\left(\rho_o = r + \beta^R \ RISK_o\right)$. We integrate [Eq: 3] and we obtain [Eq:5] .

$$\begin{aligned} Ln(X_{ojt}) = D_{oj} + \beta^R RISK_o \ P_{R,t} - \beta_t^{RxShL} \ S\hat{h}L_{oj} \ RISK_o P_{Rt} \\ + \gamma^{S\hat{h}L} \ S\hat{h}L_{oj} \ P_{Rt} + \sum_{t=to}^{2016} \mu_t \ Z_o D_t^Z + D_{jt} + e_{ojt} \end{aligned}$$

[30] 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 (0<α<1). See [Eq:2].

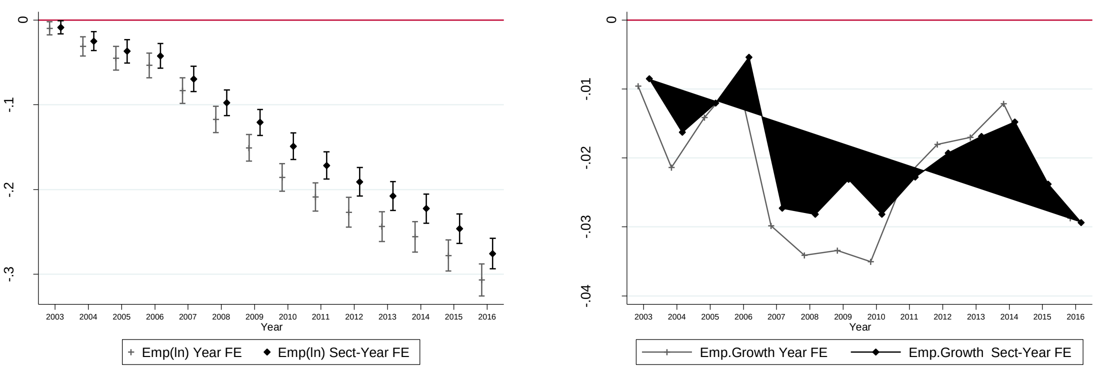
It is important to note that $\gamma^{S\hat{h}L}$ is proportional to "α" minus "r" $\left(\gamma^{S\hat{h}L} \propto (\alpha - r)\right)$, therefore the coefficient could be positive or negative. We are only able to identify dummies term interacted with deep parameters $\left(eg.\ \beta^{R}\ P_{Rt}\right)$.

Tables (4a) and (4b) and Figures (3) to (7), present our results for wage bill, employment, and wages using dummies to proxy for capital-technology price at the country level (P_{Rt}).

Figure 3: Sector-Occupation Employment, and Risk of Automation,
Controlling and not for Sectoral Shocks
Sectoral data at 3-4 NAICS dig. Level (Period 2002-2016)

3a: Employment (ln)
Coef.Columns (1)&(2), Table (4a)

3b: Change Employment (ln)
First diff.Coef. Columns (1)&(2), Table (4a)



Source: Authors´ construction.

To compare with aggregate results, Column (1) in Table (4a) presents results for (log) sector-occupation employment imposing a unique labor share across occupation-services $\left(S\hat{h}L_{oj} = cte\right)$, and controlling only for year fixed-effect $(\sigma = 1)$. Columns (2)-(5) also impose a unique labor share but control for sector-year fixed effect for (log) wage bill, (log) employment and (log) wages $(\sigma \neq 1)$, respectively. Results at the aggregate level, section 2.1, hold within industries. Controlling by sector-occupation and sector-year fixed effects, Columns (2) and (3), and Figure (4a), show that wage bill and employment in occupations at risk of automation has been falling, in relative term to other occupations within the same sector, at an annual rate of -2.45% and -2,28% per year, respectively. These falls are smaller, in absolute value than the one we get using aggregate data, -2.98% and -2.56% during the same period 2002-2016, respectively (Figure 2 and Table B1).[31] As already mentioned, aggregate data includes Federal, State, and Local government, whereas sector data does not, therefore we have to take with caution this comparison.

To see how results change once we control for sectoral shocks, Figure (3) present (log) employment results from Column (1) and (3). Without sector-year fixed effect, sector-occupation (log) employment of occupations at RISK fall -2.59% per year relative to the rest of the economy, whereas when we control for sectoral shocks this fall is -2.28% per year. Figure (3b) shows this difference originates during the 2008-2010 period. Figure (3) **suggests** there is a "cleaning effect" around the 2008 financial recession. Firms in all sectors seem to adjust more occupations which 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.

Column (4) presents the evolution of relative wages for occupations at risk of automation (Figure 5a). Their wages fall during the first half of the sample. In 2010, they are 3% lower in relative term to the other occupation vis a vis 2002. After 2010, they start to recover. By the end of the sample, they are 2% lower than in 2002. Aggregate data (Table 3a), present a similar pattern, they fall to -5.6% in 2011 and then they recover to -4.7% by the end of the period. This result reinforces the idea that sectors with a high share of employment at risk of automation have been losing employment share in the economy during our period of analysis.

[31] Average percentage for aggregate data are calculated for the same period (2002-2016). For wage bill this is $(1+(-0.413+0.068))^{1/14}-1$.

Table 4a: Sector-Occupation Employment and Risk of Automation
Sectoral data at 3-4 NAICS dig. Level (Period 2002-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Depended Var.	Emp (ln)	Wage Bill (ln)	Emp.(ln)	Wage (ln)	Wage Q90/Q10(ln)	Wage Bill (ln)	Emp.	Wage Bill (ln)	Emp. (ln)	Wage Bill (ln)	Wage Bill (ln)
Independed Var.	*RISK>0.7*	*RISK>0.7*	*RISK>0.7*	*RISK>0.7*	*RISK>0.7*	*RISK>0.7*	*RISK>0.7*	*Rout.Task*	*Rout.Task*	*Q.Rout.Task*	*FO PROB*
Ind. Var. X 2003	-0.010	-0.015	-0.008	-0.009	0.002	-0.017	-0.021	-0.009	0.005	-0.008	-0.019
	(0.004)*	(0.004)**	(0.004)*	(11.02)**	(1.15)	(3.74)**	(4.56)**	(1.91)	(0.005)	(0.006)	(0.005)**
Ind. Var. X 2004	-0.031	-0.038	-0.025	-0.016	0.009	-0.061	-0.066	-0.005	0.018	-0.004	-0.029
	(0.006)**	(0.006)**	(0.006)**	(13.43)**	(4.47)**	(8.97)**	(9.79)**	(0.67)	(0.007)*	(0.008)	(0.007)**
Ind. Var. X 2005	-0.045	-0.056	-0.037	-0.022	0.012	-0.084	-0.087	-0.012	0.020	-0.018	-0.047
	(0.007)**	(0.007)**	(0.007)**	(15.44)**	(5.06)**	(10.15)**	(10.68)**	(1.33)	(0.009)*	(0.010)	(0.009)**
Ind. Var. X 2006	-0.053	-0.067	-0.042	-0.027	0.010	-0.102	-0.105	-0.011	0.031	-0.021	-0.058
	(0.007)**	(0.007)**	(0.007)**	(17.86)**	(4.38)**	(11.76)**	(12.27)**	(1.21)	(0.009)**	(0.011)*	(0.009)**
Ind. Var. X 2007	-0.083	-0.097	-0.069	-0.031	0.005	-0.123	-0.126	-0.042	0.007	-0.060	-0.099
	(0.008)**	(0.008)**	(0.008)**	(20.07)**	(2.26)*	(13.75)**	(14.32)**	(4.34)**	(0.010)	(0.011)**	(0.010)**
Ind. Var. X 2008	-0.117	-0.125	-0.098	-0.029	-0.001	-0.137	-0.142	-0.077	-0.026	-0.096	-0.136
	(0.008)**	(0.008)**	(0.008)**	(19.07)**	(0.43)	(15.04)**	(15.79)**	(7.77)**	(0.010)*	(0.011)**	(0.010)**
Ind. Var. X 2009	-0.151	-0.145	-0.121	-0.027	0.000	-0.148	-0.154	-0.100	-0.056	-0.120	-0.170
	(0.008)**	(0.008)**	(0.008)**	(17.42)**	(0.09)	(16.11)**	(16.95)**	(9.97)**	(0.010)**	(0.011)**	(0.010)**
Ind. Var. X 2010	-0.186	-0.173	-0.149	-0.027	-0.003	-0.164	-0.173	-0.143	-0.094	-0.168	-0.209
	(0.008)**	(0.008)**	(0.008)**	(17.23)**	(1.09)	(17.41)**	(18.52)**	(13.96)**	(0.010)**	(0.011)**	(0.010)**
Ind. Var. X 2011	-0.209	-0.195	-0.172	-0.026	-0.004	-0.181	-0.192	-0.168	-0.121	-0.195	-0.234
	(0.009)**	(0.008)**	(0.008)**	(16.20)**	(1.69)	(18.52)**	(19.84)**	(16.00)**	(0.011)**	(0.012)**	(0.010)**
Ind. Var. X 2012	-0.227	-0.214	-0.191	-0.025	-0.002	-0.194	-0.209	-0.192	-0.143	-0.223	-0.264
	(0.009)**	(0.009)**	(0.009)**	(15.59)**	(1.03)	(19.03)**	(20.66)**	(17.66)**	(0.011)**	(0.012)**	(0.011)**
Ind. Var. X 2013	-0.244	-0.233	-0.208	-0.027	-0.004	-0.21	-0.226	-0.213	-0.160	-0.247	-0.289
	(0.009)**	(0.009)**	(0.009)**	(16.51)**	(1.76)	(20.45)**	(22.24)**	(19.18)**	(0.011)**	(0.012)**	(0.011)**
Ind. Var. X 2014	-0.256	-0.247	-0.223	-0.026	-0.006	-0.223	-0.24	-0.227	-0.175	-0.265	-0.308
	(0.009)**	(0.009)**	(0.009)**	(15.59)**	(2.61)**	(21.45)**	(23.29)**	(20.00)**	(0.011)**	(0.013)**	(0.011)**
Ind. Var. X 2015	-0.278	-0.268	-0.246	-0.022	-0.011	-0.24	-0.258	-0.252	-0.203	-0.296	-0.335
	(0.009)**	(0.009)**	(0.009)**	(13.00)**	(4.52)**	(22.62)**	(24.57)**	(21.76)**	(0.012)**	(0.013)**	(0.011)**
Ind. Var. X 2016	-0.307	-0.293	-0.276	-0.016	-0.012	-0.262	-0.285	-0.273	-0.227	-0.324	-0.368
	(0.010)**	(0.009)**	(0.009)**	(9.74)**	(5.09)**	(24.20)**	(26.47)**	(22.99)**	(0.012)**	(0.013)**	(0.011)**
Fixed effects	Sect-Occ & Year	Sect-Occ & Sect-Year		Sect-Occ & Sect-Year		Sect-Occ & Sect-Year		Sect-Occ & Sect-Year		Sect-Occ & Sect-Year	
Ini.Wage (ln) x D.Year	No	No	No	No	No	Yes	Yes	No	No	No	No
Marg.Eff. 2016-02 /(p80-p20)	-0.307	-0.293	-0.276	-0.016	-0.012	0	0	-0.19	-0.16	-0.24	-0.35
OBS	536,137	531,496	536,137	531,496	500,346	531276	534997	514,291	518,442	514,291	531,496
Max.Likelihood	-282834	-263648	-259605	570862	318450	-263058	-258113	-251772	-247784	-251635	-263459

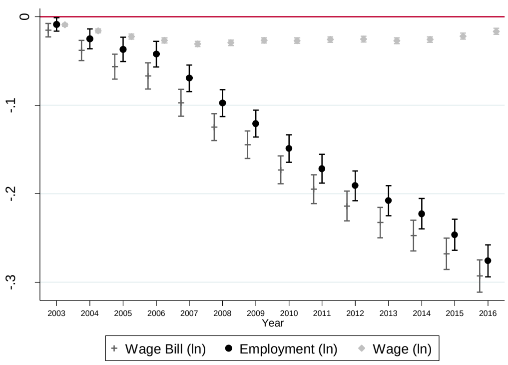
Standard errors allow for within occupation correlation * $p<0.05$; ** $p<0.01$

Note: The first row presents the regression number; the second row describes the dependent variable; the third row describes the proxy we 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) sector-occup. initial wage interacted with a year dummy as independent variables. The sector-occ. initial w*age* is the log wage of occupation "o" in sector "j" in the year 2002. We use the year 2002 because is the first year with sector-occ. data. Regressions (7) and (8) 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 Mag.Eff.2016-02 Risk (p80-p20) presents the predicted log difference between occupations in the percentile 80 and 20 of the proxy of risk of automation between 2016 and 2002. In case we use {0;1} FO RISK index, the difference is between occupations at RISK and not. Regressions use wage bill, employment and wages (ln) for 780 occupations defined and covered by the BLS Occupational Employment Statistics (OES) program at sector level. 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).

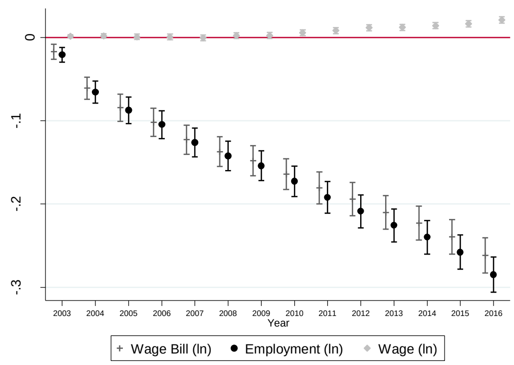
After an initial small jump, wage dispersion in occupations at risk of automation, relative to dispersion in other occupations, have been falling slightly during the whole period. The initial jump in wage inequality comes from an initial fall in wages at the bottom of the distribution larger than the 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 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 1.5% below their initial position.

Figure 4: Sector-Occupation Wage Bill and Employment, and Risk of Automation
Sectoral data at 3-4 NAICS dig. Level (Period 2002-2016)

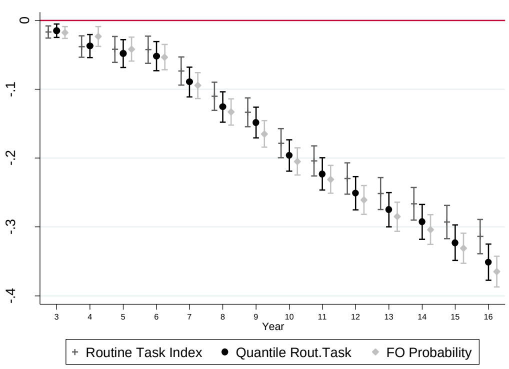
4a: Results using FO RISK index w/o controlling for initial wage



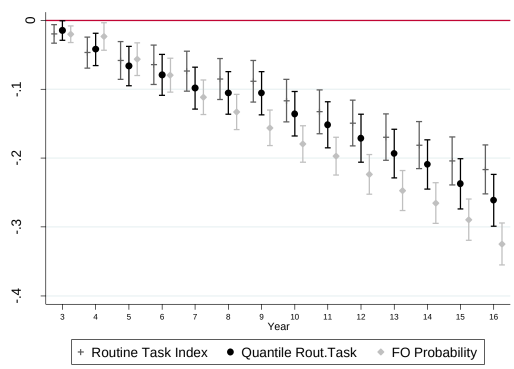
4a: Results using FO RISK index controlling for initial wage



4c: Wage-Bill using different risk proxies w/o controlling for initial wage



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



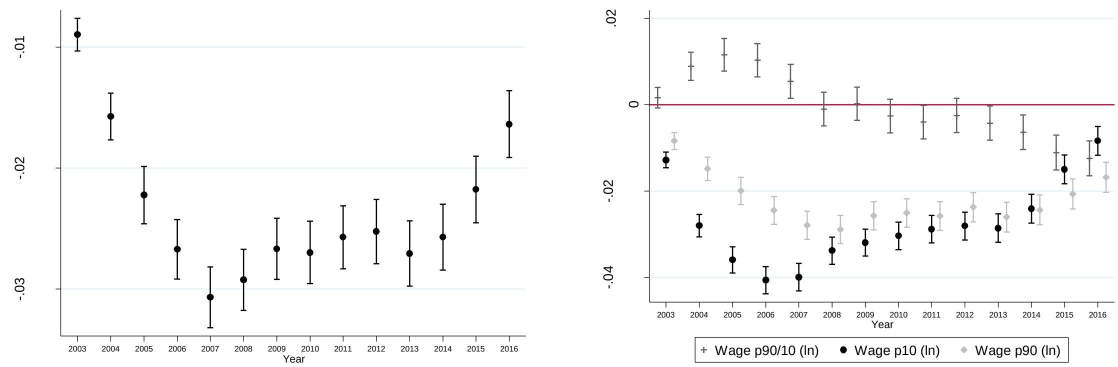
Source: Author´s estimation.
Note: Figure 4a plots results in columns (1) to (3) in Table 4a. Figure 4b plots result from columns (4) and (5) plus unreported results for average wages. In all previous cases, we report FO RISK index interacted with year dummies. In Figures 4c and 4d we report results for wage bill using Routine Tasks Index, Quantile of Routine Tasks Index and FO continuous probability of automation as a proxy for automation risk.

Results for employment and wages suggest that occupations at risk of automation suffer a demand shock within sectors, and sector 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. The negative demand shock reduces wages in the whole distribution within occupations, although the effects it is initially larger for wages at the bottom of the distributions. By the end of the period, the effect is quite similar in the whole distribution, even slightly large for wages at the top of the distribution.

Figure 5: Occupation-Wage and Risk of Automation
Sectoral data at 3-4 NAICS dig. Level (Period 2002-2016)

5a: Average Wage (ln)
Coefficient from Column (3) in Table 4.

5b: Wage Dispersion (Q90/Q10) (ln)
Wages in Q10 and Q90.



Source: Author´s estimation.
Note: Figure 5a plots results in columns (3) in Table 4a. Figure 4b plots result from column (4) and from two unreported regressions. In all cases, we report FO RISK index interacted with year dummies.

Figure (4b) presents coefficients of regressions (2) to (4) in Table (4a) now controlling for sector-occupation initial wages (log wages in 2002 interacted with a year dummy).[32] Once we control for initial wages, the wage bill and employment become almost indistinguishable. In both cases, they present a monotonic fall during the whole period. In line with results in Columns (1) to (4), wage bill and employment present a monotonic fall during the whole period. By the end of the period occupations at risk of automation have lost, relative to other occupations, -29% of their wage bill and -28% of employment. Contrary to previous results, after controlling for initial sector-occupation wages, the coefficient for the average wages at the occupation-sector level present a slightly upward trend. This result suggests that, after

[32] We include 14 dummies interacted with initial sector-occuaption wages.

controlling for initial conditions, initial occupation/sector wages interacted with year dummies may be capturing the effect of capital-technology prices on wages and vice versa.

Figure (4c) and (4d) redo the previous model regressions using 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 (interacted with time dummies) whereas (4d) does. For both sets of exercises, we find that wage bills fall monotonically during the whole period. Without initial wages controls, occupations with *Routine Task Index* in the 90th percentile reduce their relative wage bill by -31% relative to occupations with *Routine Task Index* in the 10th percentile during the whole period (See Column (7) in Table 4a). For employment, this percentage is -27% (Not reported in Table 4a). Similar to our results with FO RISK index, when we use our routine task index the contraction in the wage bill fall, in absolute term, from 31% to 26% when we control for initial wages. We obtain similar results when we use Quantile of the *Routine Task Index* instead of the continuous index (Column (10)), and when we use the continuous index FO RISK Probability (Column (11)).

Table (4b), presents previous results allowing for different labor share across occupations-services and sectors $\left(S\hat{h}L_{oj} \neq S\hat{h}L_{qh}\right)$. 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, we should expect falling coefficients for the risk parameter and the labor share parameter, and increasing for the interacted term (see Eq:5).

Columns (1) and (2), and Figure (6a), (6b) and (6c) use FO RISK Index; and column (3) and Figure (6d) use 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:6a], the solid black circle in Figure (6) shows the decreasing and monotonic evolution of the FO RISK parameter. We find the same behavior for wage bill when we control or not for the initial log sector-occupation wages (Columns (2) and (1), and Figure (6b) and (6a)), respectively, and when we use as dependent variable log employment (Figure (6d)). Also, as predicted, the coefficient for RISK interacted with the share of employment at the sector-occupation service level has the opposite trend and it is positive and increasing.

Finally, the coefficient for labor share alone is negative and decreasing, although not monotonically. Its negative sing implies that the composition effect always reduces the demand for occupation at risks relative to the base year 2002. [Eq.6a] implies that the cross elasticity of substitution between occupation services (α) is higher than the fixed component (r<α) of the elasticity of substitution between occupation employment and capital-technology $\left(\rho_o = r + \beta^R \; RISK_o\right)$. Results suggest that the composition effects at the occupation-service level is important and reduce the demand for occupations at risk of automation. When we use our routine task index instead of the FO RISK, Column (3) in Table 4b and Figure (6b) show similar results for the evolution of our proxy for risk of automation and its interaction with occupation-service labor share, although they are larger in absolute value. When we use Routine Tasks Index, the evolution of the labor share alone coefficient is different from previous ones. Its magnitude is smaller in absolute term, and it increases during the first three years relative to the base year 2002, and it only starts to fall in 2005. This result is odd, and suggest that we do not have econometric power to isolate between the composition effect of occupation-services from the two others component of the impact of capital-technology prices on labor demand when we use our routine tasks proxy.

Table 4b: Wage Bill, Employment, Risk of Automation and Occ.-Service Labor Share
Sectoral data at 3-4 NAICS dig. Level (Period 2002-2016)

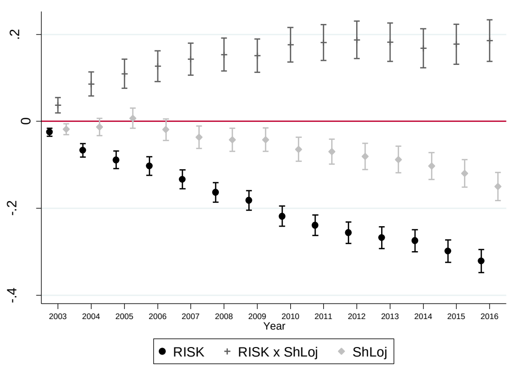
	(1)			(2)			(3)			(4)	(5)
Depended Var.	Wage Bill (ln)			Wage Bill (ln)			Wage Bill (ln)			Wage Bill (ln)	Wage Bill (ln)
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)		
Independed Var.	*RISK*	*RISK x ShL*	*ShL*	*RISK*	*RISK x ShL*	*ShL*	*Rout.Task*	*Rout.Task x ShL*	*ShL*	*RISK T.Effet*	*Rout.Task T.Effet*
Ind. Var. X 2003	-0.013	0.036	-0.000	-0.012	0.038	-0.001	-0.014	0.037	-0.001	-0.020	-0.023
	(0.003)**	(0.009)**	(0.004)	(0.004)**	(0.011)**	(0.004)	(0.004)**	(0.009)**	(0.004)	(5.15)**	(3.95)**
Ind. Var. X 2004	-0.040	0.084	0.027	-0.029	0.098	0.026	-0.049	0.085	0.026	-0.054	-0.048
	(0.005)**	(0.014)**	(0.007)**	(0.007)**	(0.018)**	(0.007)**	(0.006)**	(0.014)**	(0.007)**	(7.96)**	(4.71)**
Ind. Var. X 2005	-0.054	0.107	0.058	-0.041	0.129	0.056	-0.070	0.109	0.056	-0.068	-0.057
	(0.007)**	(0.017)**	(0.009)**	(0.009)**	(0.022)**	(0.009)**	(0.008)**	(0.017)**	(0.009)**	(7.75)**	(4.36)**
Ind. Var. X 2006	-0.063	0.124	0.040	-0.042	0.137	0.038	-0.083	0.126	0.037	-0.082	-0.066
	(0.007)**	(0.018)**	(0.009)**	(0.010)**	(0.023)**	(0.009)**	(0.009)**	(0.018)**	(0.009)**	(8.74)**	(4.76)**
Ind. Var. X 2007	-0.089	0.140	0.030	-0.074	0.161	0.028	-0.097	0.142	0.029	-0.114	-0.111
	(0.008)**	(0.018)**	(0.009)**	(0.010)**	(0.024)**	(0.009)**	(0.009)**	(0.018)**	(0.009)**	(11.86)**	(7.81)**
Ind. Var. X 2008	-0.115	0.150	0.030	-0.109	0.183	0.028	-0.110	0.151	0.029	-0.145	-0.156
	(0.008)**	(0.019)**	(0.010)**	(0.010)**	(0.024)**	(0.010)**	(0.009)**	(0.019)**	(0.010)**	(14.93)**	(10.83)**
Ind. Var. X 2009	-0.134	0.148	0.029	-0.132	0.171	0.027	-0.118	0.147	0.030	-0.167	-0.181
	(0.008)**	(0.019)**	(0.010)**	(0.010)**	(0.025)**	(0.010)**	(0.009)**	(0.019)**	(0.010)**	(16.97)**	(12.33)**
Ind. Var. X 2010	-0.163	0.172	0.019	-0.173	0.201	0.017	-0.135	0.172	0.021	-0.203	-0.238
	(0.008)**	(0.020)**	(0.010)	(0.010)**	(0.025)**	(0.010)	(0.009)**	(0.020)**	(0.010)*	(20.17)**	(15.94)**
Ind. Var. X 2011	-0.182	0.177	0.016	-0.193	0.210	0.014	-0.148	0.176	0.019	-0.226	-0.263
	(0.008)**	(0.020)**	(0.010)	(0.011)**	(0.026)**	(0.010)	(0.010)**	(0.020)**	(0.010)	(21.74)**	(17.14)**
Ind. Var. X 2012	-0.197	0.184	0.008	-0.215	0.238	0.006	-0.156	0.180	0.012	-0.245	-0.297
	(0.009)**	(0.021)**	(0.011)	(0.011)**	(0.027)**	(0.011)	(0.010)**	(0.021)**	(0.011)	(22.54)**	(18.55)**
Ind. Var. X 2013	-0.211	0.178	-0.002	-0.235	0.238	-0.003	-0.168	0.175	0.002	-0.261	-0.325
	(0.009)**	(0.022)**	(0.011)	(0.012)**	(0.028)**	(0.011)	(0.010)**	(0.022)**	(0.011)	(23.70)**	(19.79)**
Ind. Var. X 2014	-0.222	0.164	-0.023	-0.248	0.237	-0.024	-0.178	0.162	-0.019	-0.275	-0.346
	(0.009)**	(0.022)**	(0.011)*	(0.012)**	(0.029)**	(0.011)*	(0.010)**	(0.022)**	(0.011)	(24.56)**	(20.64)**
Ind. Var. X 2015	-0.243	0.174	-0.035	-0.271	0.258	-0.036	-0.197	0.172	-0.032	-0.302	-0.381
	(0.009)**	(0.023)**	(0.012)**	(0.012)**	(0.029)**	(0.012)**	(0.011)**	(0.023)**	(0.012)**	(26.40)**	(22.25)**
Ind. Var. X 2016	-0.263	0.182	-0.060	-0.279	0.278	-0.063	-0.220	0.180	-0.057	-0.330	-0.404
	(0.009)**	(0.024)**	(0.012)**	(0.012)**	(0.030)**	(0.012)**	(0.011)**	(0.024)**	(0.012)**	(28.18)**	(23.06)**
γ^{ShL} / β^{R}											
Fixed effects	Sect-Occ & Sect-Year			Sect-Occ & Sect-Year			Sect-Occ & Sect-Year			Sect-Occ & Sect-Year	
Ini.Wage (ln) x D.Year	No			Yes			No			No	No
Marg.Eff.2016-00	-0.263	0.182	-0.060				-0.220		-0.057	-0.330	-0.404
OBS	437168			436,995			437,168			437,168	437,168
Within R2 Adj.	0.01			0.015			0.010			0.012	0.009
Max.Likelihood	-198089			-197,465			-198,664			-198,228	-198,861

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

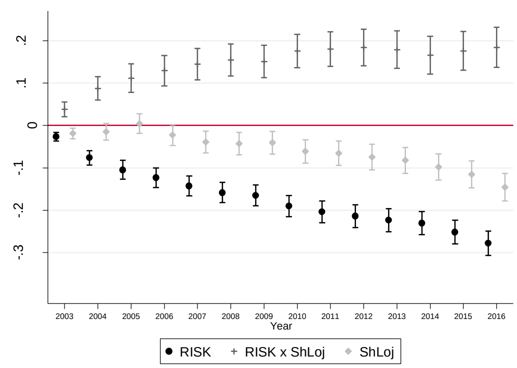
Previous results allow different values for year dummies in each of the three main independent variables: Risk of automation, Risk of automation interacted with sector-occupation labor share, and sector-occupation labor share. If time dummies account for the evolution of the price of capital-technology price, year dummies interacted with main independent variables should be the same. Columns (4) and (5) presents results for wage bill imposing the same time dummies for the three independent variables. To do so, we use a maximum likelihood model where we create a new variable that captures the three previous effects together $\left(TE_{oj} = RISK_j - \beta^{RiskxShL} RISK_j S\hat{h}L_{oj} + \beta^{ShL} S\hat{h}L_{oj}\right)$, and we interact with year dummies.

Figure 6: Wage Bill, and Risk of Automation and Occupation-Service Labor Share
Sectoral data at 3-4 NAICS dig. Level (Period 2002-2016)

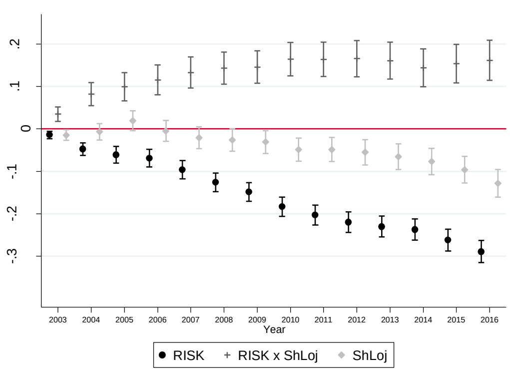
6a: Wage-Bill, FO Risk and O-S L.Share w/o controlling for initial wage



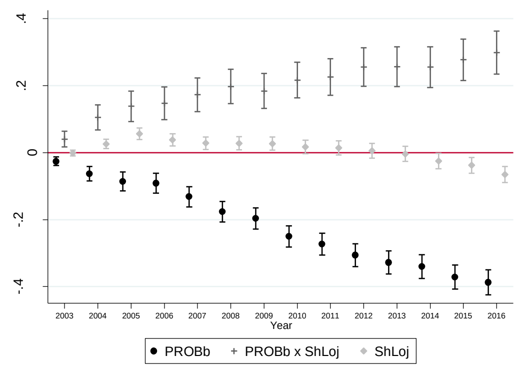
6b: Wage-Bill, FO Risk and O-S L.Share controlling for initial wage



6c: Employment, FO Risk and O-S L.Share w/o controlling for initial wage



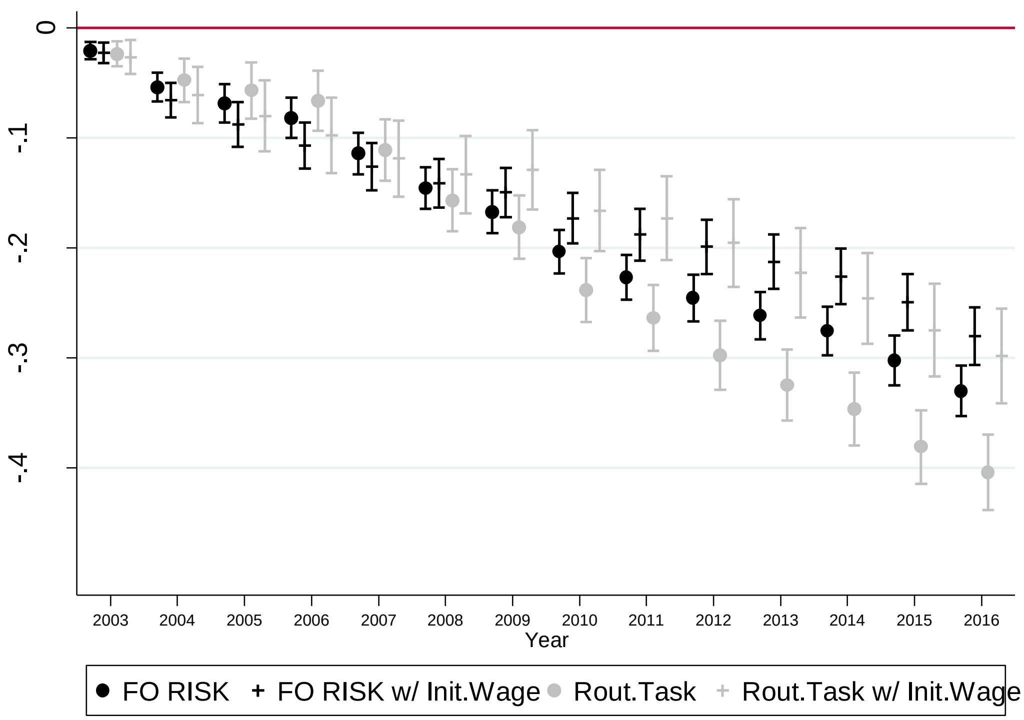
6d: Wage-Bill, Rout.Index and O-S L.Share w/o controlling for initial wage



Source: Authors´ construction.

The negative composition effect at the occupation service level implies that we should find a negative trend for TE. Figure 7 present coefficient of columns (3) and (4), which does not control for initial sector-occupation wages, and coefficient of unreported regressions that control for initial wages. In all cases, we find a negative trend. For FO RISK index wage bill falls -33% during the whole period (black circle), an average annual rate of growth of -2.8%, and -28% when we control for an initial wage (black +). When we use our Routine Task Index, we also find a clear and monotonic trend, although without controlling the wage bill falls -40%, whereas when we control this fall is -30%. These last two results reinforce the idea that without any other controls, the Routine Task Index is capturing an additional effect which seems to be related with initial occupation wages interacted with year dummies.

Figure 7: Wage Bill and Total Effect of Capital-Technology Price
Sectoral data at 3-4 NAICS dig. Level (Period 2002-2016)



Source: Authors´ construction.

Table 4a and 4b results proxy the price of capital-technology with dummies. As we already mentioned, this is a strong assumption that requires that other factors that affect the demand of occupations are orthogonal to our proxy of occupation risk of automation (Risko). As in the aggregate case, Table 5a and 5b use annual data of robots per worker at the sector level (Rpw_{jt}) instead of year dummies to proxy for capital-technology prices. We also instrument our proxy using the average value of robots per workers at the same sectoral level in EU countries. In this case, identification comes from annual changes in robot penetration at the industry level interacted with occupation risk of automation. Robots per workers are only available at a higher level of aggregation. Our econometric results allow for error correlation within sector-year that have the same data of robots per workers.

Table 4c presents ours prefer set of results for the period 2004-2016, for which we have robots' data at the sector level in the US. We control for sector composition effect using sector-year dummies, and we control for composition effect at the occupation-services level using a proxy for the initial occupation-service labor shares interacted with robots per workers. We use [Eq:6a]. Wage bill, employment and wages in occupation at risk of automation should growth less in sectors that adopt more labor replacing capital-technology (robots). The negative substitution effect should be lower (in absolute value) in occupation-services which are initially less labor intensive (first term in [Eq:6a]). We also control for the relative change in the occupation-services cost share due to the fall in the relative price of capital-technology (second term).

Columns (1) and (2); and (7) and (8) present coefficients assuming the same labor share in all occupation-services ($S\hat{h}L_{oj} = cte$), when we use FO Risk automation index and Routine Tasks index, respectively. Peer regressions control for the initial sector-occupation wages interacted with robots per workers, whereas odd regressions do not. We control for initial wages because, as we already saw, results, when we use Routine Tasks index, are sensitive to this control.

In Columns (1) and (2) the coefficient for FO Risk of Automation interacted with robots per workers at the industry level is negative and highly significant. Occupation at risk of automation reduces their relative wage bill participation by 11-12% in sectors that increase their robots penetration one standard deviation more during the whole period. There is not a difference in results if we control or not for initial wages. Columns (3) to (6) allow for different occupation-service labor shares ($S\hat{h}L_{oj} \neq S\hat{h}L_{qh}$). As predicted by [Eq:6a], the main effect of our proxy of Risk of Automation is negative and highly significant, and its interaction term with occupation-service labor share is positive. The net effect is negative, and coefficients suggest that the average occupation labor share is around 0.3. The main effect of labor share is negative.[33] These results reinforce our previous results using years dummies as a proxy for the price of capital-technology. Taking one standard deviation in each term implies that occupation at risk of automation lost 15-16% percent of their wage bill during the whole period (2004-2016). Coefficients in columns (5) and (6) imply that this percentage for employment is between 14% and 16% depending on if we control or not for initial wages.

Columns (7) to (12) present the same results but using our Routine Task Index instead of the FO Risk Index. We find similar results, although their magnitude differs if we control or not for initial log wages interacted with robot per workers. When we impose that all labor shares are the same, the wage bill coefficient in Column (7) is similar to the one we obtain in Column (1) using FO RISK, but it almost doubles when we include sector-occupation initial log wages interacted with robots per worker (column (8)). It goes from 0.12% to 0.22. Something

[33] In all regressions, we impose that the interaction term between our proxy for Risk of automation and occupation-service labor share has zero mean.

similar happens when we allow for different labor shares. The implied impact of one additional standard deviation increase in robots penetration implies a fall in wage bill of occupation with high Routine Task Index (one SD) of 14% (similar to Column (3)) or 24% depending we control or not for initial wages, respectively. In both cases, the coefficient is highly significant. Results also confirm [Eq:6a]: occupations characterized with routine tasks grow less in sectors with a higher increase of capital-technology penetration, and this effect is lower in occupations with higher initial labor share. The composition effect at the occupation-service is negative.

Table 4c: Wage Bill, Employment, Risk of Automation and Robots per Workers
Sectoral data 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)	
Independeent Var.	*RISK>0.7*				*RISK>0.7*		*Rout.Task*				*Rout.Task*	
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
Aut.Risk x Robots /worker	-0.112	-0.120	-0.102	-0.117	-0.102	-0.122	-0.120	-0.224	-0.099	-0.200	-0.095	-0.200
	(0.008)**	(0.012)**	(0.008)**	(0.012)**	(0.008)**	(0.012)**	(0.009)**	(0.024)**	(0.009)**	(0.025)**	(0.009)**	(0.024)**
Aut.Risk x ShL x Robots /worker			0.029	0.032	0.030	0.033			0.028	0.024	0.031	0.027
			(0.008)**	(0.008)**	(0.007)**	(0.008)**			(0.009)**	(0.009)**	(0.009)**	(0.009)**
ShL x Robots /worker			-0.074	-0.077	-0.068	-0.072			-0.069	-0.064	-0.065	-0.061
			(0.008)**	(0.008)**	(0.007)**	(0.008)**			(0.008)**	(0.009)**	(0.008)**	(0.008)**
Fixed effects	Sector-Occupation and Sector-Year						Sector-Occupation and Sector-Year					
Ini.Wage (ln) x Robots/Worker	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Marg.Eff. one SD	-0.112	-0.120	-0.147	-0.162	-0.140	-0.161	-0.120	-0.224	-0.140	-0.240	-0.129	-0.234
OBS	461,319	461,319	461,197	423,944	423,840	426,906	426,062	444,895	444,773	410,073	409,969	412,735
Max.Likelihood	-195,707	-195,707	-195,706	-174,943	-175,052	-169,603	-169,052	-183,443	-184,398	-164,248	-165,089	-159,068

Standard errors allow for within occupation correlation * $p<0.05$; ** $p<0.01$.
The first row presents the regression number; the second row describes the dependent variable; the third row describes the independent variables we use for automation. The fourth row describes the econometric model used. In the case of IV, we instrument robots per workers in the US using the simple average of robots per workers in EU country. All regression have sector-occupation and sector year fixed effects. RISK>0.7 is a dummy variable equals to one if the FO probability is higher than 0.7. Regressions (1), (2), (7) and (8) impose the same occupation-service labor share. Other regressions allow for different labor shares. In all regression, we impose that the mean value of Aut.Risk and Labor Share are equals to zero. Rout.Task is our Routine Task Index that uses Autor et al (2003) approach to construct an index of the relative importance of routine tasks in each occupation (PROBb in Section 1). Peer columns control for initial sector-occupation log wages interacted with robots per workers. Odd columns do not. Mag.Eff.one SD reports the marginal effect of one standard deviation change in the independent variable on the dependent variable. For columns that allow for different labor shares, these columns report the resulting effect on the dependent variable to increase each of the independent variables by one standard deviation.

Columns (11) and (12) also shows a negative impact of robot penetration on the employment of occupation with a high component of routine task. We find similar results.

For robustness, Table 5b redoes Table 5a using first differences instead of fixed effect. We allow for dynamics using Anderson and Hsiao (1982) model. We include the lag of the dependent variable instrumented with its second lag. All models have a sector-year fixed effect to control for sectoral shocks. We allow for error correlation within sector-year that have the same data for the first difference of robots per workers.

Results in Table 4c are larger in absolute term. For example, Column (1) in Table 4b implies that occupations at risk of automation have an average annual growth rate -0.8% lower than other occupations in a sector with an increase of robot per workers penetration one standard deviation higher. The same implied percentage is -1.8% in Column (1) in Table 5b. In all cases, we have the same expected sign in independent variables. All results are significant at standard levels but the interaction term between the risk of automation and occupation service labor share when we use our Routine Task Index as a proxy for risk of automation. Appendix C presents the same set of results for the rate of growth between 2004 and 2016. We lost econometric power. Results for the main coefficient of occupation at risk of automation remains stable and significant at standard level. The interaction term with labor share keeps a similar magnitude although in most cases it is not significant at standard level. This lost of econometric power it is not surprising if we consider that we are including sector dummies and we allow error correlation within occupation-sectors that are in the same aggregate sector for which we have data for robots per workers (22 aggregate sectors).

Results within industries provide empirical evidence that automation is having a displacement effect in the US. Our results suggest that occupation in sectors at risk of automation have on average an annual rate of growth around -1% and -2% less than the rest of occupations in sectors with one standard deviation more of robots per worker during the period 2004-2016. Our empirical approach allowed us to control for any type of shock at the sector-year level. Therefore, results are not affected by Chinese or Mexican import penetration, nor for sector demand shocks or for the financial distress that affected aggregate and sector demands, nor by any other shock that might have impacted at the sector level.

Table 5c: First Difference: Wage Bill, Emp., Risk of Automation and Robots per Workers
Sectoral data at 3-4 NAICS dig.Level (Period 2004-2016)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Var.	Diff.Wage Bill (ln)				Diff.Emp. (ln)		Dif.Wage Bill (ln)				Change Emp. (ln)	
Independeent Var.	*RISK>0.7*				*RISK>0.7*		*Rout.Task*				*Rout.Task*	
	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV	IV
Diff. Aut.Risk x Robots /worker	-0.018	-0.022	-0.017	-0.021	-0.016	-0.019	-0.019	-0.044	-0.017	-0.042	-0.015	-0.023
	(0.005)**	(0.007)**	(0.005)**	(0.007)**	(0.005)**	(0.007)**	(0.005)**	(0.014)**	(0.004)**	(0.014)**	(0.005)**	(0.009)**
Diff. Aut.Risk x ShL x Robots /worker			0.004	0.005	0.004	0.004			0.003	0.002	0.004	0.003
			(0.002)+	(0.003)+	(0.002)	(0.003)+			(0.002)	(0.002)	(0.002)	(0.002)
Diff. ShL x Robots /worker			-0.010	-0.011	-0.009	-0.010			-0.009	-0.008	-0.008	-0.008
			(0.003)**	(0.004)**	(0.003)**	(0.003)**			(0.003)**	(0.003)*	(0.003)*	(0.003)*
Lag Diff. Dependent Var.(ln)	-0.136	-0.136	-0.131	-0.130	-0.119	-0.119			-0.129	-0.129	-0.117	-0.117
	(0.024)**	(0.023)**	(0.024)**	(0.024)**	(0.024)**	(0.024)**			(0.024)**	(0.024)**	(0.024)**	(0.024)**
Fixed effects	Sector-Year						Sector-Year					
Ini.Wage (ln) x Robots/Worker	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Marg.Eff. one SD	-0.018	-0.022	-0.023	-0.027	-0.021	-0.025	-0.019	-0.044	-0.023	-0.048	-0.019	-0.028
OBS	309,750	317,646	317,607	307,954	307,915	310,432	309,995	309,603	309,564	300,502	300,463	302,832
Max.Likelihood	-84,781	-169,454	-169,388	-158,195	-158,160	-151,158	-150,949	-161,498	-161,691	-150,894	-151,084	-144,040

Standard errors allow for within sector-year that have the same data for robots per worker + p<0.1; * p<0.05; ** p<0.01.

The first row presents the regression number; the second row describes the dependent variable; the third row describes the independent variables we use for automation. The fourth row describes the econometric model used. In the case of IV, we instrument the change of robots per workers in the US using the simple average of the change in robots per workers in EU country. We also instrument the first Lag Diff. Dependent Var. with its second lag. All regression have sector fixed effects. RISK>0.7 is a dummy variable equals to one if the FO probability is higher than 0.7. Regressions (1), (2), (7) and (8) impose the same occupation-service labor share. Other regressions allow for different labor shares. In all regressions, we impose that the mean value of the first difference of Aut.Risk and Labor Share are equals to zero. Rout.Task is our Routine Task Index that uses Autor et al (2003) approach to construct an index of the relative importance of routine tasks in each occupation (PROBb in Section 1). Peer columns control for the first difference in initial wages interacted with robots per workers. Odd columns do not. Mag.Eff.one SD reports the marginal effect of one standard deviation change in the independent variable on the dependent variable average rate of growth during 2004 and 2016. For columns that allow for different labor shares, this row reports the resulting effect on the dependent variable to increase each of the independent variables one standard deviation.

Wage Bill, Employment and Wages: Sector Level

The previous sections, 2.1 and 2.2, present the relative impact of automation on occupations prone to automation. To study the impact of automation at the sector level we collapse occupations' data at the sector level and we construct two sector level indexes of risk of automation. These are the weighted average of the FO´s risk of automation (which is equivalent to these share of workers at risk), and the weighted average of the Index of Routine Tasks. We use sector level define by BLS (NAICS 2007 3-4 digit).

Table 6a 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, we include sector and year dummy variables which account for initial conditions and aggregate shocks. In all empirical specifications, we control for financial conditions, and Chinese and Mexican sectoral exports to the US. Following Rajan and Zinagales (1998) and Raddatz (2006), we use either a measure of sectoral external financial dependence or a measure of liquidity need (initial labor share), interacted with an index of credit tightness constructed using the FED "Senior Loan Officer Opinion Survey on Bank Lending Practices" or the log credit to the private sector from the WDI.34 Following Autor et al (2013) and Acemoglu and Restrepo (2018), we use US sectoral imports from China and Mexico in 2002 and we interact it with year total Chinese and Mexican exports to the world during this period.

Figure (8) reports the coefficient for the sector share of employment at risk of automation independent variable (in 2004) over time. 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 3%, but it accelerates between 2008 and 2010.

[34] Following Rajan and Zingales (1998) we constructed Employment Finantial Dependence for sectors at 3-digit ISIC rev3. Using Compustat data. We construct a 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". The index is equal to the last year index plus 5 times NIS and NIT times one plus the interaction of NIS and NIT when they have the same sign. This last term it to take into account that when both indexes have the same sign banks should adjust more the spread level and their lending policies. Results does not change when we exclude this last multiplicative term.

During these three years, it falls by 7.2%. This reassures the “cleaning effect” hypothesis during the great financial crises. After 2010 their wage bills remain constant in a relative term.

Column (1) controls for sector external financial dependence. Sectors with high external financial dependence reduce their wage bills during periods of tight financial markets (2002-2005 and 2009-2011). The sector with external financial dependence in the 90 percentile reduces their wage bills 4.5% relative to the sectors in the 10th percentile. between 2006 and 2010. The coefficient for the external financial dependence reports the wage bill fall of one standard deviation change in the independent variable (EFD index x Financial Thighness). Chinese and Mexican imports penetration have the expected negative sign, although only the coefficient for Chinese imports is significant at standard level.

For robustness, columns (2) and (3) redo regression in Column (1) using log credit to the private sector as a percentage of GDP as a proxy for financial conditions, liquidity requirements (labor share) instead of the external financial index, respectively. Column (4) controls for external financial dependence, liquidity needs and the initial sector wage interacted with year dummies. In all cases results hold.

Column (5) and (6), and Figures (8b) and (8c) present our results for log sector total employment and log sector average wage. The relative wages of sectors with a higher share of workers at risk of automation (in 2004) fall slightly during the whole period. By 2016, a sector with one standard deviation more of employment at risk of automation in 2004 has a relative wage 3% lower. Employment shows a similar pattern than the wage bill, although its falls is larger during the financial crises. By the end of the sample, the relative employment of sector with one standard deviation more employment at risk of automation in 2004 falls by 7.7%. Our proxy for financial requirements has the expected sign. Chinese and Mexican imports penetration have the expected sign although it is significant at standard levels only for Chinese imports. For the log average wage, Chinese penetration is positive and significant at standard levels. This result is in line with the idea that Chinese import penetration reduces labor demand of low skill workers, and therefore increases the average wage in sectors most exposed to them.

The last two columns in Table 6a use the sector average of our Routine Task Index weighted by sector-occupation employment in 2004. Column (7) and Figure (8c) report results for the log wage bill and column (8) and Figure (8d) for log employment. In both cases, results are similar to the ones when we use FO RISK index.

Table 6b presents results using sector robots per workers as a proxy for the capital-technology price during 2004-2016. To avoid any reverse causality, we instrument robots per workers in the US using the average robots per workers in EU countries. We control for the initial condition using sector dummies and aggregate shocks using year dummies. In all models, we control for external financial dependence inter-acted with our proxy for Credit Thighness from the FED, and sectoral Chinese and Mexican import penetration.

Table 6a: Sector Employment and Wages, and Risk of Automation
At 3-4 NAICS dig. Level (Period 2002-2016)

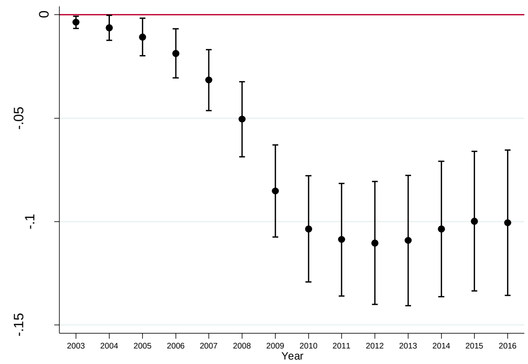
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.	Wage Bill (ln)	Wage Bill (ln)	Wage Bill (ln)	Wage Bill (ln)	Employment (ln)	Wage (ln)	Wage Bill (ln)	Employment (ln)
Independent Var.	*Mean RISK*	*Mean RISK*	*Mean RISK*	*Mean RISK*	*Mean RISK*	*Mean RISK*	*Mean Rout.Task*	*Mean Rout.Task*
Ind. Var. X 2003	-0.004	0.000	-0.003	-0.005	-0.000	-0.003	-0.005	-0.003
	(0.002)*	(0.003)	(0.002)	(0.002)*	(0.002)	(0.001)**	(0.002)**	(0.001)*
Ind. Var. X 2004	-0.006	-0.002	-0.010	-0.009	-0.001	-0.005	-0.016	-0.013
	(0.004)+	(0.004)	(0.005)+	(0.004)*	(0.003)	(0.001)**	(0.003)**	(0.003)**
Ind. Var. X 2005	-0.011	-0.007	-0.016	-0.011	-0.003	-0.008	-0.026	-0.018
	(0.005)+	(0.006)	(0.007)*	(0.006)+	(0.005)	(0.002)**	(0.005)**	(0.005)**
Ind. Var. X 2006	-0.019	-0.014	-0.024	-0.015	-0.009	-0.010	-0.038	-0.025
	(0.007)*	(0.008)+	(0.008)**	(0.008)+	(0.007)	(0.002)**	(0.007)**	(0.006)**
Ind. Var. X 2007	-0.032	-0.026	-0.034	-0.027	-0.020	-0.012	-0.052	-0.037
	(0.009)**	(0.010)**	(0.009)**	(0.009)**	(0.009)*	(0.003)**	(0.009)**	(0.008)**
Ind. Var. X 2008	-0.051	-0.047	-0.050	-0.046	-0.037	-0.013	-0.070	-0.053
	(0.011)**	(0.011)**	(0.010)**	(0.011)**	(0.010)**	(0.003)**	(0.011)**	(0.010)**
Ind. Var. X 2009	-0.085	-0.076	-0.080	-0.082	-0.071	-0.014	-0.111	-0.094
	(0.014)**	(0.014)**	(0.013)**	(0.014)**	(0.013)**	(0.003)**	(0.014)**	(0.014)**
Ind. Var. X 2010	-0.104	-0.095	-0.098	-0.105	-0.087	-0.016	-0.137	-0.121
	(0.016)**	(0.015)**	(0.015)**	(0.016)**	(0.015)**	(0.003)**	(0.017)**	(0.016)**
Ind. Var. X 2011	-0.109	-0.101	-0.104	-0.108	-0.090	-0.019	-0.135	-0.119
	(0.017)**	(0.017)**	(0.016)**	(0.017)**	(0.016)**	(0.004)**	(0.017)**	(0.017)**
Ind. Var. X 2012	-0.110	-0.103	-0.104	-0.106	-0.089	-0.021	-0.131	-0.114
	(0.018)**	(0.018)**	(0.017)**	(0.018)**	(0.017)**	(0.004)**	(0.018)**	(0.018)**
Ind. Var. X 2013	-0.109	-0.101	-0.100	-0.104	-0.086	-0.023	-0.132	-0.114
	(0.019)**	(0.019)**	(0.018)**	(0.019)**	(0.018)**	(0.004)**	(0.019)**	(0.018)**
Ind. Var. X 2014	-0.104	-0.096	-0.095	-0.101	-0.080	-0.024	-0.131	-0.113
	(0.020)**	(0.020)**	(0.019)**	(0.020)**	(0.019)**	(0.004)**	(0.019)**	(0.019)**
Ind. Var. X 2015	-0.100	-0.096	-0.090	-0.098	-0.076	-0.023	-0.131	-0.113
	(0.020)**	(0.020)**	(0.020)**	(0.021)**	(0.020)**	(0.004)**	(0.020)**	(0.020)**
Ind. Var. X 2016	-0.101	-0.096	-0.089	-0.102	-0.077	-0.023	-0.141	-0.122
	(0.021)**	(0.021)**	(0.021)**	(0.022)**	(0.021)**	(0.004)**	(0.021)**	(0.021)**
External Fin. Dependence	-0.062			-0.047	-0.058	-0.003	-0.056	-0.051
x Credit Tignteness	(0.027)*			(0.026)+	(0.025)*	(0.007)	(0.027)*	(0.024)*
Fin. External Dependence		0.181						
x Cred.Private Sector (ln)		(0.092)*						
Liquity Needs (Labor Share)			-0.088	-0.079				
x Credit Tignteness			(0.022)**	(0.021)**				
Sect. Chinese Expt. 2002	-0.975	-0.964	-1.002	-0.975	-1.296	0.321	-0.668	-1.020
x Tot.Chinese Export	(0.364)**	(0.362)**	(0.371)**	(0.364)**	(0.435)**	(0.123)**	(0.366)+	(0.438)*
Sect. Mexican Expt. 2002	-0.571	-0.577	-0.564	-0.525	-0.459	-0.112	-0.426	-0.319
x Tot.Mexican Export	(0.912)	(0.908)	(0.947)	(0.938)	(0.663)	(0.325)	(0.910)	(0.654)
Fixed effects	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year
Ini.Wage (ln) x Dummies	No	No	No	Yes	No	No	No	No
Marg.Eff. one SD	-0.101	-0.096	-0.089	-0.102	-0.077	-0.023	-0.141	-0.122
OBS	3,690	3,690	4,271	3,690	3,690	3,690	3,690	3,690
Max.Likelihood	2,416	2,430	2,681	2,437	2,593	7,521	2,512	2,703

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

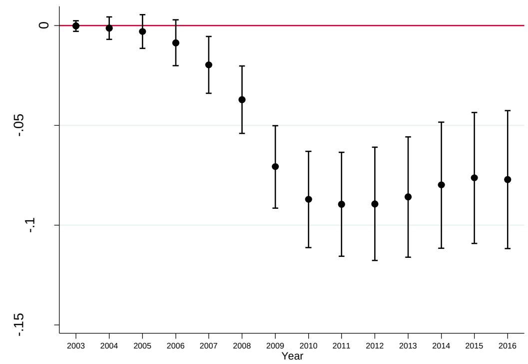
Note: The first row presents the regression number; the second row describes the dependent variable; the third row describes the proxy we use for risk of automation. Mean RISK is the share of employees at risk of automation using FO probability higher than 0.7 (equivalent to the mean weighted FO RISK index) in 2004. Mean Rout.Task is the weighted by employment average of the Routine Task Index in 2004. Fin.External 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). We use the annual average. Credit to the private sector is the WDI index of credit over GDP. The row Mag.Eff. one SD presents the effect of one standard deviation increase in the share of employment at risk of automation in 2004 on the dependent variable in 2016 relative to 2002.

Figure 8: Sector Labor Outcomes and Risk of Automation
At 3-4 NAICS dig. Level Data (Period 2002-2016)

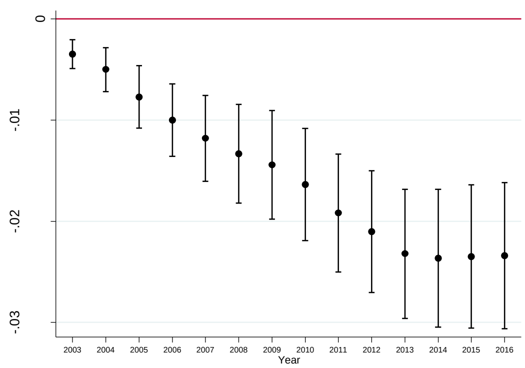
8a: Wage Bill (ln) and Mean RISK of Aut.
Coefficient from Column (1) in Table 6a.



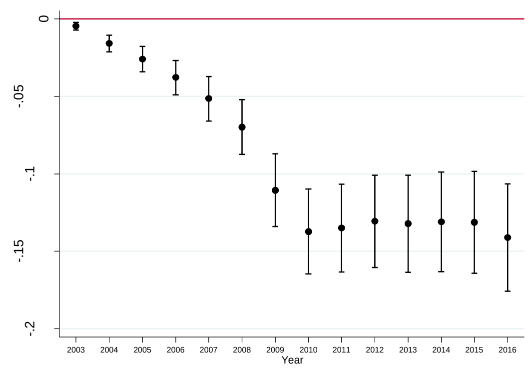
8b: Emp. (ln) and Mean RISK of Aut.
Coefficient from Column (5) in Table 6a.



8c: Wage (ln) and Mean RISK of Aut.
Coefficient from Column (6) in Table 6a.



8d: Wage Bill (ln) and Mean Rout.Task
Coefficient from Column (7) in Table 6a.



Source: Author’s construction.

Columns (1) to (3) report results using the share of workers at risk of automation at the sector level in 2004 inter-acted with robots per worker penetration. One standard deviation increase in our proxy for workers at risk interacted with the capital-technology price (Share of workers at risk x Robots per workers) reduces 14% sector wage bill relative to the whole economy. For log employment, the same percentage is slightly lower 13%, and for log average wage it is not different from 0 at standard levels. In section 3.2 we find that sector/occupation results were sensitive to the inclusion of initial wage controls. For robustness Columns (4) and (5) redo columns (1) and (2) controlling for initial log sector average wages interacted with year dummies. Results do not change. Finally, Columns (6) and (7) use the sector average of our

Routine Tasks index weighted by sector-occupation employment; results hold. The coefficient for our proxies of risk of automation is stable and its magnitudes are in line with results at the aggregate-occupation level Table 3b and sector-occupation level Table 4c. The former results should be consistent with the sum of sector and sector-occupation results.

Table 6b: 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)
Dependent Var.	Wage Bill (ln)	Emp. (ln)	Wage (ln)	Wage Bill (ln)	Emp. (ln)	Wage Bill (ln)	Emp. (ln)
Independent Var.	*Mean RISK*	*Mean RISK*	*Mean RISK*	*Mean RISK*	*Mean RISK*	*Mean Rout.Task*	*Mean Rout.Task*
	IV	IV	IV	IV	IV	IV	IV
Aut.Risk x Robots /worker	-0.209	-0.191	-0.018	-0.172	-0.191	-0.174	-0.163
	(0.094)*	(0.090)*	(0.012)	(0.076)*	(0.090)*	(0.059)**	(0.051)**
Robots /worker	-0.063	-0.049	-0.015	-0.069	-0.049	0.003	0.015
	(0.023)**	(0.020)*	(0.008)+	(0.022)**	(0.020)*	(0.029)	(0.025)
External Financial Dependence	-0.037	-0.033	-0.004	-0.036	-0.033	-0.045	-0.040
x Credit Tignteness	(0.010)**	(0.009)**	(0.003)	(0.009)**	(0.009)**	(0.011)**	(0.010)**
Sect. Chinese Expt. 2002	-1.381	-1.677	0.295	-1.352	-1.677	-0.959	-1.287
x Tot.Chinese Export	(0.207)**	(0.208)**	(0.052)**	(0.189)**	(0.208)**	(0.199)**	(0.209)**
Sect. Mexican Expt. 2002	0.722	0.691	0.030	0.296	0.691	-0.180	-0.143
x Tot.Mexican Export	(0.346)*	(0.309)*	(0.131)	(0.328)	(0.309)*	(0.353)	(0.289)
Fixed effects	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year	Sector & Year
Ini.Wage (ln) x Robots/Worker	No	No	No	Yes	Yes	No	No
Marg.Eff. one SD	-0.142	-0.130	-0.012	-0.117	-0.130	-0.152	-0.143
OBS	3,198	3,198	3,198	3,198	3,198	3,198	3,198
Max.Likelihood	2,199	2,397	6,667	2,256	2,397	2,169	2,371

Standard errors allow for correlation within sectors with equal robot penetration.* 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 we 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. The fourth row reports the model used. Fin.External 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). We use the annual average. The row Mag.Eff.one SD presents the impact of one standard deviation increase in the share of employment at risk of automation in 2004 x Robot Renetration on the dependent variable.

External financial dependence and Chinese and Mexican imports penetration have the expected signs. But for Mexican imports penetration coefficient in Columns (1) and (2), which has a positive sign. This result is not stable and vanishes in Columns (3) to (7).

Summing up, a sector that uses more occupations at risk of automation 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. With these results, we are not able to discard a reinstatement effect at the aggregate level.

Automation and Sectoral Imports

Previous models present results for labor market outcomes at the sector level. Tables 7a and b, and Figure 9, present the relationship between automation and US sectoral imports from each of its trade partners.

We use the data from the US custom collected by Schott (2008) and posteriors updates until 2016. We find that US import of commodities in sectors with a large fraction of workers at risks of automation, at the beginning of the period, reduce imports relative to the whole economy. 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 7a and Figure 9, we use year dummies as a proxy for capital-technology prices. We control for initial conditions with country-sector dummies, for aggregate factors with country-year dummies, and for financial conditions at the sector-year level with either sector external financial dependence or sector labor share (Liquidity Needs) interacted with log US credit to the private sector and exporter country log credit to the private sector.

Columns (1) and (2) use as a proxy for sector risk of automation the share of employees at risk using FO RISK index. Column (1) controls for the sector financial condition with external financial dependence and Column (2) with liquidity needs (labor share). In both cases, results are almost the same for sector automation risk coefficients. External financial dependence interacted with ln credit to the private sector is not significant at the standard level, neither for exporter countries nor for the US. Sector liquidity needs are negative and significant for the US sectors. Results suggest that firms, with higher liquidity requirement, reduce their production during times of tight financial condition (low credit), and demand for these commodities are covered by additional imports. Figure (9a) present the sector risk coefficient for Column (2). Imports of commodities fall in sectors with a higher share of jobs at risk of automation. By 2012, relative imports in these sectors are 24% lower than in 2002. After 2012 they remain stable. Column (3) control for the initial level of Chinese and Mexican imports interacted with log of total exports of these countries. Risk coefficients remain almost identical. Column (4) redoes column (2) using the weighted average of our Routine Tasks Index instead of FO´s RISK at the sector level in 2004. Mean Routine Task coefficients show a similar pattern although results are noisy.

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, we should expect that import substitution should be higher from countries that have lower penetration of automation-technologies. We split the sample into two groups of countries by their level of industrial robots per workers in 2002. There are 17 countries with high robot penetration.[35]

Table 7a: US imports and Risk of Automation in 2004

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

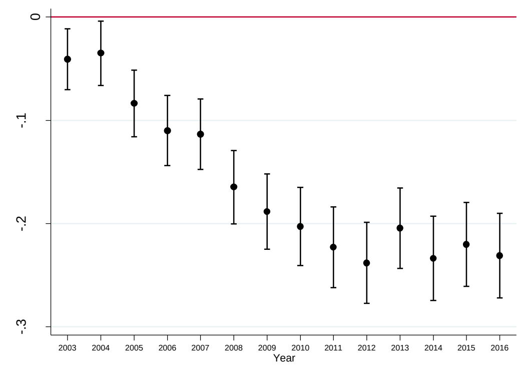
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Var.	Import (ln)	Import (ln)	Import (ln)	Import (ln)	Import (ln)	Import (ln)
Independent Var	*Mean RISK*	*Mean RISK*	*Mean RISK*	*Mean Rout.Task*	*Mean RISK*	*Mean RISK*
Ind. Var. X 2003	-0.049	-0.041	-0.042	-0.052	-0.039	-0.042
	(0.018)**	(0.018)*	(0.018)*	(0.022)*	(0.021)+	(0.028)
Ind. Var. X 2004	-0.045	-0.035	-0.036	-0.034	-0.028	-0.058
	(0.019)*	(0.019)+	(0.019)+	(0.024)	(0.022)	(0.033)+
Ind. Var. X 2005	-0.096	-0.084	-0.086	-0.056	-0.089	-0.054
	(0.020)**	(0.020)**	(0.020)**	(0.024)*	(0.023)**	(0.036)
Ind. Var. X 2006	-0.126	-0.110	-0.115	-0.045	-0.133	-0.001
	(0.022)**	(0.021)**	(0.021)**	(0.025)+	(0.024)**	(0.033)
Ind. Var. X 2007	-0.133	-0.113	-0.118	-0.051	-0.137	-0.006
	(0.023)**	(0.021)**	(0.021)**	(0.025)*	(0.024)**	(0.032)
Ind. Var. X 2008	-0.177	-0.165	-0.169	-0.098	-0.183	-0.077
	(0.023)**	(0.022)**	(0.022)**	(0.025)**	(0.025)**	(0.035)*
Ind. Var. X 2009	-0.203	-0.188	-0.193	-0.071	-0.207	-0.103
	(0.023)**	(0.022)**	(0.023)**	(0.025)**	(0.026)**	(0.036)**
Ind. Var. X 2010	-0.216	-0.203	-0.206	-0.083	-0.230	-0.081
	(0.024)**	(0.023)**	(0.023)**	(0.026)**	(0.027)**	(0.037)*
Ind. Var. X 2011	-0.232	-0.223	-0.227	-0.104	-0.246	-0.118
	(0.024)**	(0.024)**	(0.024)**	(0.028)**	(0.028)**	(0.040)**
Ind. Var. X 2012	-0.248	-0.238	-0.244	-0.094	-0.261	-0.133
	(0.024)**	(0.024)**	(0.024)**	(0.029)**	(0.028)**	(0.042)**
Ind. Var. X 2013	-0.220	-0.204	-0.210	-0.067	-0.225	-0.109
	(0.025)**	(0.024)**	(0.024)**	(0.028)*	(0.028)**	(0.039)**
Ind. Var. X 2014	-0.248	-0.234	-0.239	-0.075	-0.252	-0.147
	(0.026)**	(0.025)**	(0.025)**	(0.029)**	(0.029)**	(0.041)**
Ind. Var. X 2015	-0.233	-0.220	-0.226	-0.056	-0.241	-0.116
	(0.026)**	(0.025)**	(0.025)**	(0.028)*	(0.029)**	(0.040)**
Ind. Var. X 2016	-0.243	-0.231	-0.237	-0.073	-0.249	-0.143
	(0.026)**	(0.025)**	(0.025)**	(0.029)*	(0.029)**	(0.039)**
External Fin. Dependence	-0.020					
x Cred.Private Sector (ln) Exporter	(0.019)					
External Fin. Dependence	-0.009					
x Cred.Private Sector (ln) US	(0.083)					
Liquidity Needs		-0.323	-0.301	-0.488	-0.554	0.523
x Cred.Private Sector (ln) Exporter		(0.300)	(0.303)	(0.303)	(0.369)	(0.385)
Liquidity Needs		-5.024	-5.077	-5.800	-4.691	-6.011
x Cred.Private Sector (ln) US		(1.332)**	(1.362)**	(1.288)**	(1.567)**	(2.054)**
Fixed effects			Exp.Cty.-Sect & Exp.Cty.-Year			
Marg.Eff.	-0.243	-0.231	-0.237	-0.073	-0.249	-0.143
Sample	All Countries	All Countries	~CHN & ~MEX	All Countries	Low Rob/Work	High Rob/Work
OBS	122,354	123,501	120,785	123,501	101,759	21,742
Max.Likelihood	-189,553	-191,464	-188,380	-191,695	-164,086	-23,124

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

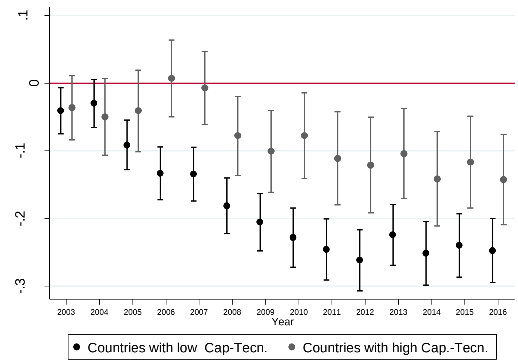
Note: The first row presents the regression number; the second row describes the dependent variable; the third row describes the proxy we use for risk of automation. Mean RISK is the share of employees at risk of automation using FO probability higher than 0.7 (equivalent to the mean weighted FO RISK index) in 2004. Mean Rout.Task is the average of the Routine Task Index weighted by employment in 2004. Fin.External 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 to the private (ln) is the log WDI index of credit over GDP in 2004. The row Mag.Eff. one SD presents the effect of one standard deviation increase in the share of employment at risk of automation in 2004 on the dependent variable in 2016 relative to 2002. 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.

Figure 9: Automation and US Imports

9a: US imports (ln) and Mean Risk of Automation.
Coefficient from Column (2) in Table 9a.



9b: US imports (ln) from different Trade Partner and Mean Risk of Automation
Coefficient from Column (2) in Table 9a.



Source: Author´s calculation.

Columns (5) and (6), redo Column (2) for countries with high and low robot penetration. Figure 9b presents the evolution of RISK coefficients for each group. Import substitution is twice as larger from countries with lower robots penetration than for countries with high penetration. For the latter group, Figure 9b shows that until 2007 there was not a systematic difference between the level of imports from sectors with a larger share of workers at risks vis a vis the whole economy. These suggest that automation is behind imports´ behavior.

In Table 7a we use both robots per workers at country level divided by total employment in the economy, and sector robots at sector level divided by total employment in the economy as a proxy for capital-technology price. We do not have sector employment for most countries, therefore, we decide to normalize robots at the sector level using total employment in the economy.[36] We control for sector financial requirement in the trade partner country and in the US, using either external financial dependence or liquidity needs interacted with

[36] Unreported results use sector robots per aggregate employment multiplied by the sector share of GDP.

log credit to the private sector. We include country-sector trade partner and trade partner-year fixed effects. Results are clustered at the sector-year level.

Columns (1) to (5) use aggregate robots per workers for the period 2002-2016. Imports from a sector with a higher share of occupations at risk of automation, at the beginning of the period 2004, presents a relatively lower rate of growth between 2002 and 2016. The share of imports from a sector with one standard deviation higher level of workers at risks falls 7% due to robots penetration during the period of analysis. From previous results, we know that these sectors substitute occupations at risks during this period, therefore this substitution seems to have increase sector comparative advantage. The estimated impact does not change once we control for liquidity needs instead of external financial dependence (Column 2), or when we instrument US robots per workers in the US with EU average (Column 3).[37] Reassuring the idea that capital/technology adoption is behind our results, the coefficient of risk of automation multiply by robots per capita in US trade partner is positive, although not statistically significant at standard levels. This result suggests that the relative difference of robots penetration is behind the increase of comparative advantage in sectors that are characterized by occupations at risk of automation.

Columns (3) use the average of our Routine Tasks Index at the sector level weighted by occupations employment at the sector level. The coefficient for robots penetration in the US is still negative and highly significant. Although the estimated parameter is lower in absolute value. The share of imports from a sector with one standard deviation higher level of workers

[37] For non EU countries the instrument is the simple average of robots per workers for 15 EU economies. For each of 15 EU countries, the instrument is the simple average of the remaining 14 economies.

with high routine task index falls 2.6-2.7 % due to robots penetration, Columns 4 and 5, respectively.

Sector financial needs, neither in the US nor in the US trade partner, do affect US imports. Coefficients are not statistically significant and shift sign from one specification to another.

Columns (5) to (10) use robots at the sector level divided by aggregate employment. In Columns (5) to (7), we use the share of workers at risk of automation. The coefficient of robots penetration in the US is negative and it varies from -5.1% when we control for external financial dependence to -10.2% when we instrument sectoral robots penetration in the US by the simple average in EU countries. It is interesting to note that the coefficient for robots penetration in US trade partner is still positive, varying from 3.0% to 4.6%, but now significant at 5 percent. When we use the average Routine Task Index the coefficient for US robots penetration falls to 2.2-2.7% in absolute values, similar to the fall we observe when we use robots per workers at the country level.

The coefficient for external financial dependence interacted with log credit in the US has the expected negative sign and significant at standard levels. Access to credit increase US production and reduces imports. We take these results with caution because once we use liquidity needs instead of external financial dependence the sign revert and it is significant at standard levels.

Results for US imports from different trade partners suggests 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: US imports and Trade Partner Robots per Workers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Var.	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)	Imports (ln)
Independent Var	*Mean RISK*			*Mean Rout.Task*		*Mean RISK*			*Mean Rout.Task*	
	OLS	OLS	IV	IV	IV	OLS	OLS	IV	IV	IV
Aut.Risk x Robots /worker	0.017	0.014	0.018	-0.018	-0.017					
US trade Partner	(0.015)	(0.014)	(0.015)	(0.011)	(0.011)					
Aut.Risk x Robots /worker	-0.073	-0.073	-0.074	-0.026	-0.027					
US	(0.009)**	(0.010)**	(0.009)**	(0.006)**	(0.006)**					
Aut.Risk x Sector Robots /worker						0.030	0.030	0.046	0.025	0.027
US trade Partner						(0.012)*	(0.012)*	(0.012)**	(0.011)*	(0.011)*
Aut.Risk x Sector Robots /worker						-0.051	-0.052	-0.102	-0.022	-0.027
US						(0.006)**	(0.006)**	(0.017)**	(0.006)**	(0.006)**
Sectoral Robots / worker Partner						0.032	0.034	0.028	0.038	0.039
						(0.010)**	(0.010)**	(0.010)**	(0.010)**	(0.010)**
External Financial Dependence	-0.019		-0.021	0.141	0.139	-0.067		-0.154	0.058	0.050
x Credit Tignteness Partner	(0.053)		(0.053)	(0.076)+	(0.076)+	(0.059)		(0.080)+	(0.057)	(0.057)
External Financial Dependence	-0.059		-0.068	0.260	0.253	-1.874		-1.815	-2.146	-2.143
x Credit Tignteness US	(0.695)		(0.693)	(0.764)	(0.763)	(0.641)**		(0.625)**	(0.673)**	(0.671)**
Liquidity Needs		-0.195					-0.155			
x Credit Tignteness Partner		(0.437)					(0.523)			
Liquidity Needs		-3.292					8.608			
x Credit Tignteness US		(2.251)					(2.306)**			
Fixed effects	Partner Sector & Partner Year					Partner Sector & Partner Year				
Marg.Eff. one SD 1	-0.073	-0.073	-0.074	-0.026	-0.027	-0.051	-0.052	-0.102	-0.022	-0.027
Period	2002 - 2016					2004- 2016				
OBS	74,666	75,460	74,666	73,653	73,653	65,401	66,094	65,401	64,509	64,509
Max.Likelihood	-103,578	-104,790	-103,578	-99,276	-99,276	-88,774	-89,820	-88,858	-85,116	-85,117

Standard errors allow for within US Trade Partner-IFR Sect.-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 we 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 average of the Routine Task Index weighted by employment in 2004. Fin.External 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 to the private (ln) is the log WDI index of credit over GDP in 2004. The row Mag.Eff. one SD presents the effect of one standard deviation increase in the share of employment at risk of automation in 2004 on the dependent variable in 2016 relative to 2002. 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.

The coefficient for external financial dependence interacted with log credit in the US has the expected negative sign and significant at standard level. Access to credit increases US production and reduces imports. We take these results with caution because once we use liquidity needs instead of external financial dependence the sign revert and it is significant at standard levels.

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 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 at the sector level in the US, instrumented by robot per workers in 15 EU countries, during 2004-2016. Finally, the paper controls for sector-year shocks. Chinese and Mexican imports 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, we are able to provide a causal interpretation. We find that occupations with a higher risk of automation have been declining at an annual rate of -2.0-2,5%. For wage bill fall 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 occupations within sectors. One standard deviation increase in robots per worker reduces employment annual growth in occupation at risk of automation by 1.25-1.45% relative to the rest of the economy.

New capital penetration implies a large labor replacement in sectors with initial low wages. At the same time, we 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). Reassuring this interpretation, we 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 robots 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, we expand the sample in 97 additional occupations using two assumptions. Firstly, for 50 occupations, defined at the 6-digit level, we 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); We use the same automation risk for 38 sub-level occupations of OES2010 "25-1000". We also use the same approximation for 12 sub-level occupations of OES2010 "29-1060" and "45-2090". Secondly, for the remaining 47 occupations, we use the risk of automation of the contiguous SOC occupation with FO information. For example, for OES2010 "27-1029" we 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 we use in the paper.[38]

Table A1 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*.[39] Column (2) presents the correlation between *FO RISK*

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

[39] 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.

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). 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).[40] There is a negative relationship between employment growth and risk of automation. The estimated coefficient is -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), we 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.

[40] We use 2004-2016 because for our main results, at occupation-sector instrumented with robots per workers, we only have data for this period.

Table A1: 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							0.003
manual physical	(0.014)							(0.002)
non-routine	-0.117							0.003
manual interpersonal	(0.014)**							(0.002)
routine	0.067							0.001
cognitive	(0.010)**							(0.002)
routine	0.006							-0.005
manual	(0.015)							(0.002)*
PROBb or *Routine Task Index*		0.081					-0.031	
		(0.003)**					(0.003)**	
FO RISK Index			-0.761	0.055	-0.028	-0.031		-0.017
			(0.035)**	(0.151)	(0.003)**	(0.003)**		(0.005)**
Dependent var. 2004 (ln)					0.001	0.000	0.000	0.000
					(0.001)	(0.000)	(0.000)	(0.000)
R2	0.589	0.541	0.374	0.000	0.106	0.121	0.117	0.149
Observations	754	754	791	795	700	695	694	694

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.

Finally, column (8) 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.

Table (A2) 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 we can study the differential impacts of automation on workers. We 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."[41]

Table (A2) presents a standard Mincer equation. Column (1) to (4) uses as a proxy of risk of automation the FO RISK Index. Column (1) controls only for industry fixed effect (267). The coefficient for FO RISK Index is -0.58 which implies 44% lower wage for an employee in occupations with a higher risk of automation (FO RISK Index=1). Wages for women are 21% lower. Column (2) controls for Industry and age (decade dummies). FO RISK Index falls in absolute value from -0.58 to -0.47. Non reported regression shows there is a U shape relationship between FO RISK Index and age. Young and old employees are in occupations with a higher risk of automation. Column (3) controls for industry, age, and education (6 categories). FO RISK Index falls in absolute value from -0.47 to -0.31. There is a monotonic negative relationship between education level and occupation risk of automation.

For robustness, Column (4) redoes column (3) without 2% extreme values for log wage. Results hold. Columns (5) and (6) use *FO RISK Probability* instead of *FO RISK Index*. In Column (6) one standard increase in the *FO RISK Probability* reduces wages by -18%.

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

Columns (7) and (8) use *Routine Task Index* as a proxy for risk of automation. In column (8) one standard increase in the *Routine Task Index* reduces wages by 19%.

Table A2: Wage (ln) and Risk of Automation
American Community Survey Dataset

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Var.	Wage (ln)	Wage (ln)	Wage (ln)	Wage (ln)	Wage (ln)	Wage (ln)	Wage (ln)
Proxy Risk Automation	*FO RISK Index*	*FO RISK Index*	*FO RISK Index*	*FO RISK Index*	*FO RISK Prob.*	*FO RISK Prob.*	*Routine Task*
Risk of Automation	*-0.58*	*-0.48*	*-0.31*	*-0.30*	*-0.36*	*-0.20*	*-0.37*
	(7.08)**	(7.26)**	(5.91)**	(6.00)**	(11.30)**	(9.03)**	(14.00)**
Women	-0.237	-0.268	-0.246	-0.222	-0.219	-0.239	-0.251
	(7.66)**	(10.62)**	(14.23)**	(13.61)**	(8.06)**	(14.50)**	(10.31)**
OBS	1,387,631	1,387,631	1,227,431	1,203,130	1,393,898	1,233,220	1,393,898
FE	Sector	Sector	Sector & Sex	Sector & Sex	Sector	Sector & Sex	Sector
		Age	Age & Educ.	Age & Educ.	Age	Age & Educ.	Age
Sample	Year 2010	Year 2010	Year 2010	w/o 2% Ext.Obs.	Year 2010	Year 2010	Year 2010

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 we use for risk of automation. FRO RISK Index is a dummy variable equal to one if FO probability of automation is higher than 0.7. FO RISK Probability is the continuous FO probability of automation. *Routine Task* is the Routine Task Index. There are 267 sectors, 8 age groups (by decades), and 6 education groups.

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.[42] 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 $\left(ShK_{oj}=1-ShL_{oj}=cte\right)$. We 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 we estimate [Eq:5] in the main text.

Due to the panel structure of the data, we 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

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

control for initial occupation wages, respectively. We 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), we 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. 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 80th of the *Routine Tasks Index* grow 45% less that occupations in the percentile 20th. The same percentage for occupation in percentile 75th and 25th is 24%. For additional robustness checks, we restrict the sample of occupations to those with FO probabilities of automation at the 4-digit level of disaggregation (698 occupations), we use the continuous probability of automation as the independent variable (*FO RISK Probability*), we use a discrete version of the routine index (five quantiles) ; and we estimate the model using employment growth as the dependent variable and we include the initial log level, instrumented with the second lag, as control. We obtain similar results.[43]

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, we should also expect that the average wage in these occupations should fall over time relative to the other occupations.[44] On the contrary, if automation replaces routine tasks of low skilled workers which are at the lower end of the wage distribution, we may 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.

[43] These results are not reported in the paper.
[44] 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.

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	-0.028	-0.027	-0.000	-0.018	-0.018	-0.000	-0.05	0.004
	(0.008)**	(0.008)**	(0.002)	(0.010)	(0.010)	(0.002)	(0.014)**	(0.004)
Ind. Var. X 2002	-0.068	-0.055	-0.012	-0.039	-0.046	0.007	-0.11	0.004
	(0.011)**	(0.011)**	(0.003)**	(0.013)**	(0.012)**	(0.003)*	(0.017)**	(0.005)
Ind. Var. X 2003	-0.085	-0.067	-0.017	-0.051	-0.059	0.007	-0.13	0.008
	(0.014)**	(0.014)**	(0.004)**	(0.016)**	(0.017)**	(0.004)	(0.023)**	(0.006)
Ind. Var. X 2004	-0.118	-0.090	-0.027	-0.067	-0.071	0.004	-0.16	-0.000
	(0.021)**	(0.021)**	(0.005)**	(0.024)**	(0.024)**	(0.005)	(0.030)**	(0.008)
Ind. Var. X 2005	-0.148	-0.117	-0.030	-0.095	-0.094	-0.001	-0.18	-0.002
	(0.024)**	(0.024)**	(0.005)**	(0.027)**	(0.026)**	(0.005)	(0.035)**	(0.007)
Ind. Var. X 2006	-0.171	-0.131	-0.039	-0.112	-0.103	-0.009	-0.20	-0.005
	(0.025)**	(0.024)**	(0.005)**	(0.028)**	(0.027)**	(0.005)	(0.035)**	(0.008)
Ind. Var. X 2007	-0.203	-0.155	-0.044	-0.147	-0.131	-0.015	-0.23	-0.013
	(0.026)**	(0.025)**	(0.005)**	(0.029)**	(0.028)**	(0.005)**	(0.037)**	(0.008)
Ind. Var. X 2008	-0.242	-0.189	-0.050	-0.181	-0.161	-0.020	-0.25	-0.023
	(0.028)**	(0.027)**	(0.006)**	(0.031)**	(0.030)**	(0.006)**	(0.040)**	(0.008)**
Ind. Var. X 2009	-0.315	-0.259	-0.051	-0.244	-0.223	-0.020	-0.32	-0.023
	(0.030)**	(0.029)**	(0.006)**	(0.033)**	(0.032)**	(0.006)**	(0.043)**	(0.008)**
Ind. Var. X 2010	-0.373	-0.315	-0.053	-0.288	-0.268	-0.020	-0.40	-0.026
	(0.032)**	(0.031)**	(0.006)**	(0.035)**	(0.035)**	(0.007)**	(0.046)**	(0.008)**
Ind. Var. X 2011	-0.383	-0.322	-0.056	-0.290	-0.269	-0.021	-0.40	-0.028
	(0.034)**	(0.033)**	(0.006)**	(0.037)**	(0.036)**	(0.007)**	(0.049)**	(0.008)**
Ind. Var. X 2012	-0.383	-0.323	-0.055	-0.285	-0.266	-0.018	-0.40	-0.027
	(0.035)**	(0.034)**	(0.007)**	(0.039)**	(0.038)**	(0.007)**	(0.052)**	(0.009)**
Ind. Var. X 2013	-0.387	-0.327	-0.055	-0.289	-0.272	-0.017	-0.39	-0.028
	(0.036)**	(0.035)**	(0.007)**	(0.040)**	(0.039)**	(0.007)*	(0.053)**	(0.009)**
Ind. Var. X 2014	-0.394	-0.339	-0.049	-0.294	-0.283	-0.011	-0.40	-0.030
	(0.037)**	(0.035)**	(0.007)**	(0.041)**	(0.039)**	(0.007)	(0.054)**	(0.009)**
Ind. Var. X 2015	-0.402	-0.345	-0.050	-0.302	-0.289	-0.013	-0.42	-0.035
	(0.038)**	(0.037)**	(0.007)**	(0.042)**	(0.041)**	(0.008)	(0.057)**	(0.010)**
Ind. Var. X 2016	-0.413	-0.359	-0.047	-0.314	-0.303	-0.011	-0.45	-0.034
	(0.039)**	(0.038)**	(0.007)**	(0.043)**	(0.043)**	(0.008)	(0.060)**	(0.010)**
Fixed effects	Occ.& Year	Occ.& Year	Occ.& Year	Occ.& Year	Occ.& Year	Occ.& Year	Occ.& Year	Occ.& Year
Ini.Wage (ln) x D.Year	No	No	No	Yes	Yes	Yes	No	No
Marg.Eff. 2016-02 (p80-p20)	-0.35	-0.30	-0.04	-0.28	-0.26	-0.02	-0.24	-0.04
OBS	13,063	13,129	13,063	13,031	13,031	13,031	12512.00	12,502
Within R2 Adj.	0.117	0.095	0.041	0.134	0.107	0.088	0.106	0.013
Max.Likelihood	3,121.985	3,479.643	22,733.482	3,239.509	3,581.133	23,022.468	3,567	17,345.755

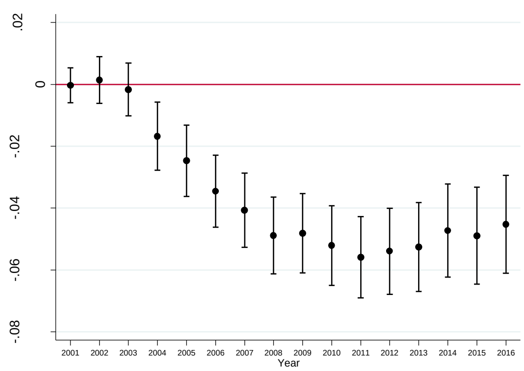
Standard errors allow for within occupation correlation * p<0.05; ** p<0.01

Note: The first row presents the regression number; the second row describes the dependent variable; the third row describes the proxy we 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. We 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 (p80-p20) presents the log difference of the dependent variable between occupations in the percentile 80 and 20 of the risk proxy in 2016 relative to 2002 (we 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).

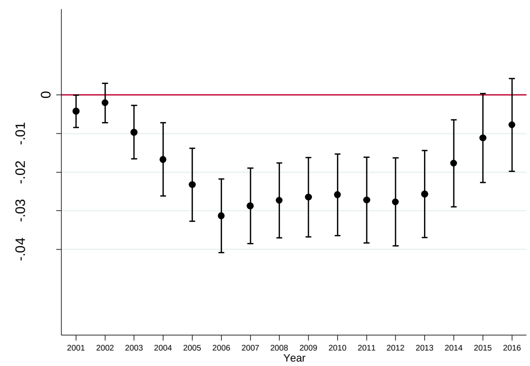
These results show that automation within occupations at risk does not explain the observed increase in wage dispersion in OES data reported in Table 1 in the main text. Wage dispersion across occupations increases because wages in occupation at risk of automation, which are on average low, fall until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

Figure B: Occupation-Wages and Risk of Automation
Aggregate Data (Period 2000-2016)

Ba: Wage Percentile 10th



Bb: Wage Percentile 90th



Source Author´s estimation. Econometric model not reported.

In previous results, we 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 we 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 we use the log robot per workers in the US instead of year dummies to proxy for capital-technology prices.[45] Following Acemougly and Restrepo (2018), we instrument our proxy using the average log value of robots per workers in EU countries to avoid a reverse causality.[46] 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. Although this is a weak assumption, it is still strong. This

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

approach becomes convincing, ounce we 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, we 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 we instrumented with robots in EU15). As in the case we use dummies as a proxy for capital-technology prices, estimated coefficients for risk of automation falls when we 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 proxy for risk of automation. Occupations in the percentile 80th in the routine index grow -1.9% than occupations in the percentile 20th. For employment, this percentage is -1.7%. Finally, column (8) present a growth model for the wage bill between 2001 and 2016.[47] The estimated annual rate of growth difference between occupations at risk and not 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 half of the sample and them

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

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

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	-0.470	-0.407	-0.055	-0.368	-0.343	-0.025			-0.377
x Robots/worker	(0.044)**	(0.042)**	(0.008)**	(0.049)**	(0.047)**	(0.009)**			(0.037)**
Routine Task Index							-0.499	-0.474	
x Robots/worker							(0.068)**	(0.065)**	
Employment 2001 (ln)									0.015
									(0.012)
Fixed effects	Occ.&Year			Occ.&Year		Occ.&Year	Occ.&Year	Occ.&Year	No
Init.Wage(ln) x Robots/Worker	No	No	No	Yes	Yes	Yes	No	No	No
Annual Growth 2016-02 (p80-p20)	-3.6%	-3.0%	-0.3%	-2.7%	-2.5%	-0.2%	-1.9%	-1.7%	-3.1%
OBS	13063	13129	13063	13031	13031	13031	12512	12512	694
Within R2 Adj.	0.108	0.088	0.030	0.125	0.101	0.062	0.122	0.099	0.137
Max.Likelihood	3061	3432	22660	3164	3527	22829	3150	3513	-462

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. We 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 2016-00 (p80-p20) presents the estimated annual rate growth difference between occupations in the percentile 80th and 20th of the risk proxy between 2002 and 2016. When we use FO RISK Index we use occupations with index equals to 1 and 0. We use 795 occupations defined by the BLS Occupational Employment Statistics (OES) program.

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. Next section present evidence in favor of this last hypothesis.