Automation Threat and Wage Bargaining

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Abstract

I analyze how the possibility of automating jobs impacts wages even in the absence of adoption of the automation technology. I build a multi-occupation search and bargaining model in which firms and workers bargain over wages and some occupations can be automated. A firm that can threaten to automate an occupation instead of hiring a worker has a higher outside option during the bargaining process. Thus, the possibility of automating improves the bargaining outcome of the firm and lowers the wage of the worker. Using data from the Current Population Survey and an index of automatability from the literature I show that, in line with the model, the threat of automation decreases workers' wages, that this effect is more pronounced in labor markets where union intensity is higher, and that the return to experience in an occupation is negatively affected by the threat of automation. These results suggest that, even if only a small number of firms automate, automation technologies may still have a large effect on the labor market.

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1. Introduction

There is a growing concern in the public debate that machines might soon replace workers in many jobs. For example, Gallup (2018) reports that 73 percent of US adults believe that artificial intelligence will "eliminate more jobs than it creates." Mirroring these concerns, the economics literature has so far focused on how the *adoption* of automation technologies impacts employment and wages. Yet technology adoption is a slow process. The rate of adoption of industrial robots, an often-used measure of automation, has been surprisingly modest in the last few decades: There are only 1.5 more robots per thousand workers in the US today than in 1993 (International Federation of Robotics, 2014).[1] Similarly, the number of self-checkouts, invented in 1994, amounts to less than 4% of the total number of cashiers in the US (RBR, 2018).[2]

Some have argued that the effects of automation on today's wage structure are therefore limited (Mishel and Bivens, 2017; Acemoglu and Restrepo, 2017).[3] In opposition to this view, this paper argues that automation technologies can have a sizable impact on the labor market even when adoption is low. Indeed, if firms and workers bargain over wages, the mere possibility of automating a job improves the firm's fallback position, which allows it to negotiate lower wages, even in the absence of technology adoption.

To analyze the impact of this "automation threat," I develop a search and matching model with wage bargaining, where firms search for both workers and automation technologies. The rate at which a firm finds an automation technology differs across occupations. A firm that finds a technology has a higher outside option during the wage

[1] Industrial robots are defined by the International Federation of Robotics as "automatically controlled, reprogrammable, and multipurpose" machines (International Federation of Robotics, 2014). The number of robots per thousand workers in the US is approximately one third the stock of robots in European countries. The rate of adoption in the US and in Europe are similar: approximately one robot per thousand workers every 15 years (Acemoglu and Restrepo, 2017).

[2] The first self-checkout was invented in 1994 by David R. Humble. RBR (2018) reports 125,000 self-checkout units in the US in 2017, while the number of workers in the cashier occupation given by the Bureau of Labor Statistics was 3,555,500 in 2016 (SOC occupation code 41-2011)

[3] Although Acemoglu and Restrepo (2017) anticipate that the impact of robots might be sizable over the next two decades, their estimates of past adoption imply less than a 0.35 percentage point decline in the employment-to-population ratio due to robots over the period from 1990 to 2007 in the US.

bargaining process because it can threaten to automate the job instead of keeping the worker. Thus, the possibility of automating increases the firm's bargaining outcome and lowers the worker's wage. The model delivers three precise predictions about how this automation threat affects wages.

First, occupations with higher automation probabilities have lower average wages. Key to this result is the impact of the automation threat on the experience premium. Because workers and firms expect automation possibilities in the future, firms agree to offer higher wages to workers ex-ante. However, once a firm finds a possibility to automate, it is able to renegotiate the worker's wage downward. Thus, a higher automation probability has two opposing effects on the wage structure: It increases wages at employment, and it increases the number of workers with a lower, renegotiated wage. The average wage in an occupation depends on the strength of these two opposite forces. In a steady state, the composition effect dominates and the average wage decreases with the automation probability.

Second, a higher probability of automation decreases the return to experience. As workers are slowly hit by the automation threat, their wages get bargained down. Thus, a higher probability of automation means that older workers receive a lower wage and the return to experience is low in occupations with high automation probability.

Third, the bargaining power of workers in the labor market amplifies the impact of the automation threat on the average wage. Intuitively, when workers have no bargaining power, they receive their reservation wage independently of the firm's outside option. When bargaining power is positive, workers receive a positive share of the surplus that depends on the firm's outside option.

To take the model to the data, I exploit information on wages and the potential for automation at the occupation level. To measure an occupation's potential for automation, I use a technological index of automatability based on the task content of occupations and built by Frey and Osborne (2017). The index aims to measure the probability that an occupation can be fully automated given the technological advances as of 2013.

A high index indicates that most of the tasks in an occupation can be fully executed by a machine. Thus, even if an occupation requires workers to operate the remaining, non-automatable tasks, an employer can keep only part of the workforce while automating the tasks that can be automated. Thus, at the individual level, the index represents the probability that one worker's job get automated.

To construct the index, Frey and Osborne (2017) draw upon advances in the fields of machine learning and mobile robotics. The authors identify several engineering bottlenecks to automation, corresponding to three task categories: perception and manipulation tasks, creative intelligence tasks, and social intelligence tasks. An occupation's probability of being automated is described as a function of these task characteristics. The authors use a Gaussian process classifier algorithm that takes advantage of the description in the O*NET database of the task content of occupations. The algorithm is trained on 70 occupations that have been classified by a panel of machine learning researchers as fully automatable or not. The algorithm is then used to estimate the probability of automation for 702 detailed occupations.

I combine this index for automation with data from the 2013 Merged Outgoing Rotation Group of the Current Population Survey (CPS) to provide estimates of the impact of the threat of automation on wages in the US labor market.[4] The data from the CPS provide information at the individual level on wage, occupation, characteristics (gender, race, education), location (at the state or metropolitan statistical area level) and union status for a representative sample of the US population.

I find support of the three channels highlighted above. First I show that automability has a sizable effect on average occupation wages. Quantitatively, the estimated coefficient implies that an increase of one standard deviation (0.3) in the likelihood of being automated reduces the wage in the occupation by about 10 percent. This effect is robust to the inclusion of measures of the routine intensity and the offshorability of occupations (as in Autor and Dorn, 2013) . Interestingly, the coefficients for routine-

[4] I use the version of the CPS provided by IPUMS (see Flood et al., 2018).

intensity and for offshorability are no longer significant once the automatability index is introduced in the regression. This is reassuring regarding my choice of the index for automatability as it shows that this index has more predictive power on occupational wages in recent years than the routine-intensity index and offshorability index used in the literature.[5] I also investigate the robustness of this result to a range of different specifications and controls.

In a second specification, I use workers' age as a proxy for their tenure at a firm. The regression includes the interaction of the automatability index with age dummies. The coefficients of these interactions are negative, and their magnitude increases with the age of the worker, indicating that the older a worker, the higher the threat effect on her wage. This is in line with the third prediction of the theory: The experience premium is lower in occupations with high automatability.

To test the third prediction of the theory, I use the union density within a local labor market as a measure of workers' bargaining power. The interaction of the automatability index with the union density in the labor market has a negative effect on wages, which indicates that union density amplifies the impact of the automation threat on wages.

Finally, as a placebo test, I show that the automatability index, which reflects technological advances as of 2013, has a decreasing impact on wages as one goes further back in time, and had no impact on wages in 1973. This is expected, as most occupations where less likely to be under the threat of automation in earlier decades.

These results suggest that, even if only a small number of firms automate, new automation technologies may still have a large effect on the labor market.

Related literature This paper is related to several strands of the literature. First, it is related to the literature analyzing the impact of technology adoption on wages and employment. Most of the theoretical literature focuses on automation in competitive

[5]This reflects the fact that neither the routine-intensity index nor offshoring predict changes in wages beyond the change predicted by the automatability index I use.

labor markets.[6] Acemoglu and Restrepo (2018c,d) show how the automation of tasks can decrease wages through the displacement of workers, but can also increase wages through an increase in demand for labor in other sectors triggered by the surge in productivity due to automation. In such environments, technology impacts wages only if it is adopted. The present paper shows that in a frictional labor market, technologies can impact wages even when they are not productive enough to be adopted.

The empirical literature on automation has been growing rapidly in recent years, partially due to the recent availability of data on industrial robots released by the International Federation of Robotics. For example, Graetz and Michaels (2017) use the evolution of the stock of industrial robots in 17 countries from 1993 to 2007 to investigate the impact of automation technologies on labor productivity, total factor productivity, employment and the labor share. Acemoglu and Restrepo (2017) also use data on industrial robots to infer robot adoption at the labor market level in the US and estimate the impact of robot adoption on wages and employment by comparing labor markets with different adoption rates. They find that robots decrease employment and wages, but the magnitude of their estimates is relatively low as discussed in Mishel and Bivens (2017).[7] The theory in this paper provides a mechanism to explain why these studies on automation adoption find a modest impact of automation on wages. These studies compare wages in labor markets before and after the adoption of robots. According to the theory in this paper, wages in labor markets with no robots are still affected by the threat of automation. Therefore, the between-markets estimators only captures the adoption part of the impact of automation technology (e.g., robots) on wages.

This paper also relates to the literature on threat effects. Threat effects are not restricted to automation possibilities. Leamer (2000) shows that the *possibility* of outsourcing production can impact prices and wages without changing the volume of

[6]One exception is Acemoglu and Restrepo (2018a) who analyze the possibility of over-automation in a frictional environment.

[7]Mishel and Bivens (2017) argue that Chinese imports had four times the annual impact of robots on the employment rate each year from 1999 to 2007.

traded goods. Pierce and Schott (2016) analyze how uncertainty about trade tariffs with China impacts employment in the US. Seamans (2013) shows that the threat of entry, proxied by geographic proximity to a potential entrant, into an incumbent's market in the TV and cable industry induces the incumbent to adopt a limit pricing strategy and produce upgrades as a response. Taschereau-dumouchel (2017) details how the *possibility* of workers unionizing affects a firm's hiring decisions, even when workers in the firm are not unionized. In line with these papers, the present paper highlights the impact of potential automation on wages, even when automation of production is not implemented.

This paper also contributes to the literature that seeks to understand the interplay between technology and institutions. Acemoglu et al. (2001) show that there is a feedback loop between technological change and unionization rates. Archanskaia et al. (2017) look at how institutions, by facilitating substitution between labor and capital, influence patterns of trade through a change in the comparative advantage in automated production. This paper, in line with this literature, argues that the impact of automation technologies on wages depends on the institutional arrangements of the labor market, especially the level of unionization and the relative bargaining power of workers and firms.

Finally, this paper extends the theoretical literature on search models. I combine a multi-occupation model of search and bargaining (see Beaudry et al., 2012) with a mechanism of on-production search for technology reminiscent of the on-the-job search mechanism in Cahuc et al. (2006).

The rest of the paper is organized as follows: Section 2 presents a model of the effect of the threat of automation on wages when automation is not productive enough to be adopted by firms hiring workers but can still be used to alter the outcome of the wage bargaining. Section 3 presents the data used in the analysis and the empirical results. Section 4 concludes.

2. Model

In this section, I present a multi-occupation search-and-matching model with wage bargaining that builds on the standard framework from Pissarides (2000). I enrich this framework by allowing firms to search for automation technologies. This provides a mechanism that endogenously alters firms' outside options in wage bargaining and therefore the wages in the economy.

2.1. Technology

Time is continuous. The economy is populated by workers and firms. There is a measure 1 of homogeneous workers. Workers live forever, are risk neutral, and discount the future at a rate ρ. There is a large number of firms, and each firm consists of one job. Each job belongs to an occupation j in the set of all occupations $\mathcal{J}$. The production technology of the firm is linear, and all firms produce the same quantity of a homogeneous good y. A firm's occupation determines its capacity to automate production, which is the only source of heterogeneity across firms.

2.2. Labor markets

Firms look for workers, and the matching between a firm and a worker is time-consuming and costly. To hire workers, firms post vacancies at a cost $c(v_j)$, with $c(\cdot)$ increasing and convex and where v_j is the total number of vacancies in the labor market for occupation j. The total number of vacancies across all the occupations is $v = \sum_{j\in\mathcal{J}} v_j$. The number of unemployed workers looking for a job is denoted by u, and the labor market tightness θ is the ratio of the total number of vacancies to the number of workers looking for a job, $\theta = v/u$. The labor market is therefore common to all occupations and searching is not occupation-specific. This setup is similar to the one in Beaudry et al. (2012).

Because looking for a job and looking for a worker take time, there is a finite number of matches per unit of time, $m(u, v)$. The matching function $m(u, v)$ is strictly concave, strictly increasing and homogeneous of degree one. Consequently, the rate at which a vacancy is filled is $\varphi(\theta) = m(u, v)/v = m(1/\theta, v)$, while the rate at which a worker finds a job is $\psi(\theta) = m(u, v)/u = m(1, \theta)$. Note that this is the probability of finding some job, i.e. it is common across all occupations. Because of the constant return to scale property of the matching function, the probability that a worker finds a job in occupation j is proportional to the share of vacancies in occupation j and is given by $\psi_j(\theta) = \psi(\theta) \cdot v_j/v$. Matches are destroyed at an exogenous rate δ.

2.3. Automation and firms

Firms can search for an automation technology at no cost. A firm in occupation j finds an automation technology at a rate λ_j, which is exogenous and occupation-specific. The technology finding rate λ_j is greater for occupations that are more likely to be automatable. The automation technology allows the firm to produce output without any workers.

Once it finds a technology, the firm can either (i) ignore the technology, (ii) separate from the worker and automate, or (iii) keep the match and renegotiate the contractual wage. The firm's choice depends on the value of automating production, denoted A, which I take as exogenous. I assume that the value of automating is the same across occupations. Hence, the only source of heterogeneity across firms comes from the finding rate λ_j. The choice of a common value of automation, A, and heterogeneity in the finding rate, λ_j,' s is motivated by the empirical exercise, where automatability is proxied by an index of the likelihood that an occupation can be fully automated, which maps naturally onto the finding rate λ_j.[8]

Let $J_j^{NA}(w)$ denote the lifetime utility of an occupation-j firm that has no technology available to automate and that is hiring a worker at a wage w. Let $J_j^A(w)$ denote the

[8]In the Appendix, I show that the results carry over if I assume that the finding rate is identical across occupations but the value of automating is occupation-specific.

lifetime utility of a firm with the knowledge of an automating technology that is hiring a worker at a given wage w, and let V_j denote the value of posting a vacancy. These value functions solve the following Bellman equations

$$\rho J_j^{NA}(w) = y - w + \delta(V_j - J_j^{NA}(w)) + \lambda_j \left[\max\left\{ \underbrace{A}_{\text{automate}}, \underbrace{J_j^A(w_j^A)}_{\text{renegotiate}}, \underbrace{J_j^{NA}(w)}_{\text{ignore}} \right\} - J_j^{NA}(w) \right], \tag{1}$$

$$\rho J_j^A(w) = y - w + \delta(V_J - J_j^A(w)), \tag{2}$$

$$\rho V_j = -c(v_j) + \varphi(\theta)(J_j^{NA}(w_j^{NA}) - V_J) + \lambda_j(\max\{A, V_j\} - V_j). \tag{3}$$

Equation (1) states that the flow of utility for the firm from hiring a worker at wage w, consists of three parts: (1) the flow of profit net of wage, $y - w$, (2) the expected change in valuation from an exogenous separation, and (3) the expected change in valuation from using the discovered automation technology. The key contribution of this paper is the third part: The $\max$ operator in the last term of Equation (1) indicates that the firm can choose to renegotiate the wage, to automate, or to keep the contract unchanged, depending on the net present value of automating, A. The renegotiated wage w_j^A depends on A through the bargaining process that is described below. Equation (2) gives the firm's continuation value once the firm has found the automation technology, but has not implemented automation. The firm gets the flow of profit net of wage, $y - w$, plus the expected loss from exogenous separation. Notice that once the worker and the firm separate, the firm loses its potential to automate and goes back to the vacancy state. Finally, Equation (3) states that the firm's value of looking for a worker is equal to the gain from finding a worker at rate $\varphi(\theta)$, plus the gain from finding an automation technology at rate λ_j, net of the cost of the vacancy $c(v_j)$. Once the firm finds a worker, the match is formed, production takes place and the agreed upon wage is the equilibrium wage at employment, denoted w_j^{NA}.

2.4. Workers

Workers are either employed or unemployed. An employed worker loses her job with probability δ, in which case she becomes unemployed. I denote $E_j^{NA}(w)$ the lifetime utility of working at a j-firm that has not found the automation technology, at a wage w. $E_j^A(w)$ is the lifetime utility of working for a wage w at a firm that can use the automation technology, and U is the lifetime value of unemployment. These continuation values solve the following Bellman equations:

$$\rho E_j^{NA}(w) = w + \delta(U - E_j^{NA}(w)) + \lambda_j \left[\mathbb{1}^A(U - E_j^{NA}(w)) + (1 - \mathbb{1}^A)(E_j^A(w_j^A) - E_j^{NA}(w)) \right], \tag{4}$$

$$\rho E_j^A(w) = w + \delta \left(U - E_j^A(w) \right). \tag{5}$$

Equation (4) states that the utility flow for a worker of being matched to a firm in occupation j with no possibility of automating is equal to the wage w, plus the change in value from losing her job at a rate δ and the change in value from the firm finding the automation technology, which can trigger automation ($\mathbb{1}^A = 1$) or renegotiation ($\mathbb{1}^A = 0$). If it triggers automation, the worker becomes unemployed. If it triggers renegotiation, the worker is employed at the new equilibrium wage w_j^A, which she values at $E_j^A(w_j^A)$.

Equation (5) shows that the flow of utility for a worker in a firm with knowledge of the automation technology is equal to her wage plus the expected loss from separation into unemployment.

An unemployed worker receives a value b of home production, and finds a job in occupation j at a rate $\psi_j(\theta) = \psi(\theta) \cdot v_j/v$. The lifetime value of an unemployed worker is therefore

$$\rho U = b + \psi(\theta) \left(\sum_{j \in \mathcal{J}} \frac{v_j}{v} E_j^{NA}(w_j^{NA}) - U \right). \tag{6}$$

2.5. Firms' decision to automate

The firm automates if the value from doing so is greater than the value of keeping the worker at the lowest possible wage. As I show in the Appendix, the lowest wage a worker is willing to accept is $\underline{w} = \rho U$ and is identical across all occupations. For a firm that can automate, keeping the worker at this minimum wage $\underline{w}$ has a present discounted value of $J^A(\underline{w})$. Therefore, the firm automates if $A > J_j^A(\underline{w})$, in which case $\mathbb{1}^A = 1$.

2.6. Wages

For a given occupation j, there are two types of wage: the wage w_j^{NA}, determined upon employment of the worker, and the wage w_j^A, determined after renegotiation, once the firm has found the automation technology. Both wages are determined as the outcome of a game that delivers the generalized Nash-bargaining solution where the worker receives a constant share κ of the match rent. The parameter κ is the worker's bargaining power. The bargaining processes for the two wages differ in the outside option used by the firm, hence the total surplus of the match.

Wage out of unemployment w_j^{NA}

When an unemployed worker meets an occupation-j firm without knowledge of the automation technology, the total surplus S_j^{NA} is

$$S_j^{NA} = J_j^{NA}(w) - V_j + E_j^{NA}(w) - U. \tag{7}$$

As usual in random search models with linear utility, since utility is directly transferable between workers and firms, the match surplus is independent of the wage w. The bargained wage w_j^{NA} solves the following equation,

$$\kappa(J_j(w_j^{NA}) - V_j) = (1-\kappa)(E_j(w_j^{NA}) - U). \tag{8}$$

Wage after renegotiation w_j^A

When a firm finds an automation technology, the situation becomes more favorable to the firm. It can use this new option to force the worker to compete in the bargaining process with the automation technology. The bargaining can be seen as an auction between the worker and the automation technology where they both offer a contract to the firm that stipulates its flow of profit, and where the bidder with the highest bid pays the second price. The worker will not offer a contract with a wage below her reservation wage $\underline{w}$, which the firm values at $J_j^A(\underline{w})$. Therefore, if the value of automating A is higher than $J_j^A(\underline{w})$, the firm automates. If the value of automating is lower than $J_j^A(\underline{w})$, the firm can always use the automation technology instead of hiring a worker, so the value of automating A is the firm's new fallback position in this new negotiation game. The auction still forces the worker to accept a lower wage than her current equilibrium wage w_j^{NA}. The surplus of the match between a worker and a firm that can automate is therefore

$$S_j^A = J_j^A(w) - \max\{V_j, A\} + E_j^A(w) - U. \tag{9}$$

The outcome of this renegotiation game is the wage w_j^A, which solves the following equation

$$\kappa(J_j^A(w_j^A) - A) = (1-\kappa)(E_j^A(w_j^A) - U). \tag{10}$$

Of course, renegotiation only takes place if it is in the firm's interest, which depends on the value of automating the job, A. If the automation technology has a lower value than opening a vacancy, i.e., $A < V_j$, the firm's outside option is to open a vacancy and therefore is unaffected by the automation technology A. In that case, the firm does not trigger renegotiation.

Notice that renegotiation does not actually require the value from automation A to be greater than the pre-renegotiation value captured from the match surplus by the firm, $J_j(w_j^{NA})$. The reason is that the renegotiation game can be seen as a two-stage game, as in Cahuc et al. (2006): The firm first chooses either to keep the status quo or to automate; if the firm decides to automate, some time elapses before renegotiation starts with the worker. During that time, the worker finds herself unemployed. The firm knowing that the worker will join the negotiation with the same outside option (the value of unemployment), it is enough for the firm to make the move towards automation in order to increase its outside option and decrease the renegotiated wage, as long as $A > V_j$. Knowing this and to avoid wasting time (which is costly), the worker immediately accepts the renegotiated wage w_j^A. At equilibrium, the firm never moves towards automation, and there is no actual adoption of the technology.

The next proposition formalizes this discussion.

Proposition 1. *There exist two values, A_j^{low} and A_j^{high}, such that*

1. *If $A > A_j^{high}$, then the firm breaks the match and automates;*
2. *If $A < A_j^{low}$, then the possibility of automation does not impact the wage: the worker keeps her wage w;*
3. *If $A_j^{low} \leqslant A \leqslant A_j^{high}$, then the firm renegotiates the wage to w_j^A.*

The values of the thresholds are $A_j^{low} = V_j$ and $A_j^{high} = \dfrac{y - \rho U + \delta V_j}{\rho + \delta}$.

For the remainder of the paper, I assume that A is such that 3. above is satisfied. This corresponds to the case of "so-so technologies": The firm might still prefer, at the given wage, employing the worker than automating, yet as automating provides a better outside option than searching for a worker, the firm triggers renegotiation. Of course, it can also be the case that the firm prefers, at the given wage, using the technology, yet there exists a wage that makes production more efficient with the worker, and the worker is willing to work at this wage. One can interpret this situation as a period of technological transition, during which the technology is still developing and being implemented by only a few firms. In the model, these few firms are the firms that are looking to fill vacancies and that find the technology before finding workers. The firms that hire workers and subsequently find the technology only use the technology as a threat to renegotiate wages.

I can now characterize the wages that are the solution of the bargaining equations (8) and (10).

Proposition 2. *Under the assumption that A is such that 3. in Proposition 1 holds, the wage at employment w_j^{NA} and the renegotiated wage w_j^A are given by*

$$w_j^{NA} = \kappa y + (1-\kappa)\rho U - \kappa\rho V_j + \lambda_j \kappa (A - V_j),$$
$$w_j^{A} = \kappa y + (1-\kappa)\rho U - \kappa\rho V_j - \kappa(\rho+\delta)(A - V_j).$$

Proof. See Appendix B. ■

Start paragraph with: Proposition 2 characterizes the equilibrium wages for firms with and without the automation technology. The wages have both a common component and a specific component. The common component is given by $\kappa y + (1-\kappa)\rho U - \kappa\rho V_j$. It has the form of the wage in a usual random search and matching model without the technology search mechanism. It is increasing in the productivity of the worker (y) and her outside option (ρU), and decreasing in the firm's outside option (ρV_j). The distinct component differs between the wage at employment w_j^{NA} and in the renegotiated wage w_j^A. In the wage at employment, w_j^{NA}, it corresponds to the premium that the worker asks for in order to work at a firm that is likely to renegotiate wages later on. This premium is increasing in λ_j, as well as in the difference between the new and the old outside options of the firm $A - V_j$. In the expression of the renegotiated wage, w_j^A, the second term corresponds to the discounted value of the change in the surplus that the worker is losing due to the renegotiation. Finally, notice that if $A = V_j$, the threat mechanism is absent, and both wages are equal.

As the above expressions for the wages show, the value of the wage at employment is increasing in the occupation's probability of being automated, λ_j, while the renegotiated wage is independent of λ_j. The average wage in an occupation is a convex combination of these two wages and depends on λ_j because w_j^A depends on λ_j but also because the share of workers at each wage level depends on λ_j in the steady state.

2.7. Steady-state conditions

In a steady state, the flows in and out of unemployment in a given occupation at a given wage must be equal. In particular, the flows in and out of unemployment are equal and

$$e_j \delta = u\psi(\theta), \tag{11}$$

where e_j is the number of workers in occupation j. The left-hand side of this equation gives the flow of workers who become unemployed, while the right-hand side gives the flow of workers who get hired out of unemployment. Because all workers who are hired out of unemployment are hired at the wage w_j^{NA}, and workers leave the category either because they get separated at rate δ or because their wages get renegotiated at rate λ_j, the flows must satisfy

$$e_j \mu_j^{NA}(\delta + \lambda_j) = u\psi(\theta). \tag{12}$$

where μ_j^{NA} is the share of workers in occupation j who are paid w_j^{NA}. For workers with the renegotiated wages, $\tilde{w}_j^A$, the flows satisfy

$$e_j \mu_j^A \delta = e_j \mu_j^{NA} \lambda, \tag{13}$$

where μ_j^A is the share of workers paid w_j^A and $\mu_j^{NA} + \mu_j^A = 1$. The left-hand side corresponds to the flow of workers who get separated from the firm, and the right-hand side corresponds to the flow of workers who join the category of workers with renegotiated wages from the category of workers with an initial wage (at rate λ).

2.8. Stationary equilibrium

Free entry of firms: I assume that there is a free entry of firms in each occupational labor market. The entry of firms increases the number of vacancies v_j, which increases the cost of posting one vacancy $c(v_j)$, until the value of a vacancy V_j is equal to zero. The cost function $c(\cdot)$ represents the value of creating a marginal job and is increasing in the number of vacancies in a given occupation, perhaps due to limited local entrepreneurial talent. If the cost were a constant, the entry of firms in the labor market would result in the specialization of the labor market in one occupation only (the occupation with the highest value of vacancy, V_j). Since I consider an environment without complete specialization, I assume that $c(\cdot)$ is increasing.

Definition 1. *A steady-state equilibrium is a collection of value functions for workers $\left\{E_j^{NA}, E_j^A, U\right\}_{j\in\mathcal{J}}$ and for firms $\left\{J_j^{NA}, J_j^A, V_j\right\}_{j\in\mathcal{J}}$, a labor market tightness θ, vacancies $\{v_j\}_{j\in\mathcal{J}}$, and wage schedules $\left\{w_j^{NA}, w_j^A\right\}_{j\in\mathcal{J}}$ such that*

1. *the value functions solve the Bellman equations;*
2. *the wage schedules satisfy the generalized Nash bargaining problems;*
3. *unemployment and employment in each occupation for each level of wage are stationary, according to equations (11) to (13);*
4. *there is free entry such that the value of a vacancy is zero for all occupations.*

In the steady state, the average wage in each occupation is given by the following proposition:

Proposition 3. *The average wage in an occupation is*

$$\bar{w}_j = (1-\mu_j^A)w_j^{NA} + \mu^A w_j^A = \kappa y + (1-\kappa)\rho U - \kappa\delta\frac{\lambda_j}{\delta+\lambda_j}A, \tag{14}$$

where $\mu_j^A = \dfrac{\lambda_j}{\delta+\lambda_j}$ is the share of workers with a renegotiated wage in occupation j.

2.9. Predictions

From the analytical expression of the wages before and after renegotiation, and the average wage in each occupation, I derive three precise predictions about how the automation threat affects wages.

Prediction 1. *In a given labor market, the average wage in an occupation is decreasing in the probability of automation,*

$$\lambda_j \geqslant \lambda_k \Longrightarrow \bar{w}_j \leqslant \bar{w}_k$$

This proposition reflects the fact that with a high probability of automation λ_j, there are more workers under a contract with a low renegotiated wage w_j^A, i.e., μ_j^A is higher. Although the initial wage w_j^{NA} is actually increasing in λ_j, this is not enough to compensate for the composition effect, and the average wage decreases with the probability of automation.

Prediction 2. *The experience premium is lower in an occupation with higher automation probability,*

$$\lambda_j \geqslant \lambda_k \Longrightarrow w_j^A - w_j^{NA} \leqslant w_k^A - w_k^{NA}$$

The intuition of this prediction is that workers get slowly hit by the possibility of automation. In firms with a high threat, the wages of older workers who have stayed at the firm longer get bargained down, and their wages are lower than those of younger workers who just got hired. Note that the model has the counterfactual prediction that workers with more experience have on average a lower wage than workers who have just joined a firm. This is because I abstracted from any mechanism of learning-by-doing that increases wage as workers get more experienced. Including this feature would not alter the prediction that the experience premium is lower in an occupation with a higher automation threat.

Prediction 3. *The differences in the average wages across occupations with different au-*

tomation probabilities is increasing in the bargaining power of workers in the labor market, κ, as

$$\frac{\partial}{\partial \kappa} \cdot \frac{\partial \bar{w}_j}{\partial \lambda_j}\Big|_U < 0$$

To understand the mechanism behind this prediction, consider the extreme case in which workers do not have any bargaining power ($\kappa = 0$). In that case, the wage they obtain from the bargaining game is simply their outside option, ρU, which is identical in all occupations. There is therefore a single wage in the entire economy, which is also the average wage in each occupation. As workers' bargaining power increases, they receive a share of the surplus on top of their reservation wage, and the match surplus differs across firms.

3. Empirical Results

This section provides empirical evidence that the three predictions derived in the previous section hold in the data. I first show that the automation potential of an occupation is negatively associated with the average wage in the occupation. I then provide evidence that the return to experience is on average lower in occupations with higher threat of automation . Finally, I show that the effect of the automation potential on wages is amplified in labor market with higher union density. To do so, I use data from the Merged Outgoing Rotation Group of the 2013 Current Population Survey and the automatability index developed by Frey and Osborne (2017). I first provide a description of the data. I then describe the regressions and empirical results.

3.1. Data

3.1.1. Technological index

To measure an occupation's potential for automation, I use Frey and Osborne's (2017) automatability index. The index is specifically built to measure how feasible it is to automate existing jobs given technological advances as of 2017. Frey and Osborne's (2017) index builds on, and complements, previous attempts at quantifying the possibility of automating occupations based on the tasks workers complete.

In their seminal work, Autor et al. (2003) propose a framework that distinguishes between routine and non-routine tasks. Because routine tasks follow well-defined repetitive procedures, they can easily be translated into an algorithm and performed by computers (Acemoglu and Autor, 2011). Many studies have used this framework to explain the shift of employment from middle-income occupations, which are routine-intensive and can be automated more easily, towards low-income service occupations, which are not easily automatable because they require physical adaptability and dexterity (Autor et al., 2003; Autor and Dorn, 2013; Goos and Manning, 2007).

Yet, this routine versus nonroutine framework presents important limitations. As argued by Mishel et al. (2013) and Acemoglu and Restrepo (2018b), the pattern of employment polarization breaks after the 2000s, so there is no longer a clear increase in employment in low income service occupations compared to middle-income occupations. Second, and in relation to the first point, the recent developments of artificial intelligence technology, machine vision, machine learning, and mobile robotics, combined with the accumulation of big data, have enabled drastic improvements in the automation possibilities of nonroutine tasks, increasing the automation threat to occupations that have so far been considered non-automatable (Acemoglu and Restrepo, 2018b; Brynjolfsson and McAfee, 2014). Fourteen years ago, Levy and Murnane (2005) argued that driving in traffic was an example of a non-routine occupation that was unlikely to be automated. The development of sensor technologies, the accumulation of data on traffic, and the perfection of algorithms have rendered self-driving technology today's reality. Overall, the potential for automation is increasingly attributable to the possibility to accumulate enough data that algorithms can use to learn and detect patterns than to the routine/nonroutine nature of tasks. This paradigm shift in what can and can't be automated justifies the use of the technological index by Osborne and Frey rather than the routine intensity measure by Autor et al. (2003). Besides, in the empirical analysis, I show that the automatability index predicts wages better than the routine intensity measure.

To construct the index, the authors draw upon workshops held at the University of Oxford's Engineering Sciences Department in which a panel of experts identified engineering bottlenecks to the automation of jobs. These bottlenecks belong to three main task categories: perception and manipulation, creative intelligence, and social intelligence. Using the panel of experts, the authors select 70 occupations and identify those among them that can be fully automated.[9] Second, the authors take advantage of O*NET, an online service developed for the US Department of Labor that contains information on 903 detailed occupations. Notably, O*NET defines the key features of an occupation as a standardized and measurable set of variables. The authors identify nine variables in O*NET that correspond to the three broad categories. An occupation's probability of being automated is then described as a function of these task variables. Using the 70 classified occupations, the authors train a probabilistic classification algorithm that is used to predict the automation probability of 703 detailed occupations.

Frey and Osborne's (2017) methodology has been applied in a number of complementary studies on the German labor market (Brzeski and Burk, 2015), the Finnish labor market (Pajarinen et al., 2015), and countries in the OECD (Arntz et al., 2017; World Bank, 2016).

3.1.2. Current Population Survey

The Current Population Survey data provide a representative sample of the US population, every year since 1962. Individuals are surveyed every month for 4 months, then dropped out of the sample for 8 months, and then surveyed again for 4 months. I use

[9] They answer the question, "Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state-of-the-art computer-controlled equipment?" The list of occupations that are flagged as fully automatable and the ones flagged as non-automatable are given in the Appendix.

information from the Outgoing Rotation Group (ORG CPS). The ORG CPS comprises the subsample of individuals in their fourth and 12th months of the survey. The data include individual characteristics such as age, gender, ethnicity/race, and educational achievement. They also include individuals' locations, especially the MSA (Metropolitan Statistical Area) and the state of residence. MSAs include urban areas as well as their economically associated regions and covered approximately 75% of the US population in 2013. Finally, they include labor market information, such as the occupations of working individuals, the trade union membership status of each individual, and each individual's weekly earnings. In my main regression, I use data from 2013, as this is the year for which the index for the threat of automation was built by Frey and Osborne (2017). I also use data from 1990 to compute the change in occupational employment from 1990 to 2013 , which I use to control for the change in occupational labor demand. To run a placebo test, I use information from 1973 on. As earnings information is not reliable before 1989 in the ORG CPS, I use information from the March Supplement (ASEC) to the CPS from 1973 on.

3.2. Results

In this section, I empirically test predictions 1-3 of the model. First, I use the variation of the automatability index across occupations to analyze the association between the threat index and the average wage in each occupation. Second, I use individuals' the experience, proxied by their age, to test whether the automation threat decreases the experience premium, as stated in prediction 2. Third, I use across-market variation in union membership rates to show that the differences in wages across occupations due to the threat index are amplified by workers' bargaining power in the labor market. Finally, as a placebo test, I show that the automatability index has no association with wages in 1973 and that the (negative) association is more pronounced as the year gets closer to 2013, when the index was built.

3.3. Prediction 1: Automation threat and average wages

Table 1 presents my main result for the impact of the automation threat on wages. Data come from the Outgoing Rotation Group from the CPS 2013, as well as the automatability index from Frey and Osborne (2017). The outcome variable is the logarithm of weekly earnings for each individual in the sample. I only keep individuals between 16 and 65 years old, employed in the private sector. Standard errors are clustered at the occupation level and state level (or MSA level, when appropriate) and robust against heteroskedasticity.

The specification of the regression is, at the individual level,

$$w_{ijdm} = \beta\, threat_j + \delta_d + \delta_{s(m)} + \gamma \mathbf{X}_i + \eta \mathbf{X}_m + \varepsilon_i, \tag{15}$$

where w_{ijdm} is the logarithm of weekly earnings of individual i in occupation j, industry d, and MSA m, and $threat_j$ is the technological index associated with occupation j, δ_d is an industry fixed effect, $\delta_{s(m)}$ is a state fixed effect (where m is the MSA), $\mathbf{X}_i$ is a vector of observable individual characteristics (age, gender, years of education and race dummies), and $\mathbf{X}_m$ is a vector of labor market characteristics (change in occupational employment and unemployment rate). Prediction 1 from the theory predicts that $\beta < 0$.

The results are presented in Table 1. Column 1 presents the most parsimonious specification, which includes the automatability index and state fixed effects and I control for individual characteristics with dummy variables (age, gender, race, and years of education). I estimate a strong negative relationship between an occupation's threat and an individual's wage with a coefficient $\beta = -0.35$.

In column 2, I add industry fixed effects to the specification. I use 19 industry categories identical to the categories used in Acemoglu and Restrepo (2017). This allows me to control for important sectors as well as to preserve enough variation in the types of occupations within each industry.[10] This only slightly increases the coefficient of in-

[10] I thank Pascual Restrepo for sharing their crosswalk with me. The industries correspond to the fol-

	(1)	(2)	(3)	(4)
Automatability	-0.35***	-0.37***	-0.36***	-0.36***
	(0.080)	(0.075)	(0.074)	(0.074)
Controls:				
State	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Industry		✓	✓	✓
Change in emp.			✓	✓
Unemployment rate				✓
mean of dependent var.	6.4595	6.4595	6.4588	6.4588
s.d. of depndent var.	.8799	.8799	.8797	.8797
Obs.	121718	121718	121500	121500

The table presents estimates of the impact of the threat of automation on earnings. The dependent variable is the logarithm of weekly earnings and the independent variable is the automatability index for each occupation from Frey and Osborne (2017). The covariates for each regression are reported at the bottom of the table. Column 1 include States dummies as well as individuals' demographic characteristics (age, gender, race, education). Column 2 adds industry dummies for a set 19 industries, as in Acemoglu and Restrepo (2017). Column 3 adds the change in employment at the state level from 1990 to 2013 for each occupation, and column 4 adds the unemployment rate at the MSA level. Standard errors are robust against heteroscedasticity and are clustered at the occupation level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

Table 1: Impact of Automatability Threat on Wages

terest, which indicates that the negative association is not driven by the composition of occupations across industries.

One concern is that occupations that are likely to be automated and have a high threat index might already have been automated in some firms. This adoption of automation technology decreases the demand for labor in these occupations, which might decrease wages. I therefore additionally control for the change in occupation shares in the labor market in column 3, as well as the unemployment rate at the MSA level in column 4. The changes in occupational employment levels and the unemployment rates may themselves be outcomes of the threat of automation, so the coefficients in the regression might be biased. However, the fact that adding these controls does not substantially impact the coefficients of interest mitigates concerns that the negative association between the index and wages is driven by direct changes in labor demand.

Overall, Table 1 is consistent with the first prediction of the model: occupations under higher threat of automation have lower wages on average.

In Table 2, I offer additional evidence for this mechanism by controlling for other characteristics of occupations that might be correlated with both the automatability of an occupation and its average wage: the potential impact of imports on manufacturing jobs, the potential disappearance of routine jobs, and offshoring. In particular, I control for a measure of routine-intensity and an index of the offshorability of jobs, as in Autor and Dorn (2013) and Autor et al. (2015). These indexes are constructed based on the task content of occupations. Column 1 does not include the threat index but includes the routine-intensity index as a covariate. The coefficient of the routine-intensity index shows a negative association with earnings. However, the association between tasks' routine-intensity and earnings becomes insignificant when I add the automatability index in the regression in column 2. Similarly, in column 3, an occu-

lowing broad categories: Automotive, Plastic and chemicals, Electronics, Metal products, Wood and Furniture, Food and beverages, Basic metals, Metal machinery, Glass and ceramics, Other transport vehicles, Services and other sectors, Utilities, Construction, Agriculture, Education, research, and development, Mining, Paper and printing, Textiles, Miscellaneous, toys, and others. See Acemoglu and Restrepo (2017).

pation's offshorability index has, by itself, a strong negative association with earnings. However, this association becomes insignificant when the automatability index enters the regression (column 4). These results suggest that the automatability index, which is specifically built to capture how feasible it is to automate an occupation, has better predictive power on wages.

In table 3 I show additional regressions with more controls: restricting the sample to occupations that have experienced an increase in the level of employment or the share of employment since 1990 does not impact the coefficient of interest. I also restrict the sample to the non-manufacturing sector. The coefficient is not affected. This indicates that trade or other shocks related to the manufacturing sector are not driving the result.

3.4. Prediction 2: Automation threat and experience premium

I now turn to the second prediction of the model: the effect of the automation threat on the experience premium. Because workers at a given firm get slowly hit by the renegotiation of their wage, workers in occupations with higher threats of automation see their wages renegotiated downwards more frequently. The experience premium should therefore decrease with the level of automatabaility. To test this prediction, I proxy the tenure at a firm with the age of the individual and run the following specification:

$$\begin{aligned}\log(earnings)_{ijdm} =& \beta\, threat_j + \sum_{k=16}^{65} \Gamma_k \mathbf{1}_{age_i=k} \times threat_j \\ & + \delta_d + \delta_{s(m)} + \gamma \mathbf{X}_i + \eta \mathbf{X}_m. \end{aligned} \tag{16}$$

The theory suggests that the coefficients Γ_k decrease with k, the age of the worker. I plot the coefficients Γ_k from the regression in Figure 1. As the figure shows, the coefficients are negative, and their magnitudes increase with the age of the worker, indicating that the experience premium decreases with the automation threat in an occupation.

To test the robustness of the effect of the automation threat on the experience premium, I run an alternative specification. I define three groups based on individuals'

	(1)	(2)	(3)	(4)
Automatability		-0.39***		-0.41***
		(0.054)		(0.053)
Routine intensity	-0.042***	-0.015		
	(0.0097)	(0.011)		
Offshorability			-0.047***	-0.0082
			(0.013)	(0.013)
Controls:				
State	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Change in emp.	✓	✓	✓	✓
Unemployment rate	✓	✓	✓	✓
mean of dependent var.	6.4887	6.4887	6.4914	6.4914
s.d. of depndent var.	.894	.894	.8942	.8942
Obs.	90121	90121	91225	91225

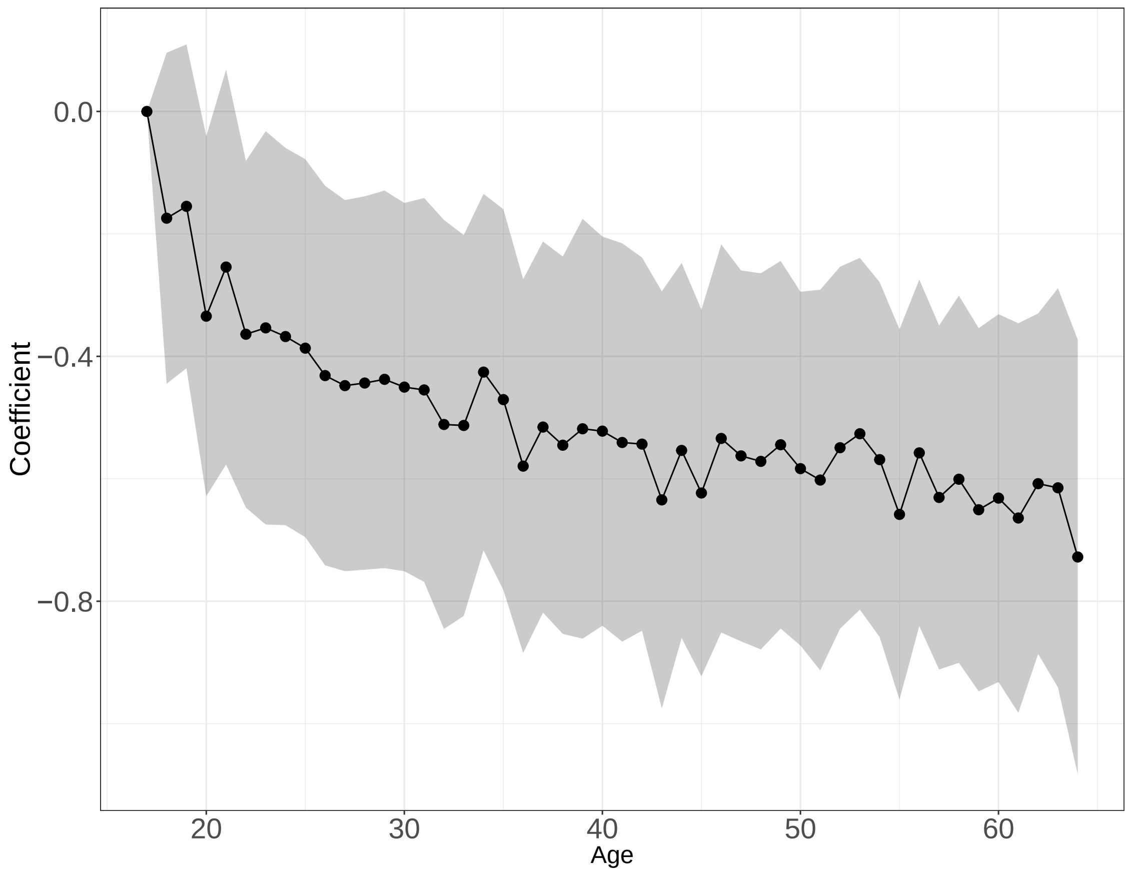
The table presents estimates of the impact of the threat of automation on earnings. The dependent variable is the logarithm of weekly earnings. The control variables for each regression are: state fixed effects, demographics (age, gender, race, years of education), industry fixed effect, the change in employment at the state level from 1990 to 2013 for each occupation and the unemployment rate at the MSA level. In column 1, I regress the dependent variable on the routine intensitiy index while in column 4, I regress the dependent variable on the offshorability index, as in Autor and Dorn (2013). Columns 2 and 4 add the automatability index as a regressor. Standard errors are robust against heteroscedasticity and are clustered at the occupation level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

Table 2: Impact of Automatability Threat on Wages vs routine-intensity and offshorability

	(1)	(2)	(3)	(4)
Automatability	-0.38***	-0.38***	-0.32***	-0.36***
	(0.075)	(0.090)	(0.11)	(0.082)
Controls:				
State	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Industry	✓	✓	✓	✓
Change in emp. share	✓			
Change in emp. by occ x state		✓	✓	✓
Unemployment rate	✓	✓	✓	✓
Positive change in level		✓		
Positive change in shares			✓	
Non-Manufacturing sector				✓
Obs.	121536	89814	63523	79839

The table presents estimates of the impact of the threat of automation on earnings. The dependent variable is the logarithm of weekly earnings and the independent variable is the automatability index for each occupation from Frey and Osborne (2017). The covariates for each regression are reported at the bottom of the table. All regressions include state dummies as well as individuals' demographic characteristics (age, gender, race, education), industry fixed effects and unemployment rate at the MSA level. Column 1 controls for the change in occupational employment share from 1990 to 2013 at the state level. Column 2 to 4 control for the change in the logarithm of employment by occupation at the state level. Column 2 only includes occupations with a positive change in employment. Column 3 only includes occupations with a positive change in occupational employment share. Column 4 only includes the non-manufacturing sector. Standard errors are robust against heteroscedasticity and are clustered at the occupation level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

Table 3: Impact of Automatability Threat on Wages (robustness)



This figure shows the point estimates of the impact of the interaction of the threat of automation and the age variable on wages. The dashed line corresponds to the 95% confidence interval of the point estimates.

Figure 1: The impact of the threat on the return to experience.

age: below 30 years old (group 1), 30 to 50 years old (group 2) and above 50 years old (group 3). I run the following regression

$$w_{ijdm} = \beta\, threat_j + \beta_{g(i)} threat_j \times \mathbf{1}_g + \delta_d + \delta_{s(m)} + \gamma \mathbf{X}_i + \eta \mathbf{X}_m, \tag{17}$$

where $g(i) \in \{1,2,3\}$ is the age group of the individual. The theory predicts that $\beta_1 > \beta_2 > \beta_3$. The results of this regression are in Table 4. The coefficients of the interaction between the group dummies and the threat index are in line with the prediction of the model.

3.5. Prediction 3: Automation threat and bargaining power

Finally I turn to the last prediction of the theory, the impact of the interaction between threat and bargaining power on wages. Because the impact of the threat on wages is driven by the bargaining over wages, as suggested by the theory, I estimate a variant of equation (17) that sheds light on the role of bargaining. In the model, the worker's bargaining parameter is κ. In Prediction 3, I showed that the effect of the threat index is higher the higher kappa. To implement this prediction, I use the union density in the labor market as a proxy for the bargaining power κ. I estimate the following equation,

$$\begin{aligned} \log(earnings)_{ijdm} =& \beta\, threat_j + \beta_{union} union_m + \beta_{threat \times union}\, threat_j \times union_m \\ &+ \delta_d + \delta_{s(m)} + \gamma \mathbf{X}_i + \eta \mathbf{X}_m, \end{aligned} \tag{18}$$

where in addition to the covariates already present in equation 17, I add the union density in the MSA as a proxy for the bargaining power of the workers in the labor market and its interaction with the automatability index. The prediction from the model is that $\beta_{threat \times union} < 0$.

The results are reported in Table 5. Column 1 only includes state fixed effects and individual characteristics (age, gender, race, education) as controls. I find a precisely-estimated, statistically significant, negative effect of the automatability index's interaction with union density on earnings. This effect is robust to the inclusion of different

	(1)
Automatability	-0.23***
	(0.076)
Automatability × age below 30	0
	(.)
Automatability × age 30-50	-0.16***
	(0.044)
Automatability × age above 50	-0.23***
	(0.051)
Controls:	
State FE., Demographics dummies, Industry FE.	
Obs.	121718

The table presents estimates of the impact of the threat of automation on the experience premium. The dependent variable is the logarithm of weekly earnings and the independent variable is the automatability index for each occupation from Frey and Osborne (2017) and its interaction with age groups. The regression includes, as control variables, state dummies as well as individuals' demographic characteristics (age, gender, race, education), industry fixed effects and unemployment rate at the MSA level. Standard errors are robust against heteroscedasticity and are clustered at the occupation level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

Table 4: Threat impact and Experience Premium

controls. Controlling for industries (column 2) increases the coefficient of the interaction from -0.47 to -0.41. In column (3) and (4) I add controls for the change in occupational employment and for the unemployment rate in the MSA. The coefficient of interest slightly decrease to -0.39.

3.6. Placebo check

One concern with the above cross-sectional regressions is that the identification of the threat effect exploits between-occupation variation in the threat index. This implies that other occupation-specific factors that are correlated with the automation index could cause the difference in wages between occupations. To alleviate this concern, I use a placebo strategy. In particular, I run the same regression independently on each year from 1973 (the first year with information on union density at the state level) to 2013.[11] If the automatability index correctly captures the possibility of automation as of 2013, this index should be much less correlated with automation possibilities in 1973. Thus, I expect that in 1973, its association with wages is not statistically significant, and that the coefficient becomes more negative and significant over time, as more occupations come under the threat of automation. I estimate the following equation for each year from 1973 to 2013,

$$w_{ijdm} = \beta_0 + \beta threat_j + \beta_{union} union_s + \beta_{union \times threat} threat \times union_s + \delta_d + \gamma \mathbf{X}_i + \eta \mathbf{X}_m, . \tag{19}$$

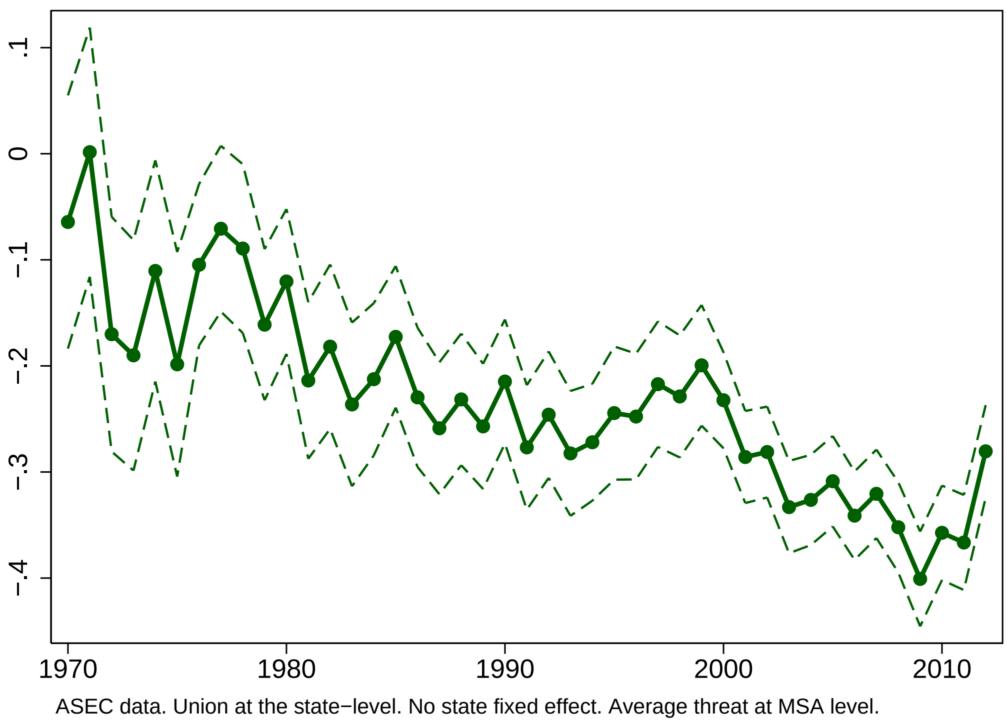
This regression differs from regression(18) as I use the union density at the state level, because that is the only available information on unions before 1983. Figure 2 shows the evolution of the coefficient β_1 that captures the association between automatability and earnings over time. It is clear from the figure that the coefficient β gets closer to zero as one goes back in time, and is not significant in 1973.

[11] I use the March supplement to the CPS files instead of the ORG CPS files because information on earnings is only available in the March supplement files from 1973 on.

	(1)	(2)	(3)	(4)
Threat	-0.30***	-0.33***	-0.31***	-0.31***
	(0.076)	(0.071)	(0.071)	(0.071)
Union rate	0.30**	0.27*	0.27*	0.34**
	(0.15)	(0.15)	(0.15)	(0.16)
Threat x Union rate	-0.47***	-0.41***	-0.39***	-0.39***
	(0.11)	(0.11)	(0.11)	(0.11)
Controls:				
State	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Industry		✓	✓	✓
Change in occ. emp			✓	✓
Unemployment rate				✓
Mean of Log(wage)	6.4595	6.4595	6.4534	6.4534
S.d. of Log(wage)	.8799	.8799	.8781	.8781
Obs.	121718	121718	119348	119348

The table presents estimates of the impact of the threat of automation and its interaction with union density on wages. The dependent variable is the logarithm of weekly earnings and the independent variables are the automatability index for each occupation from Frey and Osborne (2017), the union density in the MSA and their interaction. The covariates for each regression are reported at the bottom of the table. Column 1 include States dummies as well as individuals' demographic characteristics (age, gender, race, education). Column 2 adds industry dummies for a set of 19 industries, as in Acemoglu and Restrepo (2017). Column 3 adds the change in employment at the state level from 1990 to 2013 for each occupation, and column 4 adds the unemployment rate at the MSA level. Standard errors are robust against heteroscedasticity and are clustered at the occupation level. The coefficients with *** are significant at the 1% confidence level; with ** are significant at the 5% confidence level; and with * are significant at the 10% confidence level.

Table 5: Threat impact and Union interaction



This figure shows the point estimates of the impact of the threat of automation on wages each year from 1973 to 2013. The dashed line corresponds to the 95% confidence interval of the point estimates.

Figure 2: Evolution of the association between automatability index and earnings over time.

4. Concluding Remarks

In this paper, I build a of multi-sector search and bargaining model with on-production search for automation technology. The on-production search for technology constitutes the automation threat as it enables the firms to re-negotiate contracts with workers and lower their wages. From the model, I derive three testable predictions: (i) the average wage in a given occupation is decreasing in the automation threat of the occupation, (ii) a higher automation threat lowers the returns to experience, and (iii) the impact of the threat on the average wage in a given occupation is increasing with the bargaining power of workers in the labor market. Using CPS data and an index of automatability from the literature, I find evidence for these predictions in the US labor market. These findings suggest that even if a only small number of firms automate occupations, new automation technologies may still have a large effect on the labor market.

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5. Appendix A: Data

5.1. Automatability index

The construction of the index of automatability is described in Frey and Osborne (2017). In this appendix I provide the main steps.

First, with a group of machine learning researchers, the authors classified each of 70 occupations as either fully automatable or not. The classification was based on the description in the O*NET database of the tasks required to perform each occupation and was done in collaboration with researchers at the Oxford University Engineering Sciences Department. This labeling was made by answering the following question: "Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment?". A value of 1 (fully automatable) is only assigned if all tasks in the occupation can be fully automatable. The set of these 70 occupations, their SOC code and the label given to them (0 or 1) is given in Table 7.

Second, the authors identify three engineering bottlenecks to the automation of occupations. These bottlenecks correspond to tasks in the three following categories: perception and manipulation, creativity, and social intelligence. To objectively measure the level of these tasks in each occupation, the authors identify nine variables in the O*NET database that describe these attributes. These variables are the following: finger dexterity, manual dexterity, cramped work space and awkward positions, originality, fine arts, social perceptiveness, negotiation, persuasion, and assisting and caring for others. For each occupation, each of these variables is assigned a level (low, medium or high).

The authors develop an algorithm to provide a probability of automatability for each occupations using the nine variables identified in O*NET, and the set of 70 classified occupations. The 70 occupations constitute a training set (with label $y \in \{0, 1\}$ and $x \in \mathbf{R}^9$). Because the relationship between automatability and these nine variables has no reason to be linear, the author used a Gaussian process classifier with exponentiated quadratic model, which allows for more complex, non-linear interactions between variables: for example, perhaps one variable is not of importance unless the value of another variable is sufficiently large. This algorithm is then used to predict the probability of automation for a set of 703 occupations.

Table 7: Classification of 70 occupations as fully automatable or not

SOC code	Label	Description
11-1011	0	Chief Executives
11-3071	0	Transportation, Storage, and Distribution Managers
11-9031	0	Education Administrators, Preschool and Childcare Center/Program
11-9151	0	Social and Community Service Managers
13-1041	0	Compliance Officers
13-1121	0	Meeting, Convention, and Event Planners
17-1012	0	Landscape Architects
17-2051	0	Civil Engineers
17-2071	0	Electrical Engineers
19-1023	0	Zoologists and Wildlife Biologists
19-2012	0	Physicists

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Table 7 – *Continued from previous page*

SOC code	Label	Description
19-3011	0	Economists
21-1011	0	Substance Abuse and Behavioral Disorder Counselors
21-1013	0	Marriage and Family Therapists
21-2011	0	Clergy
23-1011	0	Lawyers
23-1023	0	Judges, Magistrate Judges, and Magistrates
25-2011	0	Preschool Teachers, Except Special Education
27-1022	0	Fashion Designers
27-2021	0	Athletes and Sports Competitors
29-1021	0	Dentists, General
29-1060	0	Physicians and Surgeons
29-1111	0	Registered Nurses
29-9799	0	Healthcare Practitioners and Technical Workers, All Other
35-1011	0	Chefs and Head Cooks
35-3031	0	Waiters and Waitresses

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Table 7 – *Continued from previous page*

SOC code	Label	Description
37-2012	0	Maids and Housekeeping Cleaners
39-5012	0	Hairdressers, Hairstylists, and Cosmetologists
39-6012	0	Concierges
39-9011	0	Childcare Workers
45-3021	0	Hunters and Trappers
47-2152	0	Plumbers, Pipefitters, and Steamfitters
53-2031	0	Flight Attendants
13-1031	1	Claims Adjusters, Examiners, and Investigators
13-1051	1	Cost Estimators
13-1074	1	Farm Labor Contractors
13-1161	1	Market Research Analysts and Marketing Specialists
13-2011	1	Accountants and Auditors
13-2041	1	Credit Analysts
13-2053	1	Insurance Underwriters
13-2072	1	Loan Officers

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Table 7 – *Continued from previous page*

SOC code	Label	Description
13-2081	1	Tax Examiners and Collectors, and Revenue Agents
17-1022	1	Surveyors
17-3012	1	Electrical and Electronics Drafters
17-3022	1	Civil Engineering Technicians
23-1012	1	Judicial Law Clerks
23-2011	1	Paralegals and Legal Assistants
27-3042	1	Technical Writers
31-9094	1	Medical Transcriptionists
35-2011	1	Cooks, Fast Food
35-9021	1	Dishwashers
39-3011	1	Gaming Dealers
41-2011	1	Cashiers
43-2011	1	Switchboard Operators, Including Answering Service
43-4041	1	Credit Authorizers, Checkers, and Clerks
43-4071	1	File Clerks

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Table 7 – *Continued from previous page*

SOC code	Label	Description
43-4161	1	Human Resources Assistants, Except Payroll and Timekeeping
43-5021	1	Couriers and Messengers
43-5041	1	Meter Readers, Utilities
43-9021	1	Data Entry Keyers
47-2211	1	Sheet Metal Workers
51-2022	1	Electrical and Electronic Equipment Assemblers
51-4011	1	Computer-Controlled Machine Tool Operators, Metal and Plastic
51-6031	1	Sewing Machine Operators
53-3021	1	Bus Drivers, Transit and Intercity
53-3033	1	Light Truck or Delivery Services Drivers
53-3041	1	Taxi Drivers and Chauffeurs
53-5022	1	Motorboat Operators
53-6021	1	Parking Lot Attendants
53-7051	1	Industrial Truck and Tractor Operators

Source: Frey and Osborne (2017).

6. Appendix B: Proofs

6.1. Derivation of the initial and renegotiated wages

Let us denote $\underline{w}_j$ the lowest wage a worker is willing to accept. The value of a match at a firm with and without automation technology, for a wage $\underline{w}_j$ is given by

$$\rho E_j^{NA}(\underline{w}_j) = \underline{w}_j + \delta(U - E_j^{NA}(\underline{w}_j)),$$
$$\rho E_j^{A}(\underline{w}_j) = \underline{w}_j + \delta(U - E_j^{A}(\underline{w}_j).$$

Notice that the expressions of both values are identical because no downward renegotiation of the wage is possible, as the worker would then prefer to be unemployed. At the wage $\underline{w}_j$, the worker is indifferent between working and being unemployed such that $\rho E_j^{NA}(\underline{w}_j) = U$. Thus $\underline{w}_j = \rho U$, for all occupations.

Because at wage $w = \underline{w}$, the firm cannot renegotiate downwards the wage, the value of a match is identical for firms with and without the automation technology, such that

$$J_j^{NA}(\underline{w}) = J_j^{A}(\underline{w}).$$

One can therefore rewrite the match surpluses as

$$S_j^{NA} = J_j^{NA}(\underline{w}) - V_j,$$
$$S_j^{A} = J_j^{A}(\underline{w}) - A,$$

Therefore

$$S_j^{NA} - S_j^{A} = -(A - V_j).$$

Besides, the equilibrium wages w_j^{NA} and w_j^{A} are such that the firm gets its outside option plus a share $(1-\kappa)$ of the match surplus, i.e.,

$$J_j^{NA}(w_j^{NA}) = V_j + (1-\kappa)S_j^{NA},$$
$$J_j^{A}(w_j^{A}) = A + (1-\kappa)S_j^{A}.$$

Hence

$$J_j^A - J_j^{NA} = (A - V_j) + (1-\kappa)\Delta S = A - V_j - (1-\kappa)(A - V_j) = \kappa(A - V_j)$$

From the Nash Bargaining equation, the wage at employment w_j^{NA} is such that

$$\kappa(\rho+\delta)(J_j^{NA}(w_j^{NA}) - V) = (1-\kappa)(\rho+\delta)(E_j(w_j^{NA}) - U)$$

$$\kappa(y - w_j^{NA} + \delta V + \lambda_j\kappa(A - V_j) - \kappa(\rho+\delta)V = (1-\kappa)(w_j^{NA} + \delta U - \lambda_j\kappa(A - V_j)) - (1-\kappa)(\rho+\delta)U$$

$$w_j^{NA} = \kappa y + (1-\kappa)\rho U - \kappa\rho V_j + \lambda_j\kappa(A - V_j)$$

Similarly for the renegotiated wage w_j^A, the Nash bargaining equation gives

$$w_j^A = \kappa y + (1-\kappa)\rho U - \kappa\rho V_j - \kappa(\rho+\delta)(A - V_j)$$

6.2. Derivation of the average wage

Using the inflow-outflow conditions for steady state, one can easily derive

$$\mu^{NA} = \frac{\delta}{\delta+\lambda_j}, \mu^A = \frac{\lambda_j}{\delta+\lambda_j}.$$

The average wage is therefore given by

$$\begin{aligned}
\bar{w}_j &= \mu^{NA} w_j^{NA} + (1-\mu^A) w_j^A \\
\bar{w}_j &= \kappa y + (1-\kappa)\rho U - \kappa\rho V_j + \frac{\delta}{\delta+\lambda_j}\lambda_j\kappa(A - V_j) - \frac{\lambda_j}{\delta+\lambda_j}\kappa(\rho+\delta)(A - V_j) \\
\bar{w}_j &= \kappa y + (1-\kappa)\rho U - \kappa\rho V_j - \rho\frac{\lambda_j}{\delta+\lambda_j}\kappa(A - V_j)
\end{aligned}$$

This expression, together with the free entry condition $V_j = 0$ implies

$$\bar{w}_j = \kappa y + (1-\kappa)\rho U - \rho\frac{\lambda_j}{\delta+\lambda_j}.\kappa A \tag{20}$$

6.3. Derivation of the predictions

Given the equation 20, it is easy to see that, for a given labor market (i.e. for a given value of unemployment U), the average wage $\bar{w}_j$ is decreasing in the automation probability

λ_j (Prediction 1), and that this effect is amplified by the bargaining power κ (Prediction 3).

Besides, the experience premium is decreasing in λ_j (Prediction 2) because

$$w_j^A - w_j^{NA} = -\kappa(\rho+\delta)A - \lambda_j \kappa A$$

6.4. Extension: Model with heterogeneous A_j

I show that the predictions carry over when the technology finding rate λ is identical across occupations but the value of automating A_j is occupation dependent. Indeed, the average wage in a given occupation is given by

$$\bar{w}_j = \kappa y + (1-\kappa)\rho U - \rho \frac{\lambda}{\delta+\lambda} \kappa A_j.$$

Thus, the average wage is decreasing in the value of automating A_j, and this effect is amplified by workers' bargaining power in the labor market κ. Besides, the difference between the renegotiated wage and the initial wage is given by

$$w_j^A - w_j^{NA} = -\kappa(\rho+\delta+\lambda)A_j$$

This experience premium is decreasing in A_j.