Robotization and Labor Supply in the Context of a Dynamic Monopsony: Novel Evidence from South Korea

Ahmed J. Saade, Constantinos Alexiou, and Yacine Belghitar

We estimate the effects of robotization on labor supply in Manufacturing, Services and the whole of the South Korean economy using exponential hazard and a random effects logit methodologies over the period 1999-2019. Our findings suggest that a larger operational stock of industrial robots in manufacturing is associated with manufacturing (non-manufacturing) workers becoming more (less) responsive to a change in wages in their decision to quit to non-employment, whilst the ease with which firms can poach workers is found to be unaffected by robotization.

Keywords: Automation, Dynamic monopsony, Elasticity of labor supply, Industrial robots, Labor share, South Korea.

JEL Classification: J2, J3, J42

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I. Introduction

Discussion surrounding robots is not new and we seem to have been carrying in our imagination, for millennia, the thought of competition between men and intelligent machines. While this may have once appeared as a wild fantasy, it has very much been brought to reality by contemporary industrial *robots* which are deployed in numerous manufacturing establishments around the globe.

In the realm of technological innovation, robotization has been the recipient of attention from many social scientists with a wide array of research interests. Such diversity in contemporary academic research relating to robotization is reflected *inter alia* by themes that explore the relationship between robots and the gender pay gap (Aksoy *et al.* 2019); basic income as a means of protection against technological unemployment (Pulkka, 2017); training as a mitigating factor against the risk of being replaced by robots (Koster and Brunori, 2021); the interaction between demographics and technological change (Jimeno, 2019); employee representation in automating firms (Belloc *et al.* 2020); robotization and election outcomes (Frey *et al.* 2018); robotization and workers' bargaining power (Leduc and Liu, 2020) and many other.

Yet, and overwhelmingly so, the primary motivation behind much of the efforts spent on exploring robots and other automated technologies' effects can be summarized with a simple question: Should workers worry about robots? This simple question, however, remains without a clear and definitive answer, as different works keep on offering divergent and often contradictory findings (Barbieri *et al.* 2019).

In this paper, we seek to contribute to the strand of literature on industrial robots' effects on workers, taking robotization in South Korean manufacturing as our case study. Our choice of South Korea is primarily motivated by a few reasons such as: a) the South Korean economy has the highest robot density in the world (IFR, 2021); b) its labour share of income and its movements remain little understood; and c) there is a lack of diversity in terms of countries explored within the strands of the literature relevant to our research, South Korea being one such neglected country.

Certainly, the determinants and economic significance of robotization have been subject to scholars' scrutiny for a long time (see the early works of Hamidi-Noori and Templer 1983; Benedetti 1977), and so even in the case of South Korea (Torii 1989)[1]. Yet, we believe that our take on the topic brings novel and "different insights to the table. Indeed, by focusing on two main actors, namely the employers and the workers, we ask: 1) How do robots impact employers' labor market power? 2) How do workers respond to robotization? and 3) How does robotization affect the labor share of income?

In this direction, we adopt a dynamic monopsony framework to explore these questions, an approach we believe to be both adequate and efficient in that by studying the elasticity of labor supply to the firm and making use of its properties, we can generate insightful results about the effects of robotization on a) monopsony power, b) workers' responsiveness to wage changes[2], and c) the share of labor income. Indeed, the elasticity of labor supply indicates the extent of wage-setting power held by firms or, in other words, their ability to pay workers less than their marginal product. The elasticity of labor supply is inversely related to Pigou's (1924) rate of exploitation (the gap between marginal product of labor and the wage) and so, by estimating robots' impacts on this elasticity, we are able to comment on robotization's effects on the labor share.

We make a number of contributions to different strands of literature. Firstly, the empirical work on dynamic monopsony, while certainly growing, remains fairly limited. Secondly, the vast majority of researchers investigating the impact of robots on workers concentrate their efforts on labor demand, disregarding potential ramifications on labor supply and workers' response to technological change in the process. Our study enriches the extant literature, by providing a novel or alternative way of exploring robotization's effects as categorized by Acemoglu and Restrepo (2019). We pay particular attention to the "composition effect (the reallocation of economic activity from one sector to another) and observe whether and how robotization in manufacturing

[1] The literature on robotization in South Korea was limited compared to another East Asian economy which was synonym with rapid technological change: Japan. See Hasegawa (1979), Okubayashi (1986) and Yonemoto (1981) for explorations on determinants and effects of this early robotization.

[2] Dauth *el al.* (2017) explore this question from a different angle. They show that workers more exposed to robots have more stable jobs, while we are interested in finding out whether robotization affects workers' responsiveness to wage changes.

affects workers in services. Thirdly, in spite of the large and growing body of work investigating technological change, we are not aware of any study which engages into an in-depth exploration of industrial robots' effects on Korean workers. In fact, there is a lack of diversity in the literature on robotization when it comes to the economies investigated. Barbieri *et al.* (2019) show that studies on automation in developing economies are extremely limited, in spite of them witnessing rapid technological change. Furthermore, the need to explore different countries in more depth is necessary, as evidenced by Faber (2020), Carbonero *et al.* (2020) and de Vries *et al.* (2020) who show that workers in countries at different stages of their development do not face the same robot-induced challenges.

The rest of the paper is organized as follows: Section 2 expounds upon the existing literature pertinent to our framework of analysis, whilst section 3 spells out the empirical methodology utilized in this study. Section 4 presents the empirical evidence and section 5 discusses and interprets the results. Finally, section 6 provides some concluding remarks.

II. Relevant literature

At the origin of much of the anxiety when it comes to the risks posed by robots are those studies which attempt to estimate the number of jobs at risk of disappearing. Autor *et al.* (2003) develop and test a model where computerization impacts different types of tasks (routine/repetitive, non-routine, cognitive and manual). They posit that computerization negatively impacts routine/repetitive cognitive and manual tasks, and that as computers' capabilities develop, they will cause an increase in productivity for non-routine cognitive workers. Goos and Manning (2007) show that this "routinization hypothesis offers a valuable (although incomplete) explanation for the job polarization (between high-wage and low-wage occupations) that has been occurring in the UK since 1975. Frey and Osborne (2017) categorize 702 US occupations and conclude that 47% of US jobs are at risk of disappearing at the hand of automation.

Yet, Arntz *et al.* (2019) suggest that anticipating cataclysmic consequences to robotization may be unfounded, as studies spreading this panic often ignore the heterogeneity of tasks within one same occupation, the actual time it takes to automate, and workers' ability to adjust for automation. A number of studies also point towards this direction, particularly those which assess the risk of automation by conducting their analysis on a job-level such as Arntz *et al.* (2016), Arntz *et al.* (2017) and Nedelkoska and Quintini (2018) for the US, Pouliakas (2018) for the EU and Dengler and Matthes (2018) for Germany. They all report much lower percentages of jobs at risk of automation compared to studies which are conducted on an occupational level such as Frey and Osborne (2017), Bowles (2014), or Pajarinen and Rouvinen (2014). Observing tasks instead of occupations indeed makes sense, as workers in one same occupation often perform different tasks (Autor and Handel 2013; Spitz-Oener 2006). Moody (2018) suggests that measuring an occupation's susceptibility to be automated amounts to almost a useless endeavour: commenting on the paradox of a growing American workforce in times of increasing robotization, he discusses how the real risk for workers lies in profitability rates, in the firm's assessment of the return on robotization investment. Cirillo *et al.* (2021) suggest that digitization could signal more worrying venues for workers than robotization. Just another false alarm, another development in a long history of technical change not worth the panic (Fernández-Macías *et al.* 2021; Miller and Atkinson 2013).

A number of studies have looked at the actual effect of robots on aggregate employment levels. In the UK, Kariel (2021) finds a positive effect of robots on employment in services, and a negative one for manufacturing. In the US and using a number of proxies for robotization, Leigh *et al.* (2020) show that robots have had a positive effect on employment in Manufacturing. Klenert *et al.* (2020) show that industrial robots have had a positive effect on European employment. In France, Aghion *et al.* (2020) show that automation technologies have a positive effect on employment at all levels (plant, firm and industry). Also in France, Acemoglu *et al.* (2020) find that the labor share and share of production of workers declined in robot-adopting firms, but that overall employment in firms was positively correlated with robotization.

Gregory *et al.* (2018) and Acemoglu and Restrepo (2019) explore some ways via which robotization and other types of technologies can affect employment. Gregory *et al.* (2018) find that technological change has created more jobs than it destroyed (1.5 million jobs between 1999 and 2010) and while they do establish that technology did replace a large number of workers, this displacement was offset by technologically induced product demand and spillover effects. The product demand effect represents the additional demand for labor caused by lower capital costs and thus lower prices. The spillover effect stands for the increase in local labor demand following the rise in income induced by the product demand effect. Such offsetting effects are theorized by Acemoglu and Restrepo (2019) in a more general manner. In their framework, robotization can displace workers, but it can also generate a productivity effect that increases labor demand, and even creates completely new tasks where workers have an advantage over technology. Robots can also cause a composition effect, meaning a reallocation of economic activity towards different sectors. Acemoglu and Restrepo (2020) apply this model in their analysis on the impact of industrial robots on jobs and wages in the US economy. They find that the productivity effect was too small to offset the displacement of workers caused by the stocks of robots, results that could be cause of concern considering the projected increase in these stocks over the upcoming years (Ford, 2015). Similarly, Chiacchio *et al.* (2018) find that the displacement effect has been largely outweighing the productivity effects of Industrial robots in the EU. However, Paba *et al.* (2020) show that the opposite is true for Italy, where robotization has led to a growth in aggregate employment via an expansion of employment in services.

Undoubtedly, much of the debate revolves around productivity-enhancing properties of robots, for that is the ground on which humans are supposed to compete with machines. Indeed, the use of industrial robots increases productivity growth and total factor productivity as reported by Graetz and Michaels (2018) from their study of a panel of 17 countries covering the period 1993 to 2007. Fujiwara and Zhu (2020) use a panel of 33 countries and find a similar positive effect on labor productivity. Graetz and Michaels (2018) show that industrial robot densification is associated with lower output prices. This is in line with the findings of Koch *et al.* (2019) and Ballestar *et al.* (2020) from Spain, and Jungmittag and Pesole (2019) from 12 EU countries who all show that robots have had a robust positive effect on productivity in manufacturing. However, Cette *et al.* (2021) work with a panel of 30 countries and show that between the introduction of industrial robots and up until 2019, robots' impact on productivity is modest (less than 0.2pp for most countries in the study).

Clearly, our understanding of the ramifications of the rapid deployment of robots in global production plants remains a work in progress. Even the reasons that push firms to automate, and whether they should, remains subject to debate. Of course, there are cases where robots come to fill a clear labor shortage, and not simply to increase profitability. Yet, industrial robots have seen a shockingly rapid deployment in places where one would not expect to see them, such as Eastern Europe, regions that are associated with relatively low labor costs (Lordan 2018; Cséfalvay 2020). In China where demographically permitted economies of scale have been key to the country's growth, robotization took place at a later time compared to "developed economies, primarily triggered by the 2008 crisis which brought with it a necessity to "upgrade industrial processes (Huang and Sharif 2017; Giuntella and Wang 2019).

In light of this wide array of conflicting findings, our study opts for a new perspective on the matter, mainly the adoption of dynamic monopsony to understand robots' effects on workers. Major milestones in the development of monopsony theory are Robinson (1933) and, much later, Manning (2003). Fundamentally, the concept of labor market monopsony relays the notion that frictions in the labor market provide employers with a certain degree of wage-setting power. The clear reality that most people think twice before accepting or quitting a job indicates some degree of imperfection and monopsony power in the market.

A number of studies have adopted dynamic monopsony to investigate a wide array of phenomena[3]. Ransom and Oaxaca (2010) work with such a framework, using separation rates to estimate the elasticity of labor supply in a chain of grocery stores by gender groups. They find that for both genders, elasticities are small but that the labor supply elasticity for females (1.5-2.5) was smaller to that of males (2.4-3). Ransom and Sims (2010) apply this methodology to the market for schoolteachers in Missouri, finding a labor supply elasticity of 3.7, and considerable wage setting power by district. Moreover, dynamic monopsony frameworks have been used for a multitude of purposes, such as studying employer switching costs (Fox, 2010), timing of buyer-seller/employer-employee contracts (Priest, 2010) among others. This wide array of applications comes as no surprise as imperfections can

[3] A 2010 issue of the *Journal of Labor Economics* was dedicated to studies on monopsony. See Ashenfelter *et al.* (2010) for a summary.

explain many abnormalities that contradict assumptions of a "perfect world. Manning (2020) surveys this literature and reviews the recent evolutions in monopsony theory and its applications on various economic problems[4].

While we do not come across a paper studying robotization from a dynamic monopsony perspective, we notice some common grounds between these two strands of literature. For instance, Eeckhout *et al.* (2019) make use of spatial sorting, a topic much touched upon in papers relating to monopsony, to develop and test a model which links location, automation, and job polarization. Also, Bachmann *et al.* (2019) reconcile the factually increasing labor market polarization in Germany with monopsony theory and, using a dynamic model of monopsony, find that workers performing more routine tasks face less monopsony power than those who do not, thus depicting a clear relationship between task content and monopsony faced by workers.

The entirety of the above listed literature contributed to the way we frame our study, but the main inspirations for this research and the methodology we adopt are Manning (2003) for the adoption of a monopsony framework, Ransom and Oaxaca (2010), Ransom and Sims (2010) and Hirsch *et al.* (2018) for the estimation of the wage elasticity of separations, and Acemoglu and Restrepo (2019) and Acemoglu and Restrepo (2020) for the interpretation of robotization's effects on workers.

III. Empirical investigation

In dynamic monopsony, the elasticity of the labor supply curve facing the firm can be decomposed into the wage elasticities of separations to employment ϵ_S^N and to non-employment ϵ_S^E, and the wage elasticity of the share of recruits coming from employment β_W (see Appendix A). In this paper, the object of interest is not to draw an estimate of the elasticity of labor supply, but rather to observe how it is affected by robotization. We thus concentrate our efforts on the interaction between robots and the three elasticities ϵ_S^E, ϵ_S^N and β_W.

To arrive at estimates of the separation rate elasticities to employment

[4] See Bhaskar *et al.* (2002) for an earlier review of the areas where frameworks based on monopsonistic competition could prove advantageous.

and non-employment, we follow the approach of Hirsch *et al.* (2010) and Hirsch *et al.* (2018) who, using Manning (2003: 100–104), model the separation rates of job *i* belonging to worker *m(i)* as exponential models:

$$s_i^{\rho}(x_i^{\rho}, \upsilon_{m(i)}^{\rho}) = \exp(x_i^{\rho}(t)\beta^{\rho})\upsilon_{m(i)}^{\rho}, \tag{1}$$

with route ρ = E (quit to employment) and N (quit to non-employment), a vector of time-varying covariates $x_{i(t)}^{\rho}$, a vector of coefficients β^{ρ}, and unobserved worker heterogeneity $v_{m(i)}^{\rho}$ independent of covariates $x_{i(t)}^{\rho}$, assumed to follow a gamma distribution[5]. Among our covariates are the log wage (real wage) and an interaction term between the log wage and operational stock of industrial robots $R_i(t)$, so that the wage elasticity of separations to employment is obtained by

$$\varepsilon_S^E = \beta_{\log wage}^E + \beta_{\log wage \times R}^E \times R_i(t), \tag{2}$$

and the wage elasticity of separations to non-employment by

$$\varepsilon_S^E = \beta_{\log wage}^N + \beta_{\log wage \times R}^N \times R_i(t), \tag{3}$$

Our approach to estimating the effect of robots on wage elasticities of separations is thus in line with Hirsch *et al.* (2018) who examine the cyclicality of the elasticity of labor supply by using an interaction term between the log wage and the unemployment rate.

For the estimation of ϵ_S^N, we use the whole sample of job spells (whether the job ends with employment or non-employment), while for the estimation of ϵ_S^E our sample includes only the job spells that end with employment, thus following Manning's (2003, p.101) approach. Since we are interested in the effect of wages on workers' separation decisions, we only consider voluntary quits and right-censor involuntary quits and layoffs, a method rendered possible by our dataset which shows the reason why a worker's job spell ended.[6] Moreover, Manning (2003, p.104)

[5] See Abbring and van den Berg (2007) for the convergence of heterogeneity towards a Gamma distribution in hazard models with proportional heterogeneity.

[6] Hirsch *et al.* (2018) cannot distinguish voluntary and involuntary separations due to the information provided in their dataset, and thus attempt to partially remedy this issue by disregarding jobs ending in the year the corresponding plant closed and controlling for a number of plant characteristics.

explains that the separation elasticity is biased towards zero, and that shortening the time horizon over which the data is observed reduces this bias. To deal with this unobserved heterogeneity' induced bias, our duration models are estimated with a monthly time period. Note that, following the recommendation of Manning (2003), we do not control for length of tenure as firms may increase wages to keep certain workers and prevent potential quits, which increases tenure.[7]

To obtain the wage elasticity of the share of recruits hired from employment β_W presented in equation (A9), we follow Hirsch *et al.* (2010) and Hirsch *et al.* (2018) and estimate a random-effects logit model for the probability that a recruit is hired from employment[8]. The use of a random-effect logit model is justified by our modelling of the share of recruits coming from employment $\theta^R(w)$ as a logistic function based on Manning (2003, p.100) and explained above, with the additional assumption that unobserved heterogeneity follows a normal distribution with mean zero and finite variance. We thus have

$$\Pr = [y_i = 1 \mid x_i, \upsilon_{m(i)}] = \Lambda(x_i^{'}\beta + \upsilon_{m(i)}), \tag{4}$$

where y_i is a dummy variable taking the value of 1 if a recruit comes from employment and 0 otherwise, Λ shows the cumulative distribution function of the standard logistic distribution, and unobserved worker heterogeneity $v_{m(i)}$ is Gaussian. Similar to our previous estimations, our covariates include the log wage and an interaction term between the wage and robots, hence the wage elasticity of the share of recruits from employment becomes:

$$\beta_w = \beta_{\log wage} + \beta_{\log wage \times R} \times R_i(t). \tag{5}$$

For the two wage elasticities of separations, we expect a negative coefficient $\beta_{log\ wage}$ in both estimations, as an increase in offered wages should logically be met with lower voluntary quits, whereas we anticipate a positive coefficient $\beta_{log\ wage}$ in the estimation of the wage elasticity of the share of recruits coming from employment, since a

[7] Manning (2003, p. 102-103) controls for tenure when estimating separation elasticities for four samples and shows that controlling for tenure always reduces the wage elasticity in absolute value.

[8] This shows why β_W hints at firms' ability to poach workers.

firm offering higher wages should find itself able to poach workers with greater ease. Fundamentally, this study revolves around the interaction term in each of these three estimations: if the interaction term is positive (negative) in our estimation of the elasticities of separations, then the stock of operational robots would be lowering (increasing) the wage elasticities of separations in absolute value and thus increasing (decreasing) the degree of monopsonistic competition in the market ceteris paribus. If the interaction term is positive (negative) in the estimation of the wage elasticity of the share of recruits from employment, then the stock of operational robots would be increasing (decreasing) the capability of firms to poach workers, and also increasing (decreasing) the degree of monopsonistic competition ceteris paribus.

A. Data, variables, and estimation

In terms of data used and the specification of our variables, we combine three datasets from the Korea Labor and Income Panel Study (KLIPS): The Work History, Individual and Household datasets. KLIPS is South Korea's only labor market panel survey, annually tracking all members of around 7,000 households.

The Work History dataset provides data on all jobs held by an individual since entry in the labor market. The original datasets include both wage earners and non-wage earners but considering the objectives of our study, we concern ourselves with wage earners only and disregard non-wage earners. Additionally, the questionnaire used to construct the Work History dataset is conducted on a job level, hence a same person could be observed more than once in a particular year. Having disregarded non-wage-earning jobs, we maintain the possibility of one same individual having two wage-earning jobs at a particular point in time and treat these two jobs as distinct observations. Finally, we concern ourselves only with jobs surveyed starting the fourth wave of KLIPS due to the frequency of missing values in prior waves. Table 1 provides an overview of the sample we work with.

The Individual dataset uses the individual as its unit of analysis, whereas the Work History dataset uses jobs as mentioned earlier. We are able to combine these two datasets using a key identifying variable for each individual, and we maintain job spells as our unit of observation throughout our study. The Individual dataset provides

Table 1
Sample Description

Job Spells	34513
Records	95,181
Workers	16,521
Separations to employment	2,883
Separations to non-employment	11,998
Censored job spells	19,632

Notes: The data set used comes from wave 4 to wave 22 of the 22nd version of the Korean Labor and Income Panel Study (KLIPS), restricted to wage earners with job spells starting from 1990 until 2019.

a rich source of information on respondents, such as gender, age, education, location, health status, marital status, job satisfaction, wage satisfaction, leisure satisfaction and state of economic activity.

A key value-point of the KLIPS survey and consequently of this paper is that we are able to control for relevant factors which, to the best of our knowledge, have been omitted in other studies using estimations of the wage elasticity of labor supply (*e.g.* Health condition, family financial status). The Household dataset uses households as a unit of analysis, but we are able to link each individual, and thus job spell, to the relevant household using a key household identifying variable. Some of the information contained in this dataset includes one's household size, whether the household owns the place of residence or rents, living expenses, ownership of real estate, financial support given or received by the household, average total earnings of the household, other sources of income, number of social benefits recipients in the household, existence and value of savings, burdensome expenses, debt and current financial condition among others.

For our measure of the operational stock of industrial robots in a labor market, we use data from the International Federation of Robotics (IFR). The IFR follows the ISO 8373:2012 definition of an industrial robot: "an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications (IFR, 2020; pp.23). For its estimations of the industrial robots' operational stocks and installations/shipments in South Korea, the IFR obtains data from the Korean Association of Robot Industry (KAR) since 2015 and the Korean Machine Tool Manufacturers Association (KOMMA) before that.

We collect data on the annual operational stocks of industrial robots in each industry from the IFR, covering the period of 2004 to 2019. The industries covered are food and beverages; textiles; wood and furniture; paper; plastic and chemicals; glass and ceramics; basic metals; metal products; metal machinery; electronics; automotive; other vehicles; other manufacturing industries (*e.g.* recycling); construction; and electricity, gas and water. We omit agriculture and mining and quarrying.

To estimate the impact of industrial robots on the wage elasticity, we must first establish a measure for the degree of penetration of robots in the economy. We model the Korean economy as a two-sector economy (Manufacturing *vs.* Services) and define a local labor market as a single sector geographical unit. We use provinces as the geographical unit in order to avoid problems associated with overly small labor markets, such as fluidity due to commuting workers (Tolbert and Sizer 1996; Pischke and Velling 1997).

Having defined local labor markets, we now move on to determine the number of robots in each local labor market, after which we are able to estimate the effect of robot penetration on the three wage. We use the Local Area Labour Force Survey to obtain data on employment per local labor market, and the Mining and Manufacturing Survey to extract the value of machinery in manufacturing in each province and distribute the stock of robots proportionally, so that our variable for robot penetration in a local labor market becomes *robots in manufacturing per thousand workers in manufacturing*.

For robustness, we use three proxies for robot penetration, constructed the following way: 1) we extract the number of manufacturing establishments with more than 10 employees in each province from the Mining and Manufacturing Survey and construct a *robots in manufacturing per manufacturing establishment* variable, 2) we extract the total number of workers in all industries in a province from the Economically Active Population Survey and define a *robots in manufacturing industry per thousand workers in all industries*, and 3) we use data from the Mining and Manufacturing Survey and the Economically Active Population Survey to construct a *value of machinery in manufacturing (in million wons) per thousand workers in* *all industries*. Note that for the last proxy, our estimations cover the period from 1999 to 2019 since we are not limited by the IFR data that begins in 2004.

IV. Results

In this section, we present the results for our estimation of the wage elasticity of quits to non-employment, the wage elasticity of quits to employment, and the wage elasticity of the share of recruits coming from employment. Our primary interest is in observing the coefficients of the interaction terms for the wage and robots, which would indicate whether robotization in manufacturing has any significant effect on the degree of monopsony in the labor market in question and, if so, the nature of that effect. In addition to the control variables discussed in the previous section and which are reported under each table, all our estimations include macro controls, year dummies, province dummies, industry dummies and provincial unemployment rate.

A. The wage elasticity of quits to non-employment

We begin by estimating the wage elasticity of quits to non-employment for manufacturing, services and all industries, the results of which are reported in table 2. Model 1 measures robot penetration in terms of number of robots per manufacturing establishment, while model 2 measures it as number of robots per thousand manufacturing workers. Both models exhibit the same results, all of which are statistically significant at the 1% level.

As expected, the coefficients of log wage are negative for all estimations. Any different result would have been surprising since it would imply that higher wages are associated with more voluntary separations.

The rows reporting the estimated coefficients for the log wage and its interaction with robots (*log real wage x log robots*) report some interesting findings. For manufacturing, we see that a larger operational stock of industrial robots increases the wage elasticity of quits to non-employment in absolute value, with both models showing negative coefficients for the interaction term. The story is different for services, as a greater use of industrial robots in manufacturing appears to lower the wage elasticity of quits to non-employment as evidenced by the

TABLE 2
ESTIMATION RESULTS: WAGE ELASTICITY OF QUITS TO NON-EMPLOYMENT

	Manufacturing		Services		All Industries	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Model 1: robots=Robots per manufacturing establishment (2004-2019)						
log real wage	-0.555***	(0.067)	-0.469***	(0.025)	-0.467***	(0.023)
log real wage x log robots	-0.119***	(0.032)	0.043***	(0.01)	0.032***	(0.009)
Model 2: robots=Robots per thousand manufacturing workers (2004-2019)						
log real wage	-0.322***	(0.109)	-0.628***	(0.042)	-0.592***	(0.037)
log real wage x log robots	-0.063**	(0.031)	0.05***	(0.01)	0.039***	(0.01)

Notes: All estimations include the following controls; year dummies, province dummies, industry dummies, 3 Age dummies, Gender, Health condition, household financial condition, marital status, 3 education dummies, currently studying dummy, overtime work dummy, existence of union dummy, 4 type of employer dummies, 3 dummies for firm size, 8 dummies for firm-provided benefits, the unemployment rate (province level), and log number of manufacturing establishments in city. For estimations pertinent to manufacturing only, we also control for the log number of industrial robots per manufacturing establishment. For the other estimations, we control for the log total number of industrial robots in the economy per thousand workers in all sectors, and the country ICT index (2015=100). ***; ** denote statistical significance at the 1% and 5% levels respectively.

positive coefficients for the interaction term for wages and robots in both models. The effect of robots in manufacturing on the elasticity for all industries is similar to that in services, with positive coefficients for the interaction terms in both models, suggesting a depressing effect of robots on the elasticity of quits in the Korean labor market.

To further test the robustness of this inter-sectoral effect of manufacturing robotization, we estimate two other models using different proxies for robotization the results of which are reported in table 3[9].

In our first round of estimations, we define the robots' variable as *number of robots in manufacturing industry per thousand workers in*

[9] The correlation matrix of all three proxies for robotization used in the study suggests that these are highly correlated with the correlation coefficients raging from 0.73 to 0.98.

TABLE 3
ESTIMATION RESULTS: WAGE ELASTICITY OF QUITS TO NON-EMPLOYMENT (PROXIES)

	Services		All Industries	
	Coefficient	SE	Coefficient	SE
Proxy1: Robots in manufacturing industry per thousand workers in all industries (2004-2019)				
log real wage	-0.498***	(0.025)	-0.489***	(0.023)
log real wage x log proxy1	0.033***	(0.009)	0.024***	(0.009)
Proxy2: Machinery (mill. KRW) in manufacturing industry per thousand workers in all industries (1999-2019)				
log real wage	-0.752***	(0.083)	-0.706***	(0.075)
log real wage x log proxy2	0.033***	(0.01)	0.028***	(0.009)

Notes: Both estimations include the following controls; year dummies, province dummies, industry dummies, 3 Age dummies, Gender, Health condition, household financial condition, marital status, 3 education dummies, currently studying dummy, overtime work dummy, existence of union dummy, 4 type of employer dummies, 3 dummies for firm size, 8 dummies for firm-provided benefits, the unemployment rate (province level), log number of manufacturing establishments in city, and the country ICT index (2015=100). For the 2004-2019 estimation, we further control for the log total number of industrial robots in the economy per thousand workers of all sectors. ***; ** denote statistical significance at the 1% and 5% levels respectively.

all industries. The results are in accordance with those reported in table 2, mainly that a greater operational stock of industrial robots in manufacturing lowers the wage elasticity of quits to non-employment in absolute value in both services and the economy. In our second round of estimations, we substitute industrial robots for the value of machinery in the manufacturing sector, and our estimations encompass a longer time period (1999-2019). The positive coefficients for the interaction term between the wage and machinery support the findings of the previous three models, suggesting that a greater deployment in machinery in manufacturing depresses the elasticity of quits to non-employment in other sectors.

Intuitively, these results suggest that greater robotization in manufacturing lowers the degree of monopsonistic competition in the manufacturing sector and increases it in services and other parts of the economy. In other words, higher robotization in manufacturing lowers

Pigouvian exploitation in manufacturing while it increases it in other sectors, or that manufacturing robotization is associated with workers becoming more responsive to a change in wages in manufacturing, and less responsive in other sectors. Of course, the net effect of robotization on the labor supply elasticity depends also on the two other elasticities to be investigated: the wage elasticity of quits to employment and the wage elasticity of the share of recruits coming from employment.

B. The wage elasticity of quits to employment

We move on to the estimations of the elasticities of quits to employment, the results of which are reported in table 4. As expected,

Table 4

Estimation results: wage elasticity of quits to employment

2004 – 2019	Coefficient	SE
Manufacturing		
log real wage	-0.752***	(0.246)
log real wage x log robots	-0.004	(0.07)
Services		
log real wage	-0.77***	(0.095)
log real wage x log robots	0.046	(0.027)
All Industries		
log real wage	-0.776***	(0.085)
log real wage x log robots	0.038	(0.024)

Note: “robots” is defined as the number of industrial robots per thousand manufacturing workers. Insignificant coefficients for the interaction term are also obtained when defining “robots” as number of industrial robots per manufacturing establishment. All estimations include the following controls; year dummies, province dummies, industry dummies, 3 Age dummies, Gender, Health condition, household financial condition, marital status, 3 education dummies, currently studying dummy, overtime work dummy, existence of union dummy, 4 type of employer dummies, 3 dummies for firm size, 8 dummies for firm-provided benefits, the unemployment rate (province level), log number of manufacturing establishments in city, log total number of industrial robots in the economy per thousand workers of all sectors, and the country ICT index (2015=100). ***; ** denote statistical significance at the 1% and 5% levels respectively.

coefficients for the log wage are all negative and statistically significant at the 1% level, hence higher wages are associated with lower quits towards other jobs. Turning our attention towards the effects of robotization on these elasticities, we observe that the interaction term for wages and robots is insignificant in all estimations, implying that robotization in manufacturing has no effect on a worker's decision to quit for another job. These findings come as no surprise considering that a separation to employment reflects the manifestation of an alternative option for the worker; given that our estimations use only voluntary quits as the dependent binary variable, one would have no reason to expect any impact of robotization on the nature of the worker's decision, *i.e.* to opt for the best of available career options depending on the worker's idiosyncrasies. By and large, these results suggest that there is no additional, discernible effect for robotization on the degree of monopsony in either sector.

C. The wage elasticity of the share of recruits coming from employment

The third and final group of elasticities we have to estimate is the wage elasticity of the share of recruits coming from employment. This elasticity represents the ease with which firms can attract workers from competitors, hence a positive coefficient of the interaction term for the wage and robots would imply that firms can poach workers with more ease. Since intuition dictates that firms paying higher wages should be able to poach workers, we expect positive coefficients for the log wage, and such is the case for all estimations as shown in table 5. However, the effect of robots proves to be statistically insignificant, suggesting that robotization in manufacturing has little to no effect on the ease with which firms can poach workers, be it in manufacturing or other sectors of the economy.

The results of our combined estimations for the three wage elasticities show that robotization in the manufacturing sector increases the labor supply elasticity in manufacturing and lowers it in services with a net depressing effect on the labor supply elasticity for the whole economy. These effects on the degree of monopsonistic competition in different parts of the market are manifested through one channel: a robotization-induced' modification in workers' responsiveness to changes in wages in their decision to quit to non-employment. Our findings show this with the significant coefficients in front of the interaction terms for wages

Table 5
Estimation results: random effects logit model for probability hire comes from employment

2004 – 2019	Coefficient	SE
Manufacturing		
log real wage	0.719***	(0.24)
log real wage x log robots	-0.144	(0.147)
Services		
log real wage	0.863***	(0.096)
log real wage x log robots	0.001	(0.051)
All Industries		
log real wage	0.82***	(0.082)
log real wage x log robots	-0.002	(0.045)

Note: "robots" is defined as the number of industrial robots per manufacturing establishment. Insignificant coefficients for the interaction term are also obtained when defining "robots" as number of industrial robots per thousand manufacturing workers. All estimations include the following controls; year dummies, province dummies, industry dummies, 3 Age dummies, Gender, Health condition, household financial condition, marital status, 3 education dummies, currently studying dummy, existence of union dummy, 4 type of employer dummies, 3 dummies for firm size, 8 dummies for firm-provided benefits, the unemployment rate (province level), log number of manufacturing establishments in city, log number of industrial robots per manufacturing establishment, log total number of industrial robots in the economy per thousand workers of all sectors, and the country ICT index (2015=100). ***; ** denote statistical significance at the 1% and 5% levels respectively.

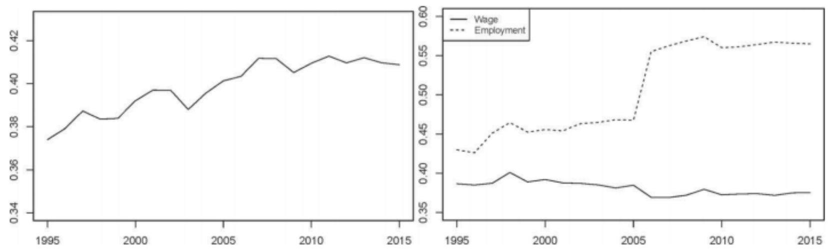
and robots in our estimations of the wage elasticities of quits to non-employment, and the insignificant results when estimating the other components of the labor supply elasticity. Simply, we see that more robots in manufacturing make manufacturing workers more prone to separate for wage-related reasons, while the opposite can be observed for non-manufacturing workers.

V. Discussion

In the context of South Korea, there is no consensus as to whether the labor share of income has decreased or not. Indeed, Karabarbounis and Neiman (2014) find that Korea is among the few countries to experience an increase in labor share in the corporate sector, while Song (2021) does find a declining labor share in the country. This comes as no surprise considering the complexity of measuring the labor share, with different methodologies often generating different results (Lee, 2015).

Our findings report a significant and negative (positive) effect of robotization on the degree of monopsonistic competition in manufacturing (services) sector, suggesting a lower (higher) Pigouvian rate of exploitation and thus a positive (negative) impact on the labor share of income in this sector. Our results also show that a larger operational stock of industrial robots in manufacturing increases the degree of monopsonistic competition in the Korean economy, indicating a negative effect on the labor share of income on an aggregate level.

One way to interpret the greater degree of monopsony in services due to robotization in manufacturing is with a composition effect going from manufacturing to services as described in Acemoglu and Restrepo (2019): a reallocation of value added towards services where productivity is growing faster than wages, hence the increasing Pigouvian exploitation associated with robotization. This interpretation finds support in Rieu and Park (2020) who observe sectoral rates of surplus value to study recent macro-trends and structural changes in the Korean economy. Looking at figures (1a) and (1b) jointly, we can see that the labor share of value added in "unproductive sectors has experienced an almost steady decline between 1995 and 2015, and Rieu and Park (2020) further support this observation by showing how the Marxian rate of exploitation continuously intensified over that same period. We can relate this observation on stagnating wages to Lee (2016) who shows that Korea experienced an increase in corporate savings that is superior to that in the majority of developed economies, and that this increase is associated with a lower labor share of income and higher inequality. The National Assembly Budget Office (2014) also reports an increase in retained earnings simultaneously accompanied by a deceleration in the rate of investments between 1995-2011, which suggest negative effects



(a) Value added (b) Employment and compensation

Source: Rieu and Park (2020)

FIGURE 1

(A, B) THE SHARE OF UNPRODUCTIVE SECTORS IN SOUTH KOREA

on the labor share (Chen *et al.* 2017; Karabarbounis and Neiman, 2014). Kim (2015) further supports this and finds that in the case of the top 50 Korean firms, only a small portion of retained earnings are directed towards investment.

In this context, our study joins the body of work investigating whether the fall in labor share in an economy is due to a fall on an intra-industry level, or because of a sectoral recomposition whereby activity is reallocated to industries where the labor share is naturally lower. Rodriguez and Jayadev (2013) and Karabarbounis and Neiman (2014) suggest that the former is true, mainly that the decline in labor share is due to intra-industry movements and not a sectoral reallocation of activity. Song (2021) finds that the falling labor share in Korea can mostly be attributed to a decline within capital-intensive industries, thus refuting the hypothesis which posits that a growth in services is to blame for the falling labor share.

However, our findings cast doubt on this hypothesis when it comes to the effect of robotization in manufacturing on the degree of monopsony in services and the aggregate economy, as our study signals an inter-sectoral effect to manufacturing robot density.

Furthermore, we qualify the following potential channels via which, individually or jointly, robotization is lowering the degree of exploitation in manufacturing, thus increasing the labor share. Firstly, robot adoption may be generating a productivity effect that outweighs robots' displacement effect in the manufacturing sector (Acemoglu and Restrepo, 2019; Autor and Salomons, 2018): because of enhanced productivity, that same sector witnesses greater demand for labor in non-robotized tasks, a demand for workers that is larger than the number of those displaced by robots, hence a net positive change in labor demand. This would be in contrast to the findings of Kariel (2021) for the UK, and more in line with Leigh *et al.* (2020) and Barth *et al.* (2020). Moreover, this positive effect on employment is accompanied by a larger labor-share of value added thanks to high union density in large manufacturing firms (Kim and Kim, 2020; Blanchard and Giavazzi, 2003). One may also postulate that robotization is creating completely new tasks and thus new jobs in the manufacturing sector, a "reinstatement effect whereby the task content of production has tilted in favour of workers thus increasing the workers' share of value added (Acemoglu and Restrepo, 2019).

The statistically insignificant effect of robots on the ease with which firms can poach workers is intriguing, since considerable literature shows how robot' adopting firms largely dominate their competitors in share of employment (Acemoglu *et al.* 2020). Autor *et al.* (2020) show that firms with high productivity, high markups and low labor share of value added (what they refer to as "superstar firms) reap the benefits of technological change and increase their dominance over product markets. In Korea, Kim (2016) and Kim and Kim (2020) show that higher markups and market concentration have caused a decline in labor share. Autor and Salomons (2018) find that technological progress lowers the share of labor from value-added, even though it may have a positive aggregate effect on employment, which could be a reflection of the expansion of the "superstar firms described in Autor *et al.* (2020). Barkai (2020) finds that, should capital have a role to play in the fall of labor share, then it is likely to be by increasing profitability and lowering the degree of competition. Clearly, whether and how lower competition in product markets affects the wage elasticity of labor supply is an interesting avenue for future research.

VI. Concluding remarks

In this paper, we have examined a new channel via which robotization impacts workers. Using a dynamic monopsony framework, we estimated the effect of an increase in the operational stock of industrial robots in Korean manufacturing on the labor supply elasticity of manufacturing and non-manufacturing workers. Using Manning (2003), we ran duration models to estimate the effects of robotization on the wage elasticity of quits to non-employment and employment, and a random effects logit model for the estimation of the wage elasticity of the share of recruits coming from employment, effects which we observe using an interaction term for the wage and robot adoption. Our results show that robotization in manufacturing has no statistically significant effect on the elasticity of quits to employment nor the elasticity of the share of recruits coming from employment for either sector. However, we observe statistically significant (1%) effects on the wage elasticity of quits to non-employment, increasing it in absolute value for manufacturing while depressing it for services and the whole economy. We interpret these findings as evidence for a displacement effect in manufacturing that has been outweighed by productivity effects, and a composition effect whereby value added is being transferred towards services where the labor share of income is in decline. We also interpret our findings in terms of Pigouvian exploitation and the labor share of income, and postulate that the considerable union density in large manufacturing establishments has secured workers' share of value added, while higher retained earnings and lower investment in services has diminished the share of workers.

Our findings should prove interesting for policy makers, particularly in the current Korean context. Indeed, the Moon Jae-In government has opted for an income-led growth strategy since 2017, a direction criticized in Jeong and Jeong (2020). This policy framework affects the reservation position among the Korean labor force, which directly relates to workers' wage responsiveness. Furthermore, a greater reservation position for workers could very well impact the rate at which robots are deployed in manufacturing, with profitability taking centre stage in the firm's decision whether to invest or save (Moody, 2018). Finally, a particular concern for Korean policy makers should be the direction taken by services where workers are losing both in terms of wage responsiveness and share of value added (Pyo and Rhee, 2018; Rieu and Park, 2020). This trend is worrying considering that the Korean economy is experiencing further transformation towards a service-led growth.

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Appendix A - Theoretical framework

In a simple model of dynamic monopsony, the firm faces an upward sloping labor supply (L_t) curve in discrete time given by

$$L_t = [1 - S(w)]L_{t-1} + R(w), \tag{A1}$$

where $S(w)$ represents the rate of separations of workers from the firm and $R(w)$ being the flow of recruits, depending negatively and positively on the paid wage respectively, thus $S' < 0$ and $R' > 0$.[1]

In a steady state, separations and recruits balance and $L_t = L_{t-1}$ thus

$$L(w) = \frac{R(w)}{S(w)}, \tag{A2}$$

and taking logs and differentiating with respect to w, we obtain

$$\varepsilon_{LW} = \varepsilon_{RW} - \varepsilon_{SW} \tag{A3}$$

where ϵ_{LW} is the long-run wage elasticity of labor supply faced by the firm, ϵ_{RW} is the wage elasticity of recruitment, and ϵ_{SW} is the wage elasticity of separations. ϵ_{LW} hints at the distribution of bargaining power between workers and the monopsonist as well as the labor share of income, as it correlates with the proportional gap between marginal revenue product of labor and the real wage in the following way as shown by Manning (2003, p.30):

$$\frac{MRP_L - w}{w} = \frac{1}{\varepsilon_{LW}}. \tag{A4}$$

Under perfect competition, $\varepsilon_{LW} = \infty$ and $MRP_L = w$. The difference between MRP_L and w is the Pigouvian rate of exploitation (Pigou, 1924), revisited in Robinson (1933) and explored in depth by Persky and Tsang (1973)[2].

[1] See Card and Krueger (1995, pp. 374)

[2] Flatau (2001) compares Pigou (1924) and Robinson's (1933) notions of

Equation (A3) can further be decomposed in the following way:

$$\varepsilon_{LW} = \theta^R \varepsilon_R^E + (1 - \theta^R)\varepsilon_R^N - \theta^s \varepsilon_s^E - (1 - \theta^s)\varepsilon_s^N, \tag{A5}$$

which shows that the long-run elasticity of labor supply to the firm is the difference in weighted average of the elasticity of recruitment broken down into the elasticity of recruitment from employment (ϵ_R^E) and elasticity of recruitment from nonemployment (ϵ_R^N), and the elasticity of separation broken down into the elasticity of separation to employment (ϵ_S^E) and the elasticity of separation to nonemployment (ϵ_S^N). The weights θ^R and θ^S represent the share of recruits from employment and the share of separations to employment, respectively, and in a steady state we have $\theta^R = \theta^S$.

We are able to estimate the wage elasticities of separations using the job-flow data at our disposal, but estimating the wage elasticities of recruitment is a more complex task that would require data on all job offers received by workers to observe their reactions, information which we do not have for our sample of workers. Manning (2003) proposes a way to circumvent this problem, enabling us to estimate elasticities of recruitment with the data at our disposal.

Building on Burdett and Mortensen (1998), Manning (2003, p.97) shows that the wage elasticity of recruitment from employment can be expressed as:

$$\varepsilon_R^E = \frac{-\theta^S \varepsilon_S^E}{\theta^R}, \tag{A6}$$

and thus, in a steady state (or when $\theta^R = \theta^S$) we have

$$\varepsilon_R^E = -\varepsilon_S^E. \tag{A7}$$

Since estimating the elasticity of separations ϵ_S^E can be accomplished using our job-flow data, equation (A7) shows that in doing so, we would be estimating ϵ_R^E indirectly, thus remedying the initial complication

exploitation to show that, contrary to general belief, they are not identical. This fallacious consensus can, to a certain extent, be attributed to Robinson's adoption of Pigou's definition of exploitation and her later acknowledgement of Pigou as being the main influencer for her 1933 book *The Economics of Imperfect Competition* (Robinson,1978,pp:ix) faced.

For the elasticity of recruitment from nonemployment, Manning (2003, p.100) shows that it can be written as:

$$\varepsilon_R^N = \varepsilon_R^E - \frac{w\theta'^R(w)}{\theta^R(w)[1-\theta^R(w)]}. \tag{A8}$$

The second term on the righthand side shows the wage responsiveness of the share of recruits from employment, thus informing us on the ability with which firms can poach workers. Manning (2003) further shows us that we can model $\theta^R(w)$ as a logistic function $e^{\beta x}/(1+e^{\beta x})$ and, taking x as the log wage, we get:

$$\frac{w\theta'^R(w)}{\theta^R(w)[1-\theta^R(w)]} = \beta_w, \tag{A9}$$

with β_W being the coefficient on the log wage. The wage elasticity of the share of recruits can thus easily be obtained.

Appendix B – Descriptive statistics

	Manufacturing				Services			
	Mean	SD	Min.	Max	Mean	SD	Min.	Max.
Real monthly pay (10,000 KRW)	192.867	116.443	5.572	3786.648	162,619	112	1.743	3787.383
Single	0.226	0.418	0	1	0.281	0.450	0	1
Married	0.693	0.461	0	1	0.608	0.488	0	1
Age	43.234	12.019	17	80	42.158	14.091	15	80
Gender (1 = male)	0.728	0.445	0	1	0.443	0.497	0	1
Government job dummy	0.003	0.053	0	1	0.092	0.289	0	1
Private company job dummy	0.9	0.301	0	1	0.755	0.43	0	1
Foreign company job dummy	0.008	0.087	0	1	0.005	0.07	0	1
Existence of union	0.103	0.305	0	1	0.106	0.308	0	1
Work overtime dummy	0.049	0.216	0	1	0.019	0.138	0	1
Poor household financial condition dummy	0.455	0.498	0	1	0.43	0.495	0	0
Household size (number of family members)	3.302	1.259	1	10	3.216	1.279	1	10

Note: Data used comes from wave 4 to wave 22 of the 22nd version of the Korean Labor and Income Panel Study (KLIPS), restricted to wage earners with job spells starting from 1990 till 2019. In KLIPS, we use the Work History dataset, the Individual dataset and the Household dataset.

References

Abbring, Jaap H., and Gerard J. Ven Den Berg. The unobserved heterogeneity distribution in duration analysis. *Biometrika* 94(No.1 2007): 87–99.

Acemoglu, D. and Restrepo, P. Automation and New Tasks: How Technology Displaces and Reinstates Labor. *Journal of Economic Perspectives* 33(No.2 2019): 3–30.

Acemoglu, D. and Restrepo, P. Robots and jobs: Evidence from US labor markets. *Journal of Political Economy* 128 (No.6 2020): 2188–2244.

Acemoglu, D., Lelarge, Claire and Pascual Restrepo. Forthcoming. Competing with Robots: Firm-Level Evidence from France. *AEA Papers and Proceedings* 110 (2020): 383–88

Acemoglu, D., Manera, A., and Restrepo, P. *Does the US Tax Code Favor Automation?*. NBER Working Paper No. w27052.

Aghion, P., Antonin, C., Bunel, S. and Xavier J. *What are the labor and product market effects of automation? New evidence from France.* CEPR Discussion Paper 14443, 2020.

Aksoy, C. G., Ozkan B., and Philipp, J. Robots and the Gender Pay Gap: Evidence from Europe *European Economic Review* 134 (2021): 103693.

Arntz, M., Gregory, T., and Zierahn, U. *The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis.* OECD Social, Employment and Migration Working Papers, No.189, OECD Publishing, Paris, 2016.

Arntz, M., Gregory, T., and Zierahn, U. Revisiting the risk of automation. *Economics Letters* 159(2017): 157–160.

Arntz, M., Gregory, T., and Zierahn, U. *Digitalization and the future of work: Macroeconomic consequences.* ZEW Discussion Papers, No. 19-024, ZEW–Leibniz-Zentrum für Europäische Wirtschaftsforschung, Mannheim, 2019.

Ashenfelter, Orley C., Farber, H., and Ransom, M. R. Labor Market Monopsony. *Journal of Labor Economics* 28 (No.2 2010): 203–210

Atkinson, Robert D. *The Case Against Taxing Robots.* Information Technology & Innovation Foundation, April 8, 2019.

Autor, D., and Salomons, A. *Is Automation Labor Share-Displacing?* Productivity Growth, Employment, and the Labor Share.

Brookings Papers on Economic Activity Spring: 1–87.

Autor, D., and Handel. M. J., “Putting tasks to the test: Human capital, job tasks, and wages. *Journal of Labor Economics* 31 (No.2 2013): 59–96.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. “The Fall of the Labor Share and the Rise of Superstar Firms. *The Quarterly Journal of Economics* 135 (No.2 2020): 645–709.

Autor, D., Levy, F., and Murnane, R. J., “The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics* 118 (No.4 2003): 1279–1333.

Bachmann, R., Gökay, D., and Frings, H.. *Labour Market Polarisation and Monopsony Power*. IZA Conference Paper, 2019.

Ballestar, M. T., Díaz-Chao, ., Sainz, J., and Torrent-Sellens, J. Knowledge, robots and productivity in SMEs: Explaining the second digital wave. *Journal of Business Research* 108(2020): 119–131.

Barbieri, L., Mussida, C., Piva, M., and Vivarelli, M., *Testing the Employment Impact of Automation, Robots and AI: A Survey and Some Methodological Issues.* IZA Discussion Papers No. 12612, Institute of Labor Economics (IZA), Bonn, 2019.

Barkai, S. Declining Labor and Capital Shares. *The Journal of Finance* 75 (No.5 2020): 2421–2463.

Barth, E., Roed, M., Schone, P., and Umblijs, J., *How Robots Change Within-Firm Wage Inequality.* IZA Discussion Papers No. 13605, Institute of Labor Economics (IZA), Bonn

Belloc, Filippo., Burdin, Gabriel and Fabio Landini. 2020. *Robots and Worker Voice: An Empirical Exploration.* IZA Discussion Papers No. 13799, Institute of Labor Economics (IZA), Bonn.

Benedetti, M. The economics of robots in industrial applications. *Industrial Robot* 4 (No.3 1977): 109-118.

Bhaskar, V., Manning, A., and To. T. Oligopsony and monopsonistic competition in labor markets. *Journal of Economic Perspectives* 16(No.2 2002): 155–174.

Blanchard, O., and Giavazzi. F. Macroeconomic Effects of Regulation and Deregulation in Goods and Labor Markets. *The Quarterly Journal of Economics* 118 (No.3 2003): 879–907.

Bowles, J., *The computerisation of european jobs.* https://www.bruegel.org/2014/07/the-computerisation-of-european-jobs/, 2014.

Burdett, K., and Mortensen, D. T. Wage differentials, employer size, and unemployment. *International Economic Review* 39 (No.2 1998): 257–73.

Carbonero, F., Ernst, E., and Weber, E. *Robots Worldwide: The Impact of Automation on Employment and Trade.* Beiträge zur Jahrestagung des Vereins für Socialpolitik: Gender Economics, ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg, 2020.

Card, D., and Krueger, A. B., *Myth and Measurement: The New Economics of the Minimum Wage.* Princeton, NJ: Princeton University Press, 1995.

Cette, G., Devillard, A., and Spiezia, V. The contribution of robots to productivity growth in 30 OECD countries over 1975–2019. *Economics Letters* 200 (2021): 109762.

Chen, P., Karabarbounis, L., Neiman, B. The global rise of corporate saving. *Journal of Monetary Economics* 89 (2017): 1-19.

Chiacchio, F., Petropoulos, G., and Pichler, D. *The impact of industrial robots on EU employment and wages: A local labour market approach.* Bruegel Working Papers Issue 2, 2018.

Cirillo,V. Rinaldini, M., Staccioli, J., and Virgillito, M. E., "Technology vs. workers: the case of Italy's Industry 4.0 factories. *Structural Change and Economic Dynamics* 56(2021): 166-183.

Cséfalvay Z. Robotisation in Central and Eastern Europe: catching up or dependence?. *European Planning Studies* 28 (No.8 2020): 1534-1553.

Dauth, W., Findeisen, S., Südekum, J., and Woessner, N. *The rise of robots in the German labour market.* VoxEU.org, 2017.

De Vries, G. J., Gentile, E., Miroudot, S., and Wacker, K. M. The rise of robots and the fall of routine jobs. *Labour Economics* 66 (2020): 101885.

Eeckhout, J., Hedtrich, C., and Pinheiro, R. *Automation, Spatial Sorting, and Job Polarization.* 2019 meeting Papers 581, Society for Economic Dynamics, 2019.

Faber, M. Robots and reshoring: Evidence from Mexican labor markets. *Journal of International Economics* 127 (2020).

Fernández-Macías, E., Klenert, D., and Antón, J. I. Not so disruptive yet? Characteristics, distribution and determinants of robots in Europe. *Structural Change and Economic Dynamics* 58 (2021): 76-89.

Flatau, P. Some Reflections on the 'Pigou-Robinson' Theory of

Exploitation. *History of Economics Review* 33 (No.1 2001): 1–16.

Ford, M. *The Rise of the Robots*. New York: Basic Books, 2015.

Fox, J T. Estimating the employer switching costs and wage responses of forward-looking engineers. *Journal of Labor Economics* 28 (No.2 2010): 357–412.

Frey, C. B. and Osborne, M. A. "The Future of Employment: How Susceptible are Jobs to Computerisation?. *Technological Forecasting and Social Change* 114 (No.C 2017): 254–280

Frey, C. B., Thor, B., and Chen, C. Political machinery: did robots swing the 2016 US presidential election?. *Oxford Review of Economic Policy* 34 (No.3 2016): 418–442.

Fujiwara, I., and Feng Z. *Robots and labour: implications for inflation dynamics. BIS Paper*, 111c, 2020.

Giuntella, O., and Tianyi W. *Is an Army of Robots Marching on Chinese Jobs?*. IZA Discussion Papers No. 12281, Institute of Labor Economics (IZA), Bonn, 2019.

Goos, M., and Manning, A. Lousy and Lovely Jobs: The Rising polarization of Work in Britain. *The Review of Economics and Statistics* 89 (No.1 2007): 118–133.

Graetz, G. and Michaels, G. Robots at Work. *The Review of Economics and Statistics* 100 (No.5 2018): 753–768.

Gregory, T., Salomons, A., and Zierahn, U. *Racing with or against the machine? Evidence from Europe*. CESifo Working Papers 7247, 2018.

Hamidi-Noori, A. and Templer, A. Factors Affecting the Introduction of Industrial Robots. *International Journal of Operations & Production Management* 3 (No.2 1983): 46-57.

Hasegawa, Y. New developments in the field of industrial robots. *International Journal of Production Research* 17 (No.5 1979): 447–454.

Hirsch B., Jahn, E. J., and Schnabel, C. Do Employers Have More Monopsony Power in Slack Labor Markets? ILR Review 71 (No.3 2018): 676-704.

Hirsch, B., Thorsten, S., and Schnabel, C. Differences in labor supply to monopsonistic firms and the gender pay gap: An empirical analysis using linked employer-employee data from Germany. *Journal of Labor Economics* 28 (No.2 2010): 291–330.

Huang, Y., and Naubahar S., From 'Labour Dividend' to 'Robot Dividend': Technological Change and Workers' Power in South

China. *Agrarian South: Journal of Political Economy* 6 (No.1 2017): 53–78.

International Federation of Robotics. 2020. *World Robotics: Industrial Robots.*

International Federation of Robotics. 2021. *The World Robotics 2021: Industrial Robots,* https://ifr.org/ifr-press-releases/news/robot-sales-rise-again.

Jeong, G., and Jeong S. Trends of Marxian Ratios in South Korea, 1980–2014. *Journal of Contemporary Asia* 50 (No.2 2020): 260-283.

Jimeno, Juan F. *Fewer babies and more robots: economic growth in a new era of demographic and technological changes. SERIEs* 10: 93–114, 2019.

Jungmittag, A., and Pesole, A. *The impact of robots on labour productivity: A panel data approach covering 9 industries and 12 countries.* JRC Working Papers Series on Labour, Education and Technology No. 2019/08, European Commission, Joint Research Centre (JRC), Seville, 2019.

Karabarbounis, L. and Neiman B. The Global Decline of the Labor Share. *The Quarterly Journal of Economics* 129 (No.1 2014): 61–103.

Kariel, J. Job Creators or Job Killers? Heterogeneous Effects of Industrial Robots on UK Employment. *Labour* 35(No.1 2021): 52–78.

Kim, B. G., Explaining movements of the labor share in the Korean economy: factor substitution, markups and bargaining power. *J Econ Inequal* 14 (2016): 327–352.

Kim, D., and Kim, W.Y. What drives the labor share of income in South Korea? A regional analysis. *Growth and Change* 51 (No.3 2020): 1304-1335.

Kim, S. J. Analysis of Generation and Distribution of Value-Added at Top 50 Enterprises (2002-2013). *Economic Reform Report*, 2015–1 (in Korean).

Klenert, D., Fernández-Macías, E., and Antón J.I. *Don't blame it on the machines: Robots and employment in Europe.* VoxEU.org, 2020.

Koch, M., Manuylov, I., and Smolka, M. *Robots and firms.* CESifo Working Paper No. 7608, Center for Economic Studies and ifo Institute (CESifo), Munich, 2019.

Koster, S., and Brunori, C. What to do when the robots come? Nonformal education in jobs affected by automation. *International Journal of Manpower* 42(No.8 2021): 1397–1419.

Leduc, S., and Zheng L. *Robots or Workers? A Macro Analysis of Automation and Labor Markets.* Federal Reserve Bank of San Francisco working paper 2019–17, 2020.

Lee, B. H. *Labour Income Share in Korea: Measuring Issues and Trends.* e-Labor News No.159, Issue paper, Korea Labor Institute, 2015.

Lee, B. H. *Labor Income Share and Income Inequality in Korea.* Labor Market & Employment Policies Working Paper 2016-01, Korea Labor Institute, 2015.

Leigh, N. G., Kraft, B., and Lee H. Robots, skill demand and manufacturing in US regional labour markets. *Cambridge Journal of Regions, Economy and Society* 13(2020): 77–97.

Lordan, G. *Robots at work. A report on automatable and non-automatable employment shares in Europe.* Directorate-General for Employment, Social Affairs and Inclusion, European Commission, 2018.

Manning, A. *Monopsony in Motion: Imperfect Competition in Labor Markets*. Princeton, NJ: Princeton University Press, 2003.

Manning, A. Monopsony in labor markets: a review. *Industrial and Labor Relations Review* 74 (No.1 2020): 3–26.

Miller, B and R. D. Atkinson. *Are Robots Taking Our Jobs, or Making Them?*, Information Technology & Innovation Foundation, September, 2013.

Kim, M. High Tech, Low Growth: Robots and the Future of Work. *Historical Materialism* 26 (No.4 2018): 3–34.

National Assembly Budget Office. *Corporate Internal Reserve: Status and Economic Impact.* Economic Trends and Issues, No. 30 (in Korean), 2014.

Nedelkoska, L., and Quintini, G. *Automation, skill use and training.* OECD Social, Employment and Migration Working Papers, No. 202., 2018.

Okubayashi, K. The Impacts of Industrial Robots on Working Life in Japan. *Journal of General Management* 11 (No.4 1986): 22–34.

Paba, S., Solinas, G., Bonacini, L., and Fareri, S. *Robots, Trade and Employment in Italian Local Labour Systems.* DEMB Working Paper Series N. 183, Dipartimento di Economia Marco Biagi, 2020.

Pajarinen, M, and Rouvinen P. *Computerization threatens one third of* *finnish employment.* ETLA Brief 22, 2014.

Persky, J., and Tsang H. Pigouvian Exploitation of Labor. *The Review of Economics and Statistics* 56 (No.1 1974): 52–57.

Pigou, Arthur C. *The Economics of Welfare*. London: Macmillan, 1924.

Pischke, J.S., and Velling, J. Employment Effects of Immigration to Germany: An Analysis Based on Local Labor Markets. *The Review of Economics and Statistics* 79 (No.4 1997): 594–604.

Pouliakas, K. *Determinants of automation risk in the eu labour market: A skills-needs approach.* IZA Discussion Paper No. 11829, 2018.

Priest, G. Timing "disturbances in labor market contracting: Roth's findings and the effects of labor market monopsony. *Journal of Labor Economics* 28 (No.2 2010): 447-472.

Pulkka V. V. A free lunch with robots – can a basic income stabilise the digital economy? *Transfer: European Review of Labour and Research* 23 (No.3 2017): 295–311.

Pyo, H. K. and Rhee, K. Productivity Analysis on the Service Sector in Korea: Evidence from Industry-Level and Firm-Level Data. *Seoul Journal of Economics* 31 (No.1 2021): 21–61.

Ransom, M. R. and R. L. Oaxaca. New market power models and sex differences in pay. *Journal of Labor Economics* 28 (No.2 2010): 267–289.

Ransom, M. R. and Sims D. P. Estimating the firm's labor supply curve in a "new monopsony framework: Schoolteachers in Missouri. *Journal of Labor Economics* 28 (No.2 2010): 331–355.

Rieu, D. M., and Park, H. W. Unproductive Activities and the Rate of Surplus Value at the Industry Level in Korea, 1995–2015. *Journal of Contemporary Asia* 50 (No.2 2020): 284–307.

Robinson, Joan V. *The economics of imperfect competition.* Macmillan: London, 1933.

Robinson, Joan V. *Reminiscences, in Contributions to Modern Economics,* Oxford: Blackwell, 1978

Rodriguez, F., and Jayadev, A. The Declining Labor Share of Income. *Journal of Globalization and Development* 3 (No.2 2013): 1–18.

Rodríguez, F., and Ortega, D. *Are capital shares higher in poor countries? Evidence from Industrial Surveys.* Wesleyan Economics Working Papers 2006-023, Wesleyan University, Department of Economics, 2006.

Song, E. "What drives labor share change?, Evidence from Korean industries. *Economic Modelling* 94 (2021): 370–385.

Spitz-Oener, A. Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure. *Journal of Labor Economics* 24 (No.2 2006): 235–270.

Tolbert, C. M., and Sizer. M. *U.S. Commuting Zones and Labor Market Areas. A 1990 Update.* Economic Research Service Staff Paper, No. 9614, 1996.

Torii, Y. Robotization in Korea: Trend and implications for industrial development. *Technological Forecasting and Social Change* 35 (No.2–3, 1989): 179–190.

Yonemoto, K. The socio - economic impacts of industrial robots in Japan. *Industrial Robot* 8 (No.4 1981): 238–241.