Robots and labour: implications for inflation dynamics

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Abstract

This summary investigates how robots affect several variables related to labour, and vice versa. In order to evaluate the causal relationship, we use quality-adjusted robot stock data and labour market data from 26 industries in 33 countries. According to the results obtained from three estimated models – cross-sectional regressions in line with previous studies, panel data regressions and structural panel VAR models – an increase in robot stocks results in higher labour productivity, but has only an ambiguous effect on total employment. Wage increases, but not significantly. Thus, to date, robots should not have exerted a significant influence on inflation dynamics. On the other hand, improvements in labour market conditions lead to significant decline in robot investment. An important lesson obtained in this summary is that when testing whether robots take jobs away from the human workforce, one must also consider the reverse causality from the labour market to robots.

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1. Introduction

Will machines take jobs away from the human workforce? The impact of "job-stealing" robots has become a growing concern over the last several decades, particularly amid a significant progression in artificial intelligence and algorithms in machine learning. Academics have tackled this issue from a theoretical as well as an empirical angle. Since so-called "robotisation" is a rather recent phenomenon, the data on robots have only been available for the last two to three decades, at most. In addition, compared with the number of theoretical studies on robotisation, only a few empirical studies on the relationship between robots and labour have been conducted.

Graetz and Michaels (2018), Acemoglu and Restrepo (2017a) and Dauth et al (2017) gauge the effects of the increasing usage of robots on the labour market. Implications from these previous studies are somewhat mixed, as shown in Table 1. Graetz and Michaels (2018) evaluate the effect in Europe with cross-sectional data on industries and countries, and conclude that although robotisation increases labour productivity and real wage, it causes no significant effect on labour inputs. Acemoglu and Restrepo (2017a) use US data by commuting zones and conclude that more automation leads to less labour inputs and lower real wage. Dauth et al (2017) focus on Germany, using detailed labour market data, and obtain similar conclusions to Graetz and Michaels (2018), but find no significant effect on real wage at the macro level.

Effect of robots on the labour market — Table 1

	Hours	Employment	Productivity	Wage
Graetz and Michaels (2018)	0	0	+	+
Acemoglu and Restrepo (2017)	–	–	n/a	–
Dauth et al (2017)	0	0	+	0

Notes: +, – and 0 denote positive, negative and insignificant effects, respectively.

This paper, which summarises the findings in our ongoing studies (Fujiwara et al (2019a, 2019c)), also investigates the empirical relationship between robots and labour. In contrast to previous studies, Fujiwara et al (2019a, 2019c) do not have an area focus. There are also substantial differences in data and empirical methodologies.

Regarding the data, there are three primary differences. First, we make use of the quality adjusted robot stock series[2] by using newly available data on the price of robots by industry. Second, we extend the analysis on European countries in Graetz and Michaels (2018) to include China, India, Japan and Korea. Japan and Korea are well known as the frontier countries in robot production and usage. And finally, we use updated EUKLEMS data (significant revisions have been made in the most recent EUKLEMS).

[2] To the best of our knowledge, Fujiwara et al (2019a) and Fujiwara et al (2019) are the first attempts to compute the quality-adjusted robot stock series. For details of quality adjustment, see Fujiwara et al (2019a) and Fujiwara et al (2019).

We also explore new empirical methodologies. Previous empirical studies compare the long-run growth rates of robot stocks with those of labour-related variables, say, over 20 years, with simple cross-sectional regressions. This may lead to significant bias in estimated parameters, if there are country as well as industry-specific fixed effects. Thus, we examine panel data regressions as well. In addition, the causal relationship between robots and labour is investigated by using panel structural vector autoregression (VAR) models.

Our papers, ie Fujiwara et al (2019a, 2019c), have similar conclusions to Graetz and Michaels (2018) and Dauth et al (2017). Advancements in robotics increase labour productivity and wage, but not significantly for the latter. At the same time, only ambiguous effects are observed in labour supply. Thus, we can conclude that robots should not have exerted significant influences on inflation dynamics. Structural panel VAR models show the significantly negative causal effects from improvements in the labour market to robots. This implies the importance in considering the reverse causality from the labour market to robots when testing whether robots take jobs away from the human workforce.

The rest of this summary is organised as follows. Section 2 derives the theoretical relationship between robots and labour using a simple model to obtain empirical implications. In Section 3, our empirical results are summarised. Section 4 concludes.

2. Simple model

This section lays out a simple model to obtain the empirical implications of robots on labour. Consider a social planner's problem to maximise welfare

$$u(C) - v(h),$$

subject to the resource constraint

$$C = f(h, \bar{R}).$$

The variables C, h, and $\bar{R}$ denote consumption, labour and robot stocks, respectively. For the simplicity of analysis, the supply of robots is assumed to be exogenous.

The functional forms are given by

$$u(C) := \log(C), v(h) := \left[(1-\alpha)^{\frac{1}{\varepsilon}} h^{1-\frac{1}{\varepsilon}} + \alpha^{\frac{1}{\varepsilon}} \bar{R}^{1-\frac{1}{\varepsilon}}\right].$$

Without loss of generality, the elasticity of substitution between labour and robots is set to be the same as Frisch elasticity. Then, at equilibrium, we have

$$\mathrm{d}h = (1-\varepsilon) \overbrace{\frac{\alpha \bar{R}^{\varepsilon-2} h}{[(1-\alpha)(1+\varepsilon) h^{\varepsilon-1} + 2\alpha \bar{R}^{\varepsilon-1}]}}^{\oplus} \mathrm{d}\bar{R}.$$

Thus, depending on whether robots and labour are Edgeworth complements ($\varepsilon < 1$) or substitutes ($\varepsilon > 1$), an increase in robots will increase or reduce total employment.

The total differentiation on the relationship between wage, which is equal to the marginal product of labour, and robots leads to

$$\mathrm{d}w = \frac{\overbrace{\frac{1+\varepsilon}{\varepsilon}\left(\frac{h}{1-\alpha}\right)^{\frac{1}{1-\varepsilon}} \alpha \bar{R}^{\varepsilon-2} h}^{\oplus}}{[(1-\alpha)(1+\varepsilon)h^{\varepsilon-1} + 2\alpha \bar{R}^{\varepsilon-1}]} \mathrm{d}\bar{R}.$$

Irrespective of the size of the elasticity of substitution, the effect of robots on wage is always positive.

In the next section, we empirically test whether the above implications obtained in the simple model are observed in the data.

3. Empirical results

For cross-sectional and panel regressions, the estimated equation is given by

$$Y_{c,i,t} = \beta_{1,c} + \beta_{2,i} + \beta_3 Y_{c,i,t-1} + \beta_4 X_{c,i,t-1} + \beta_5 Z_{c,i,t} + u_{c,i,t}.$$

The dependent variables Y are variables in the labour market, where changes in labour productivity is labelled as "productivity"; real wage as "wage"; total employment as "employment" and hours worked as "hours." The explanatory variables X are robot measurements, where changes in the number of robot stock is labelled as "unit"; the percentile measurement in the number of robot stocks as "percentile – unit"; changes in the quality adjusted robot stock as "value"; and the percentile measurement in the number of quality adjusted robot stocks as "percentile – value." Unit and value denote the number of robots and the quality-adjusted robot stocks, respectively. As in Graetz and Michaels (2018), we also use the percentile measurement, which is the percentile of changes in robot units. All observations are classified into 10 groups based on changes in unit measure and are assigned numbers based on the quantile. This is to evaluate the effects at the right tail of the distribution in the changes in robot stocks. The choice of the control variables Z follows Graetz and Michaels (2018). Subscript c, i and t denote country, industry and time, respectively. With cross-sectional regressions, changes are only those between 1999 and 2010 and t as well as fixed effects are not included. Lagged variables are those for the optimally chosen distributed lags in panel regressions.

We also estimate panel bivariate VAR models:

$$\begin{pmatrix} Y_{c,i,t} \\ X_{c,i,t} \end{pmatrix} = B_{1,c} + B_{2,i} + B_3 \begin{pmatrix} Y_{c,i,t-1} \\ X_{c,i,t-1} \end{pmatrix} + B_4 Z_{c,i,t} + C E_{c,i,t}$$

Elements in $E_{c,i,t}$ are orthogonal to each other. C is the lower triangular matrix, which is obtained by the Choleski decomposition of the variance-covariance matrices. The critical assumption in obtaining the structural VAR form as above is the ordering of the endogenous variables in the contemporaneous relationship. We examine all possible combinations of ordering in the bivariate VAR system, namely: (i) when the labour market moves first, ie a shock that increases the labour market variable contemporaneously also affects the robot investment contemporaneously, but a shock that increases the robot investment contemporaneously does not affect the labour market variable contemporaneously; and (2) when the robot moves first, ie a shock that increases the robot investment contemporaneously also affects the labour market variable contemporaneously, but a shock that increases the labour market variable contemporaneously does not affect the robot investment contemporaneously.

3.1. Cross section

Tables 2 and 3 show the estimated coefficients on the robot measurements, namely the effect of robots on the labour market, from cross-sectional regressions with instrumental variables. We employ two instrumental variables employed in Graetz and Michaels (2018). They are "replaceability," ie "an industry-level measure that we call replaceability," and "reaching and handling," ie "a measure of how prevalent the tasks reaching and handling were in each industry, relative to other physical demands, prior to robot adoption."[3] Tables 2 and 3 report the results from "replaceability" and "reaching and handling", respectively. *, **, and *** denote significance at 10%, 5% and 1%.

Cross section with IV: replaceability

Table 2

	Productivity	Wage	Employment	Hour
Unit	–1.289	–1.053	0.298	0.839
Percentile	0.540***	0.501***	–0.029	–0.406***
Value	–1.583	–1.045	0.276	0.667
Percentile	0.629***	0.458***	0.008	–0.301***

Notes: *, **, and *** denote significance at 10%, 5% and 1%, respectively.

With percentile measurements, an increase in robot stocks leads to an increase in labour productivity and real wage. Also, no significant effect is found on total employment. We note that the same result is obtained irrespective of whether the robot stocks are quality adjusted. These all imply that the main conclusion in Graetz and Michaels (2018) is robust even with the updated EUKLEMS data, inclusion of new countries (China, India, Japan and Korea), and quality-adjusted series of robot stocks, as long as the focus is on the right tail of the distribution in the changes in robot stocks.

Cross section with IV: reaching and handling

Table 3

	Productivity	Wage	Employment	Hour
Unit	0	0	0	0
Percentile	0.556***	0.546***	–0.131	–0.393***
Value	4.788	3.885	–1.776	–2.560
Percentile	0.869***	0.530***	–0.125	–0.348***

Notes: *, **, and *** denote significance at 10%, 5% and 1%, respectively.

An increase in robot stocks, however, significantly reduces hours worked. In Graetz and Michaels (2018) and Dauth et al (2017), the effect of robots on labour

[3] We conduct the Cragg and Donald (1993) test for the weak instruments. "Replaceability" turns out to be a weak instrument for all robot measurements, while "reaching and handling" is also a weak instrument for all percentile measurements.

input is close to zero. The negative effect on hours worked is in line with the finding in Acemoglu and Restrepo (2017a).

3.2. Panel

Table 4 summarises the sum of the estimated coefficients over lags on the robot measurements. The estimation period is from 1994 to 2010. Similar to the results from cross-sectional regressions, an increase in robot stocks results in higher labour productivity and real wage, but lower hours. The effect is significant even without resorting to percentile measurements. Contrary to conjectures made in previous studies, a stronger effect is found with annual data than with long-run data. In frequencies higher than 10 to 15 years (but still low), even small changes in robot stocks have a significant effect on the labour market. Altogether, these imply the importance in investigating the impact of robots not only in their right tail and in the long run, but throughout distribution and dynamics.

Dynamic panel — Table 4

	Productivity	Wage	Employment	Hour
Unit	0.005	–0.002	0.005	0.03
Percentile	0.012**	0.006	–0.002	0.03
Value	0.003	–0.008	0.006	0.03
Percentile	0.011*	0.009*	0.002	0.03

Notes: *, **, and *** denote significance at 10%, 5% and 1%, respectively.

3.3. VAR

Table 5 reports the directions of the impulse responses in all VAR models. + and – denote positive and negative reactions, respectively. The sign to the left of the arrow shows the direction at the initial responses, while that to the right of the arrow shows the direction of the responses over the long run. Our primary focus is the sign to the right of the arrow. * denotes the significant responses from zero with one standard deviation.

Directions of impulse responses — Table 5

	Robot shock		Labour shock	
	Robot first	Labour first	Robot first	Labour first
Productivity	+ → +	+* → +	+* → –	– → –
Wage	–* → –*	+* → –	+* → –*	–* → –*
Employment	+* → +	–* → –*	–* → –*	–* → –*
Hours	+* → +*	–* → +	–* → –*	– → –*

Notes: * denotes the significant responses from zero with one standard deviation. The sign to the left of the arrow shows the direction of the initial responses while that to the right of the arrow shows the direction of the responses over the long run.

We can again confirm similar results, in particular, over the long run. Irrespective of the assumptions about the short-run restriction, directions of the long-run effect are the same except for a single case, ie the responses in the total employment to the shock to the robot investment. Graetz and Michaels (2018) and Dauth et al (2017) also report that the responses in the total employment are not significant.

The impact of the robot on the labour productivity is positive, but those on real wage, total employment and hours worked are ambiguous. These are in line with previous studies. The responses of labour productivity are not, however, significant, in contrast to Graetz and Michaels (2018), Dauth et al (2017) and results obtained with cross-sectional and panel data regressions.

On the other hand, regarding robot demand shocks, namely, the direct shocks to the labour market variables, the responses are almost identical irrespective of the identification assumption. The long-run effects are all negative and are significantly negative except for the direct shock to labour productivity, implying a countercyclical robot investment. Improvements in labour market conditions, namely higher wage and labour input, reduce the robot investment significantly. Although we can observe significant effects from labour, the obtained results are not in line with the story offered by the directed technological change of Acemoglu (2002) and Acemoglu and Restrepo (2017b), where the scarcity or tightening of the labour market induces the robot investment. The results from panel VARs hint the importance in considering the reverse causality from the labour market to robots when testing whether robots take jobs from the human workforce.[4]

4. Conclusion

According to the results from three estimated models, while an increase in robot stocks increases labour productivity, it only has an ambiguous effect on total employment. Wage increases but not significantly. Thus, to date, robots should not have exerted significant influences on inflation dynamics. On the other hand, improvements in labour market conditions lead to a significant decline in robot investment, implying a countercyclical robot investment. One important lesson obtained in this paper is is that when testing whether robots take jobs away from the human workforce, one must consider the reverse causality from the labour market to robots.

Several extensions are being considered. First, our results also show large heterogeneity by country and industry in terms of the effects of robotisation. Fujiwara et al (2019b) conduct detailed analysis by industry and country to identify which countries and industries are heavily affected by robotisation. Second, we only estimate bivariate VAR systems, but there are possible endogenous interactions through more labour market variables. Fujiwara et al (2019c) explore the VAR with sign restriction. The directed technological change is tested by identifying a shock that increases wage and hours worked but reduces total employment in the long run and checking the impulse responses to this shock. Third, only the intensive margin

[4] The panel Granger causality test suggests that the developments in the labour market cause robot investment.

adjustments in employment within each sector are considered. Robot manufacturers should increase total employment and wages as robotisation increases. In order to gauge the aggregate effect of robots, we need to consider such extensive margin adjustments through the shifts of labour to the sectors with the most frontier technologies.[5] This topic is covered by Fujiwara, Shirota and Zhu (2019).

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