The Effects of Robotization on Foreign Direct Investment

Sungwoo Hong
Wongi Kim
Yeo Joon Yoon
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Executive Summary

This study aims to investigate the effects of robotization on foreign direct investment (FDI). We address this research question by providing a theoretical prediction derived from a simple model and then empirically testing our prediction. Theoretically, we found that an exogenous rise in industrial robots depresses both the robot rental rate and the domestic cost of task execution. Thus, it is more profitable to perform more tasks at home, leading to a decrease in FDI. Empirical results are summarized as follows. First, an increase in robotization in source countries negatively affects outward FDI. Second, this negative effect is not consistent across global regions.

**Keywords:** Robotization, FDI
**JEL Classification:** F21, F23
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1. Introduction

A recent increase in automation and robotization in production has entailed a growing body of research. Most analyses on this topic have focused on the impact of robotization on labor market outcomes. However, as robotization is causing a paradigm shift in the production process, it holds broader implications for our economy. In particular, the wide adoption of industrial robots could create disparities in factor endowments and international factor prices, thus affecting the pattern of our international economic activities, such as trade and investment.

This study aims to investigate the effects of robotization on foreign direct investment (FDI). Specifically, we try to answer the following question: “What is the impact of increased industrial robot adoption on outward FDI?” We strive to answer this...
question by providing a theoretical prediction derived from a simple model and testing our prediction empirically. Our primary argument regarding this question is as follows. As industrial robots are more readily available for domestic production, due to development in robot-producing technology or other reasons, it would become less costly to produce at home country than abroad. This circumstance, in turn, would reduce the need for FDI. Firms undertaking vertical FDI move some portions of their production process abroad to take advantage of cheaper production factors in foreign countries. However, if domestic use of robots is more prevalent, an increasing number of robots will replace foreign factors (labor), reducing the incentives for FDI. In the following chapter, we present a simple model of vertical FDI that is in line with our prediction. Then, we test our prediction empirically using greenfield FDI and industrial robot adoption data.

This paper contributes to the existing literature that provides implications for the effects of robotization in advanced economies on reshoring and offshoring. Existing research can be grouped into three categories: 1) the impact of robot adoption in advanced countries on employment (Acemoglu and Restrepo 2020; Bonfiglioli et al. 2021; Graetz and Michaels 2018; Koch et al. 2021; Krenz et al. 2021), 2) the impact of robotization in developed countries on emerging economies (Faber 2020; Gravina and Pappalardo 2022; Kugler et al. 2020), and 3) the effect of robotization in developed countries on trade patterns (Alguacil et al. 2022; Artuc et al. 2018; Cilekoglu et al. 2021).

Previous research suggests that robotization in developed countries tends to reduce employment, but its impact varies depending on job characteristics. Bonfiglioli et al. (2021) found that the effect of automation on employment varied depending on occupational characteristics, with jobs replaceable by robots and non-offshorable jobs being more negatively impacted. Graetz and Michaels (2018) analyzed that the increase in robot use did not significantly negatively affect total employment, but the

---

2 Even though, in this paper, we do not provide an explicit model, we can apply a similar logic for horizontal FDI. According to the theory of horizontal FDI, firms choose between exporting and setting up plants abroad and serving foreign customers directly (Brainard 1997; Markusen and Venables 2000; Helpman et al. 2004). In this setting, trade cost negatively affects incentives to export, while additional fixed costs of constructing plants abroad inhibit firms from undertaking horizontal FDI. Given the trade cost and fixed cost, an increase in robot endowment could reduce domestic production cost, rendering more firms to opt for exports rather than FDI.

---
employment of low-skilled labor decreased. In contrast, Koch et al. (2021) estimated that robot adoption increased the total employment of companies. This finding results from creating jobs as output increases and market share increases in robot-adopting firms, while the market share of non-adopters has been reduced, and employment decreases even if they survive; the former dominates the latter, and thus net employment increases. The results of Krenz et al. (2021), which are similar to Koch et al. (2021), indicate that the increase in robot use in the manufacturing industry raised reshoring and, in turn, the employment of workers with professional jobs but did not have a significant effect on the employment of workers with elementary-routine jobs. These findings suggest that employment for low-skilled labor does not increase as robots replace them, but high-skilled labor supplementing the robots rises.

Studies on robotization in developed countries and employment in developing countries have shown that robot adoption has reduced employment in emerging countries. Faber (2020) found that U.S. robotization reduced Mexican employment, Kugler et al. (2020) found that U.S. robotization reduced Colombian employment, and Gravina and Pappalardo (2022) found that robot adoption in the EU lowered employment in developing economies, particularly Asian countries.

Regarding the literature on robot use and trade patterns, Artuc, Bastos, and Rijkers (2018) found that robotization in OECD countries increased imports from non-OECD countries and exports to these countries within the same industry. In particular, the increase in imports from developing countries was primarily due to higher demand for intermediate goods resulting from robotization in developed countries. Additionally, Cilekoglu et al. (2021) found similar results to the literature.

Underlying the impact of robotics on trade patterns and employment is channels of reshoring or offshoring. For example, reducing imports of intermediate goods from emerging countries is likely due to increased reshoring (Artuc et al. 2018) or decreased offshoring (Bonfiglioli et al. 2021). High-skilled worker employment in developed countries increased due to reshoring caused by robotization (Krenz et al. 2021), and offshoring decreased (Bonfiglioli et al. 2021).

While some studies suggest that robotization in developed countries may increase imports of intermediate goods and, therefore, offshoring, other studies suggest that robotization may lead to increased reshoring and high-skilled employment. Therefore, the effect of robotization on reshoring or offshoring remains unclear and ambiguous. Although previous studies have examined the impact of exposure to robots on trade patterns and employment, there has been little research on how robotization
affects outward foreign direct investment (FDI).

This paper aims to fill this gap in the literature by analyzing how robotization in advanced economies affects outward FDI, which has not been examined in previous studies. The study contributes to the existing literature by providing insights into the effect of robotization on offshoring and reshoring and the potential role of outward FDI in this relationship.

Based on our prediction, we conduct empirical analysis. We construct source country-sector-host country-level panel data using fDi market data, which provides reliable greenfield FDI data, and the International Federations of Robots (IFR)'s industrial robot adoption data. Those two datasets are widely used in related literature. Our constructed dataset contains information on industrial robots adoption in a sector of a source country and outward FDI from that source country-sector to a host country from 2004 to 2019.

We estimate the effects of an increase in industrial robot intensity (a measure of robot adoption per 1,000 workers) in a sector of a source country on outward FDI to a host country using the panel fixed effects with instrumental variables to mitigate potential bias caused by measurement errors, omitted variables and reverse causality. We include various levels of fixed effects, such as source country-sector-host country fixed effects and year fixed effects, in our baseline estimation. Those fixed effects help capture the effects of time-invariant unobserved factors. Furthermore, instrumental variables can mitigate potential bias caused by measurement errors and reverse causality.

For instrumental variables, we utilize information on global robot adoption in a sector that is in line with Acemoglu and Restrepo (2020). In particular, we use global robot adoption less country-specific robot adoption in a sector. Intuitively, global-level robot adoption is likely to be driven by technology changes in robot-specific industries and is less likely to be driven by country-sector-specific shocks and bilateral FDI flows. Thus, our instrumental variables are less likely to be related to bilateral-sectoral FDI flows. Also, technology changes and consequent possible price changes in the robot industry are likely to affect robot adoption in a country. Thus, our instrumental variables are relevant. To check robustness, we use an alternative instrumental variable constructed based on the share-shifting approach (Bartik 1991).

To resolve potential econometric issues caused by many zeros and skewed distri-
bution of bilateral-sectoral level FDI, furthermore, we test several econometric specifications including different econometric methods and various data transformations. Specifically, we estimate the usual linear panel data model and panel Poisson model for dealing with many zeros and skewness. According to Wooldridge (1999) and Santos Silva and Tenreyro (2006), Poisson models are efficient and useful in dealing with that issue. We adopt the control function approach suggested by Papke and Wooldridge (2008) to use instrumental variables in the panel Poisson model.

Empirical results are summarized as follows. First, an increase in robotization in source countries negatively affects outward FDI. The estimated quantitative size varies over the models, but our baseline estimation reveals that one unit increase in industrial robots per 1000 workers reduces outward FDI by 0.7% to 0.9%, which is not negligible. Several robustness checks confirm this negative relationship, and the result is consistent with our arguments in conceptual frameworks.

Second, this negative effect is not even across global regions. Specifically, host countries which are located in East Asia, Europe, and South Asia are more likely to be affected by robot adoptions in source countries, while those located in Latin America and North America are less likely to be affected. We conduct an additional empirical analysis to shed light on this regional heterogeneity’s origins. Results reveal that host countries with higher manufacturing output shares to GDP and a higher education level measured by years of schooling are more likely to be affected negatively. This outcome can be caused by that replaceability, how easily industrial robots replace human jobs, which varies depending on labor skills and sectors. As discussed by Graetz and Michaels (2018) and Dauth et al. (2017), robot adoption more significantly affects low-skilled workers than high-skilled workers (Graetz and Michaels (2018)) and industrial robots are likely to replace human jobs in manufacturing sectors. Our results align with the literature, but we provide evidence of uneven international transmissions of robot adoption through FDI.
2. Robotization and FDI: Conceptual Frameworks

In this section, we develop a simple model of robots and FDI. We document that under a simple framework, increases in robots reduce vertical FDI. From our data, it is very challenging to distinguish between vertical and horizontal FDI. Alfaro and Charlton (2009) classify a relationship as a horizontal FDI if a foreign subsidiary shares the same Standard Industrial Classification code as its parent company and a vertical FDI if a foreign plant produces in sectors that are input to the parent company. Unfortunately, the industrial codes in our FDI data are too aggregated and lack detailed information on product types. Having said that, it would be ideal to illustrate the cases for both vertical and horizontal FDI, but in this section, we only provide a conceptual framework for vertical FDI. However, as noted in the introduction, we can also draw a similar prediction for horizontal FDI. An increase in domestic adoption of industrial robots is likely to decrease domestic production costs, and firms would choose to produce at home and export rather than perform horizontal FDI.

Turning our attention to the model, we incorporate essential ingredients from the trade in tasks model as in Grossman and Rossi-Hansberg (2008) and Acemoglu and Restrepo (2020). The economy produces and consumes a single final good $Y$. Production of final good requires a continuum of tasks on $[0, 1]$ interval indexed by $i$ as in equation (1).

$$Y = \left[ \int_0^1 y(i)^{\frac{\sigma-1}{\sigma}} \, di \right]^{\frac{\sigma}{\sigma-1}}$$

(1)

A task $y(i)$ can either be produced domestically or off-shored. If it is produced domestically robots are used as input with total factor productivity $\gamma_d$. If it is off-shored foreign labor is its only input with productivity $\gamma_f$. So we have

$$y(i) = \begin{cases} \gamma_d R(i), & \text{if produced domestically} \\ \gamma_f L_f(i), & \text{if off – shored} \end{cases}$$

(2)

where $R(i)$ and $L_f(i)$ represent the amounts of domestic robots and foreign workers employed in task $i$, respectively. Denoting rental price of robot and wage
rate for foreign workers as $r$ and $w^*$, respectively, the unit cost of performing task $i$ can be derived as follows.

$$p(i) = \begin{cases} 
\frac{1}{\gamma_d} r, & \text{if produced domestically} \\
\frac{1}{\gamma_f} w^*, & \text{if off-shored}
\end{cases} \quad (3)$$

We assume that it incurs additional costs to offshore. Particularly,

$$\frac{1}{\gamma_r} = \frac{1}{\gamma_d} t(i) \quad (4)$$

As in Grossman and Rossi-Hansberg (2008), some tasks are more costly than others, which we incorporate by ordering and indexing tasks by $i \in [0, 1]$ so that the costs are increasing in $i$. This implies that $t'(i) \geq 0$. We also assume that $t(i)$ is continuously differentiable and $t(i) \geq 1$ for all $i$.

Given the unit costs in equation (3) and the assumptions on $t(i)$, it is more profitable to offshore task $i$ as long as $\frac{1}{\gamma_d} r \geq \frac{1}{\gamma_f} w^*$ holds. It means that the cost of performing task $i$ abroad is less costly than doing it domestically. Equilibrium degree of off-shoring $I^*$ can be found when the following equation holds.

$$\frac{1}{\gamma_d} r = \frac{1}{\gamma_f} w^* \iff t(I^*) = \frac{r}{w^*} \quad (5)$$

This is the point where the unit cost of performing task $i$ domestically and abroad are equated. Because $t'(i) \geq 0$, for $i \in [0, I^*]$ all tasks are off-shored and for $i \in [I^*, 1]$ all tasks are performed domestically. Thus, we interpret $I^*$ as the degree or the amount of off-shoring.

The production of final good in equation (1) yields the demand for task $i$ as

$$y(i) = p(i)^{-\sigma} Y \quad (6)$$

Combining (2) and (6), the demand for robot and (foreign) labor are derived as
\[
\begin{align*}
R(i) &= \frac{1}{\gamma_d} y(i) = \left(\frac{1}{\gamma_d}\right)^{1-\sigma} r^{-\sigma} Y \\
L_f(i) &= \frac{t_f(i)}{\gamma_d} y(i) = \left(\frac{t_f(i)}{\gamma_d}\right)^{1-\sigma} (w^*)^{-\sigma} Y
\end{align*}
\] (7)

For simplicity, we assume that robot and foreign labor are endowed with \( R \) and \( L_f \), respectively and inelastically supplied.\(^3\) Under the equilibrium \( I^* \), the market clearing condition for robot and foreign labor are given as

\[
R = \int_{I^*}^{1} R(i) \, di = \int_{I^*}^{1} \left(\frac{1}{\gamma_d}\right)^{1-\sigma} r^{-\sigma} Y \, di = (1 - I^*) \left(\frac{1}{\gamma_d}\right)^{1-\sigma} r^{-\sigma} Y
\]

\[
L_f = \int_{0}^{I^*} L_f(i) \, di = \int_{0}^{I^*} \left(\frac{t_f(i)}{\gamma_d}\right)^{1-\sigma} (w^*)^{-\sigma} Y \, di
\] (8)

where we use equation (7). Taking ratio of these two equations we have

\[
\left(\frac{r}{w^*}\right)^{\sigma} = \frac{(1 - I^*)}{\int_{0}^{I^*} t_f(i)^{1-\sigma} \, di} \frac{L_f}{R}
\] (9)

Taking log and total differentiating equation (9), we have

\[
\frac{d I^*}{d R} = -\frac{1}{R} \left[ \sigma \frac{t'(I^*)}{t(I^*)} + \frac{1}{1 - I^*} + \frac{t(I^*)^{1-\sigma}}{\int_{0}^{I^*} t(i)^{1-\sigma} \, di} \right]^{-1} < 0
\]

It is straight-forward to show that \( \frac{d I^*}{d R} < 0 \), as \( t'(I^*) > 0 \). The model generates a result that is consistent with our prediction. An exogenous rise in industrial robots depresses both the robot rental rate and the domestic cost of performing a task as shown in equation (3). Thus, it is more profitable to perform more tasks at home and \( I^* \) decreases.

\(^3\) It would be more realistic to assume that foreign labor supply is an increasing function of relative foreign wage \( \frac{w_f}{r} \) as in Acemoglu and Restrepo (2020). This assumption, however, does not change our result.
3. Data and Econometrics

In this section, we provide a detailed discussion on data and econometric methods. First, we describe detailed sources and processes for data construction and show relevant descriptive statistics. Next, we explain detailed econometric methods and related econometric issues.

3.1. Data

Our goal is to analyze the effects of robotization in source countries on their FDI outflows to host countries. To this end, we combine three data sources. First, FDI data comes from the fDi Markets database provided by Financial Times, and robot adoption data are obtained from the International Federation of Robots (IFR). Finally, other economic data, such as employment, are taken from the OECD STAN database.

The fDi Market database provides firm-level greenfield FDI data from 2003 to onwards monthly. It is a deal-based database, meaning each data point has information on the announced dollar value of greenfield FDI for each project. This database also provides information on which firms invest and when those greenfield investments are announced. Moreover, it includes information on firms’ nationality (information on source country), detailed industry classification for firms (information on sectors), and which country that greenfield investment goes to (information on the host country). We use the fDi Market database because that information is essential for our research purpose. Furthermore, the database is used for several FDI literature, such as Andersen et al. (2022) and Crescenzi et al. (2021), and is one of the main data sources in the World Investment Report published by United Nations Conference on Trade and Development (UNCTAD), so we believe that the database is reliable.

FDI data are provided at the firm level, but robot data are provided at the industry level, so we need to transform that to industry-level data using some aggregation process. The fDi Market database provides information on sectors for each firm based on the 2012 North America Industrial Classification System (NAICS). We aggregate firm-level data by taking the sum of the dollar value of
FDI at the source country-sector-host country level each year using the NAICS code and source and host country information. Specifically, we use the most disaggregated level NAICS code (6-digit NAICS code) if available. If it is unavailable, we use a 4-digit NAICS code or a 2-digit NAICS code, depending on availability. Then, we have sectoral-level FDI data from a source country to a host country each year.

Robot adoption data are taken from IFR. This database provides sector-level robot adoption from 1993 onwards in about 60 countries. This database became popular after Acemoglu and Restrepo (2020) used this database to analyze the effects of robot adoption on employment and productivity. For example, Graetz and Michaels (2018) use this database to investigate the economic impacts of robot adoption within countries. Faber (2020) uses this data to investigate the effects of robot adoption in foreign countries on Mexico’s labor market. Artuc et al. (2018) use this database to analyze the effects of robotization on international trade.

This database provides information on robot installation and operational robot stocks in each sector, country, and year. Robot installation measures the newly installed number of industrial robots, and operational robot stocks are the total number (stocks) of operational robots. IFR constructs robot stocks using their specific depreciation rates. We use robot stocks for constructing a variable for measuring the degree of robotization. We match the sector-level FDI data, which we already discussed, and IFR data using industry code and source country information. One issue in this data matching procedure is that the FDI data is constructed based on NAICS, but IFR data are collected based on Industrial Standard Industrial Classification (ISIC) rev. 4, suggested by United Nations. To match the data, we need to convert FDI data using NAICS-ISIC rev. 4 concordance, which is provided by United Nations Statistical Department (UNSD).

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4 Jurkat et al. (2022) provide comprehensive reviews of this database and some related literature that use this database.
6 Note that the concordance provides a unique matching with 6-digit NAICS to 4-digit ISIC rev. 4. However, some FDI data are aggregated using 4- or 2-digit NAICS. It means that some FDI
After matching the FDI and IFS data, we have source country-sector-host country-level FDI and robot adoption data (FDI-Robot data).

### Table 1. Sector Classification

<table>
<thead>
<tr>
<th>Code</th>
<th>ISIC rev. 4</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>10-12</td>
<td>10-12</td>
<td>Manufacturing of food products, beverages and tobacco</td>
</tr>
<tr>
<td>13-15</td>
<td>13-15</td>
<td>Manufacture of textiles, wearing apparel, leather and related products</td>
</tr>
<tr>
<td>16</td>
<td>16, 31</td>
<td>Manufacture of wood and products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials, Manufacture of furniture</td>
</tr>
<tr>
<td>17-18</td>
<td>17, 18</td>
<td>Manufacture of paper and paper products, Printing and reproduction of recorded media</td>
</tr>
<tr>
<td>19</td>
<td>21</td>
<td>Manufacture of coke and refined petroleum products</td>
</tr>
<tr>
<td>20-21</td>
<td>19, 20</td>
<td>Manufacture of chemicals and chemical products, basic pharmaceutical products and pharmaceutical preparations</td>
</tr>
<tr>
<td>22</td>
<td>22</td>
<td>Manufacture of rubber and plastics products</td>
</tr>
<tr>
<td>23</td>
<td>23</td>
<td>Manufacture of other non-metallic mineral products</td>
</tr>
<tr>
<td>24</td>
<td>24</td>
<td>Manufacture of basic metals</td>
</tr>
<tr>
<td>25</td>
<td>25</td>
<td>Manufacture of fabricated metal products, except machinery and equipment</td>
</tr>
<tr>
<td>26-27</td>
<td>26, 27</td>
<td>Manufacture of computer, electronic and optical products, Manufacture of electrical equipment</td>
</tr>
<tr>
<td>28</td>
<td>28</td>
<td>Manufacture of machinery and equipment n.e.c.</td>
</tr>
<tr>
<td>29</td>
<td>29</td>
<td>Manufacture of motor vehicles, trailers and semi-trailers</td>
</tr>
<tr>
<td>30</td>
<td>30</td>
<td>Manufacture of other transport equipment</td>
</tr>
<tr>
<td>91</td>
<td>32, 33</td>
<td>Other manufacturing, Repair and installation of machinery and equipment</td>
</tr>
</tbody>
</table>

Note: Code means industrial classification by International Federation of Robots.
Source: Authors’ calculation.

Data are matched with multiple ISIC sectors. In this case, we divide the dollar value of FDI equally across those sectors. It adds some measurement errors to our dependent variable, but measurement errors of a dependent variable generally are not a concern, at least for consistency.
Furthermore, we focus on FDI originating from manufacturing sectors because most robots are adopted in manufacturing sectors. According to the IFR database, for example, in Germany, more than 90% of industrial robots are operating in manufacturing sectors during our sample periods (2004–2019). Also, IFR categorizes service sectors into education/research/development and other non-manufacturing sectors. This highly aggregated categorization in service sectors may lead to some incorrect conclusions. Furthermore, some previous studies, such as Walsh and Yu (2010) and Kolstad and Villanger (2008), argue that FDI in manufacturing and service sectors behave differently. Thus, we focus on manufacturing sectors. Table 1 summarizes the industry classification for our data.

Finally, we discuss industry-level data for source countries. We need information on sectoral-level labor markets data such as employment or labor hours to measure sectoral-level robotization in source countries. For example, Graetz and Michaels (2018) normalize robot stocks using labor hours and interpret that as a degree of robotization in a sector. They use the EU KLEMS database for obtaining sectoral-level labor hours. EU KLEMS provides comprehensive and detailed information on sectoral level information, but it is constructed based on NACE, slightly different from ISIC rev. 4. Also, it mainly covers countries in Europe and the U.S.; thus, information on several important countries in cross-border investment, such as Japan, are missing. Thus, we rely on the OECD STAN database, which provides information on industry-level economic activities instead of EU KLEMS. Data in OECD STAN is collected using ISIC rev. 4, including non-Europe OECD member countries. Thus, its industrial classification matches our FDI-Robot data, and it covers a broader range of countries than that of the EU KLEMS database.

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7 NACE is abbreviation of “Nomenclature générale des Activités économiques dans les Communautés Européennes.” NACE is designed for industrial economic activities in European Union.
Table 2. Top 15 Source and Host Countries

<table>
<thead>
<tr>
<th>Top 15 source countries</th>
<th>% of total FDI</th>
<th>Top 15 host countries</th>
<th>% of total FDI</th>
</tr>
</thead>
<tbody>
<tr>
<td>USA</td>
<td>18%</td>
<td>CHN</td>
<td>15%</td>
</tr>
<tr>
<td>JPN</td>
<td>11%</td>
<td>USA</td>
<td>10%</td>
</tr>
<tr>
<td>DEU</td>
<td>10%</td>
<td>IND</td>
<td>6%</td>
</tr>
<tr>
<td>CHN</td>
<td>6%</td>
<td>RUS</td>
<td>4%</td>
</tr>
<tr>
<td>KOR</td>
<td>6%</td>
<td>MEX</td>
<td>3%</td>
</tr>
<tr>
<td>FRA</td>
<td>5%</td>
<td>VNM</td>
<td>3%</td>
</tr>
<tr>
<td>GBR</td>
<td>4%</td>
<td>BRA</td>
<td>3%</td>
</tr>
<tr>
<td>NLD</td>
<td>4%</td>
<td>IDN</td>
<td>3%</td>
</tr>
<tr>
<td>TWN</td>
<td>3%</td>
<td>SAU</td>
<td>2%</td>
</tr>
<tr>
<td>CHE</td>
<td>3%</td>
<td>AUS</td>
<td>2%</td>
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<tr>
<td>ITA</td>
<td>2%</td>
<td>CAN</td>
<td>2%</td>
</tr>
<tr>
<td>IND</td>
<td>2%</td>
<td>GBR</td>
<td>2%</td>
</tr>
<tr>
<td>CAN</td>
<td>2%</td>
<td>DEU</td>
<td>2%</td>
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<tr>
<td>RUS</td>
<td>2%</td>
<td>SGP</td>
<td>2%</td>
</tr>
<tr>
<td>ESP</td>
<td>1%</td>
<td>MYS</td>
<td>2%</td>
</tr>
</tbody>
</table>

Note: Bold text indicates member of G7.
Source: Authors’ calculations based of fDi Market data.

We normalize robot stocks by the number of employments for measuring degrees of robotization. Specifically, we measure the total number of operational robots (robot stocks) per 1000 employments, which is in line with Acemoglu and Restrepo (2020) and Graetz and Michaels (2018). Note that we use employment rather than hours for normalizing because OECD STAN covers employment data for broader ranges of countries than that for hours data.

We limit our sample periods from 2004 to 2019. The starting year is dictated by data availability. Although IFR data covers robot adoption from 1993 onwards, industry-level information is unavailable for entire periods. In particular, sectoral-level information for the U.S. is available from 2004. Thus, we decide 2004 as our starting year. Furthermore, COVID-19 significantly affects worldwide economic activities after 2020. This paper investigates the effects of robotization on FDI,
not for COVID-19, so we set 2019, before COVID-19, as the end period of our sample.

In the baseline estimation, we focus on outward FDI from G7 (The US, Canada, Germany, France, Japan, Italy, and the U.K.) because those countries cover about 53% of the total FDI in our sample, as shown in Table 2. Thus, we first focus on G7 countries. However, our results are robust to using a broader range of source countries.  

8 The results are reported in section 4.

Figure 1 shows the geographic distribution of FDI from G7 countries. Regions are classified according to World Bank standards—the thicker the lines, the greater the FDI flow to those regions. Among G7 countries, the US, Germany,
and Japan have large FDI outflows. Most FDI from G7 countries goes to East Asia and Europe. Also, inflows of FDI to Latin America mainly come from the U.S. Figure 1 reveals heterogeneities of FDI across source and host countries. Sources are concentrated on advanced countries, while host countries are located mainly in East Asia and Europe.

Figure 2 shows the geographical distribution of FDI outflows from each sector of G7 countries. This figure summarizes FDI distribution across sectors to each region. As shown in Table 1, there are 15 industries. Among them, industries 20-21 (basic pharmaceutical and chemical products), 26-27 (computer, electronic and optical products, electrical equipment), 29 (motor vehicles, trailers, and semi-trailers), and 30 (other transportation equipment) are major sectors for FDI outflows.

![Figure 2. FDI from Each Sector of G7 Countries to Regions](image)

Note: The figure shows total FDI outflows from each industry in G7 countries to regions. Line becomes thicker, larger FDI flows to that region from a source country. Source: Authors’ calculations based on fDi market data.

Figure 3 shows trends in robot intensity in G7 countries. Each country shows somewhat different patterns of robot adoption. For example, robot intensity in the
The Effects of Robotization on Foreign Direct Investment

U.S. gradually increased, but that in Japan gradually decreased before 2015. Also, robot intensity in the U.K., Italy, and France seems to be affected by the global financial crisis. During 2008-2009, robot intensity suddenly decreased. The heterogeneous robot adoption behavior in each country provides sufficient variations for our analysis.

Figure 4 shows the trend of robot adoption and FDI by sectors in G7 countries. As shown in the figure, the behavior of robot adoption and FDI somewhat differs across sectors. For example, robot adoption in sector 23 (manufacture of other non-metallic mineral products) is increasing while the dollar amount of FDI is decreasing after 2008. In contrast to that sector, robot adoption and FDI moves in the same direction in sector 16 (manufacture of wood and products of wood and cork).

Note: Blue solid line indicates total Robot stocks in manufacturing sectors/total employments in manufacturing sectors in each country. Red dashed line indicates total dollar value of FDI in each country.
Source: Authors’ calculations with fDi Market data, IFR data and OECD STAN data.
Note: Blue solid line indicates total Robot stocks / total employments in each sector of total G7 countries. Red dashed line indicates dollar value of FDI in each sector of total G7 countries.

Source: Authors’ calculations with fDi Market data, IFR data and OECD STAN data.

Finally, Figure 5 shows distribution of FDI and Robot intensity across G7 countries, industries, and years. Figure clearly shows that distributions are skewed, and observations includes several zeros. This skewness remains after taking the logarithm. Because it can be a source of bias, we discuss how we deal with this issue in section 3.2.
Note: Robot/EMPE means Total Robot stocks in manufacturing sectors/total employments in manufacturing sectors in each sector, country and year. ln((1+robot/EMEP)) means logarithm of (1+robot) divided by employment. ln(1+FDI) means logarithm of (1+FDI).

Source: Authors' calculations with fDi Market data, IFR data and OECD STAN data.

### 3.2. Econometrics

We start with the following equation using the source country-sector-host country panel data, which we discuss in section 3.1:

\[
FDI_{ijkt} = \beta Robot_{ijt} + \alpha_{ijk} + \alpha_t + \epsilon_{ijkt} \tag{10}
\]

In equation (10), \(i\) means source country, \(j\) means sector, \(k\) means host country, and \(t\) means time. Thus, \(FDI_{ijkt}\) is outward FDI from sector \(j\) in country \(i\) to country \(k\) at time \(t\). \(Robot_{ijt}\) means a measure of robot adoption of sector \(j\) in country \(i\) at time \(t\). \(\alpha_{ijk}\) is a fixed effect for source country-sector-host country for controlling
unobserved factors for bilateral relations in each sector. We also include time fixed effect ($\alpha_t$) for controlling effects of common global events such as the global financial crisis. $\varepsilon_{ijkt}$ is an error term. Our goal is to estimate a consistent estimator for beta, which can be interpreted as an average effect of robot adoption on FDI outflow across sectors and countries. We consider robot intensity as a measure of robot usage, as discussed in section 3.1.

There are several issues for estimating consistent estimator for $\beta$. The first issue is data transformation. Our bilateral-sectoral level FDI includes many zeros and has a skewed distribution. Thus, if we take the logarithm for FDI, too many observations are dropped, and thus this can be a source of bias. In order to overcome this issue, we first consider FDI to estimate the effects of robot intensity on FDI. This specification is usual in gravity models in international trade, and Artuc et al. (2018) also use this specification for estimating the effects of robot adoption on bilateral trade flow. Using this data transformation, we use the following equation:

$$\ln(1 + \text{FDI}_{ijkt}) = \beta(\frac{\text{Robot employment}}{\text{employment}})_{ijt} + \alpha_{ijk} + \alpha_t + \varepsilon_{ijkt}$$

Equation (11) can be estimated using the usual panel fixed effect model. In this specification, $\beta$ can be interpreted as semi-elasticity of FDI to robot intensity, which means that $\beta$ captures percentage changes of FDI outflows to one unit change in robot intensity. Following Graetz and Michaels (2018), moreover, we consider the log of robot intensity, which is defined by the following:

$$\ln(1 + \text{FDI}_{ijkt}) = \beta \ln(\frac{1+\text{Robot employment}}{\text{employment}})_{ijt} + \alpha_{ijk} + \alpha_t + \varepsilon_{ijkt}$$

(12)

Because robot intensity also has many zeros and skewed distribution, this specification can help check the robustness of an alternative form of explanatory variables. $\beta$ can be interpreted as the elasticity of FDI to robot intensity, which means that $\beta$ captures percentage changes of FDI outflows to one percentage change in robot intensity.

This ln $(1+y)$ ($y$ is the dependent variable) specification is widely adopted for dealing with zeros in a dependent variable but is subject to criticism. In particular, Cohn et al. (2022) show that estimation results with the ln $(1+y)$ specification are not able to be interpreted as elasticity and also can be a source of bias. One potential
remedy is using the pseudo-Poisson maximum likelihood (PPML) method. It was suggested by Santos Silva and Tenreyro (2006) and Cohn et al. (2022). Damgaard et al. (2019) also use PPML to investigate the global FDI network. Also, Wooldridge (1999) shows that the Poisson model is efficient and useful for dealing with many zeros and skewness of a dependent variable. Based on their works, we also use the PPML method. Using this PPML, we use the following equation:

\[
FDI_{ijkt} = \exp \left( \beta \left( \frac{\text{Robot}}{\text{employment}} \right)_{ijt} + \alpha_{iik} + \alpha_t \right) + \epsilon_{ijkt}
\]  

(13)

In this equation, we do not use log(1+FDI); instead, we use the dollar measure of FDI. Equation (11) can be estimated using the usual (conditional) fixed effect panel Poisson model, such as in Wooldridge (1999). In this model, beta can be interpreted as a semi-elasticity of FDI to robot intensity.

The second issue is potential bias caused by measurement errors, omitted variables, and reverse causality. Our primary measure of robot intensity is defined by the ratio of operational robot stocks to the number of employees. Because the industry classification of the OECD STAN database is not perfectly matched with the classification of IFR data, we need to impute some employment data. This imputation may add some degrees of measurement errors to robot intensity. As is well known, measurement errors of independent variables can be a source of bias.

Although we include time-invariant fixed effects in the estimation, moreover, equations omit several important time-varying control variables such as factor prices, which are important for vertical FDI, and market size, which is important for horizontal FDI. One potential remedy is including some proxies for those variables. However, it is not an easy task because of data limitation. In particular, we do not have reliable data for factor prices, such as robot prices and industry-level wage data in each country.

Finally, reverse causality is a concern. International technology diffusion through FDI has long been discussed, and literature supports this channel empirically and theoretically. For example, Keller (2004) shows that FDI stimulates international technology diffusion using a theoretical model based on Eaton and Kortum (1999). Keller and Yeaple (2009) provide some empirical evidence on international technology diffusion through FDI using U.S. firm-level data. In such cases, the country's robot adoptions, as production technology, can be affected by FDI flows, which can
be a source of reverse causality.

To mitigate potential bias caused by various sources, we adopt the instrumental variable (IV) approach following Graetz and Michaels (2018) and Artuc et al. (2018).\footnote{Note that we also estimate the equation with several independent variables, and we get qualitatively consistent results with the instrumental variable approach. However, we prefer the instrumental variable approach because we still have omitted variable bias and measurement errors in the estimation with independent variables. The results with various control variables are shown in Appendix A.} We consider two different IVs. First, we consider the log of global robot stocks in sector $j$ (sum of robot stocks in sector $j$ across countries) less robot stock in sector $j$ of country $i$ as IV for sector $j$ in country $i$.

$$ IV - base_{ijt} = global \; robot \; stocks_{jt} - robot \; stocks_{ijt} $$

The idea is that global robot adoption is likely to be driven by robot-specific factors such as robot technology and is not likely to be driven by country-specific factors and bilateral FDI relationships. Also, subtracting country-sector robot adoption from global robot adoption, our IV is less likely to be related to country-specific factors.\footnote{The idea is in line with Acemoglu and Restrepo (2020). They use an average of robot adoption in 5 other countries as an IV for the U.S. They use a robot adoption trend in other countries as an IV for the U.S. In line with this idea, we use a global robot adoption trend, excluding a target country itself. We use global robot stocks instead of a selected number of other countries because we use bilateral FDI relationships. In such a specification, using an average of robot adoption trends of a few other countries is likely to be affected by bilateral relationships, which can be a source of bias. Thus, we use global robot stocks less a target country, which is not likely to be affected by bilateral relationships.}

Furthermore, the global robot adoption trend should affect the country’s robot adoptions so it can be a relevant IV. It is worth noting that we use global robot stocks rather than global robot intensity as an instrumental variable. Thus, the changes in our IV are closely related to changes in robot stocks but are less likely to be related to an employment change. Thus, estimation results with IV are mainly driven by changes in robot adoption rather than changes in employment, which provide us with some advantages for interpretation.

To check robustness, we use the alternative Bartik-style instrument, which is defined by the following:
IV - Bartik\(_{ijt}\) = average share of robot\(_{ijt}\) x global robot stocks\(_{jt}\)

Robot adoption in sector \(j\) in country \(i\) can be defined by the following:

\[
robot_{ijt} = \frac{\text{robot}_{ijt}}{\sum_i \text{robot}_{ijt}} \times \frac{\sum \text{robot}_{ijt}}{\sum \text{global robot stock in sector } j \text{ at } t}
\]

This decomposition reveals that changes in the robot stock of sector \(j\) in country \(i\) at time \(t\) have two parts: sector \(j\) in country \(i\)'s share of robot stock to global robot stock in sector \(j\) and changes in global robot stock of sector \(j\). The first share part is mainly driven by country-sector-specific shocks, which can be a source of reverse causality, but the second global robot stock part is less likely to be related to sector-country-specific shocks. To remove country-sector-specific parts, we fix the average share of robot stock across time in sector \(j\) in country \(i\). Then, changes in our Bartik-style IV are entirely driven by global robot adoption trends rather than country-sector factors. This shift-share approach is based on Bartik (1991).\(^\text{11}\)

Using those IVs and the two-stage least square method, we can estimate the equation (11) and (12). However, using IV with equation (14) and the panel Poisson model with fixed effects is not straightforward because of conditional fixed effects and their nonlinearities. We use the control function approach suggested by Papke and Wooldridge (2008) and Lin and Wooldridge (2019) to overcome this challenge. Specifically, we consider the following equation:

\[
FDI_{ijkt} = \exp (\beta \left( \frac{\text{Robot employment}}{employment} \right)_{ijt} + \delta \tilde{v}_{ijt} + \alpha_{ijk} + \alpha_t + \epsilon_{ijkt})
\]

(14)

where \(\tilde{v}_{ijt}\) is the estimated residuals defined by the following:

\[
\left( \frac{\text{Robot employment}}{employment} \right)_{ijt} = \gamma Z_{ijt} + \alpha_{ij} + \alpha_t + v_{ijt}
\]

(15)

\(^\text{11}\) More detailed discussion on Bartik instruments refers to Goldsmith-Pinkham et al. (2020).
where \( Z_{ijt} \) is an instrumental variable which we discussed. According to Papke and Wooldridge (2008) and Lin and Wooldridge (2019), plugging the estimated residuals of (15) into equation (14) helps mitigate endogeneity under some assumptions. Intuitively, plugging the residuals from equation (15) into equation (14) is to control for the variation of robot intensity, which is not explained by our IV. Consequently, \( \beta \) in equation (14) reveals the effects of robot intensity on FDI outflow netted from the endogeneity in robot intensity.

Additionally, we estimate the following equation (16), which includes lagged FDI as an independent variable because current FDI flows may be affected by past FDI flows.

\[
\ln(1 + FDI_{ijkt}) = \beta \left( \frac{\text{Robot employment}}{employment} \right)_{ijt} + \theta \ln(1 + FDI_{ijkt-1}) + \alpha_{ik} + \alpha_t + \varepsilon_{ijkt} \tag{16}
\]

To estimate equation (16), we use Arellano and Bond (1991) method to correct the bias caused by including lagged dependent variable as a control variable. In contrast to the previous approach, this approach utilizes first-difference variations rather than demeaned variations and includes lagged dependent variables. Therefore, it is useful to check robustness.

In sum, we estimate equations (11) and (12) using the usual panel fixed effects and two-stage least square with two different IVs. Also, we estimate equation (13) using the panel Poisson fixed effects and equation (14) using the control function approach. Finally, we estimate equation (16) using Arellano and Bond’s method. That helps to check robustness extensively.
4. Empirical Results

This section refers to estimation results. Because the results with IV-Bartik are similar to those with IV-base, we report the results with IV-base in this section for clarity. The results with IV-Bartik are reported in Appendix B.

Table 3 shows the baseline results. Each column shows results from different specifications. The first row shows estimation methods. FE refers to the panel fixed effects, and FE-IV refers to the two-stage least square with IV-base and fixed effects. PO refers to the fixed effect panel poisson model, and PO-IV means the control function approach with the fixed effect panel poisson model and IV-base. AB refers to Arellano-Bond (1991)’s method. As discussed in section 3.2, we use two different forms of FDI as a dependent variable: dollar value of FDI and Ln (1+FDI). The second row provides the forms of a dependent variable in each estimation. For independent variables, Ln (1+Robot/Emp) means log of (1+robot stock) divided by the number of employment. Robot/EMP means robot stock divided by the number of employment. \( \hat{\nu} \) means the estimated residual from equation (15) for the control function approach. Note that a coefficient for \( \hat{\nu} \) is statistically significant, then we can interpret that as robot intensity is endogenous.

<table>
<thead>
<tr>
<th>Estimator:</th>
<th>(1) FE</th>
<th>(2) FE-IV</th>
<th>(3) FE</th>
<th>(4) FE-IV</th>
<th>(5) PO</th>
<th>(6) PO-IV</th>
<th>(7) AB</th>
<th>(8) AB</th>
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</thead>
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<td>Dependent Variable:</td>
<td>Ln(1+FDI)</td>
<td>Ln(1+FDI)</td>
<td>Ln(1+FDI)</td>
<td>Ln(1+FDI)</td>
<td>FDI</td>
<td>FDI</td>
<td>Ln(1+FDI)</td>
<td>Ln(1+FDI)</td>
</tr>
<tr>
<td>Ln(1+Robot/Emp)</td>
<td>-0.022** (0.010)</td>
<td>-0.083** (0.039)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Robot/Emp</td>
<td>-0.001** (0.001)</td>
<td>-0.009** (0.004)</td>
<td>-0.001 (0.002)</td>
<td>-0.007** (0.003)</td>
<td></td>
<td>-0.009*** (0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \hat{\nu} )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.0068** (0.003)</td>
<td></td>
<td></td>
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<tr>
<td>L1.Ln(1+FDI)</td>
<td></td>
<td></td>
<td></td>
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<td>0.040*** (0.006)</td>
<td>0.039*** (0.006)</td>
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<td>117,222</td>
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<td>rk-F statistics</td>
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</table>

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**Table 3. Continued**

<table>
<thead>
<tr>
<th>Estimator</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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<td>AR(1)</td>
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</table>

Note: For (1), (2), (3), (4), (5), Source-Industry-Host clustered standard errors are in parentheses. For (6), Source-Industry-Host clustered bootstrap standard errors (500 replications) are reported. For (7), (8), heteroskedasticity-autocorrelation consistent errors are reported. *** p<0.01, ** p<0.05, * p<0.1. FE means the panel fixed effects, FE-IV means the panel fixed effect with IV, PO means pseudo Poisson maximum likelihood model (PPML), PO-IV is the PPLM with the control function and AB means Arellano-Bond estimator.

Source: Authors’ calculations based on estimation results.

L1.Ln (1+FDI) means a lagged value of Ln (1+FDI). # of Obs is the number of observations, Number of ID means the number of source country-sector-host country group, and avg T means average sample periods. rk-F statistics is Kleibergen-Paap Wald rk F statistic for the relevance of our IV. AR (1), AR (2) is the first and second autocorrelation test results for Arellano-Bond (1991)’s method. Hansen J-statistics is over-identification test results, and # of Instrument indicates the number of instruments for the Arellano-Bond (1991)’s method. Note that all test statistics indicate that our specifications do not have serious problems.

First, all results reveal that an increase in robot intensity in source countries reduces outward FDI, and those results are statistically significant at conventional levels. For example, FE-IV in column (2) shows that a one percent increase in robot intensity reduces outward FDI by 0.08%, and the result is statistically significant at 5%. This effect becomes much larger using AB method (column (7)). In column (7), a one percent increase in robot intensity reduces FDI outflows by 0.2%, which is 2.5 times larger than in column (2). FE-IV in column (4) shows that one unit increase in robot intensity reduce 0.9% of FDI outflows, and the result is statistically significant at 5%. Those confirm that robotization in source countries negatively affects FDI outflows. This negative effect is consistent with our stylized models’ predictions, which are provided in section 2.

Second, quantitative results with Robot/Emp (not logged form) are remarkably the same across different estimation methods. Specifically, FE-IV (column (4)), PO-IV (column (6)), and AB (column (8)) reveal that one unit increase in robot intensity reduces FDI outflows by 0.7% - 0.9%. It means that the estimated quantitative results are robust to different economic specifications.
Table 4. Robustness

<table>
<thead>
<tr>
<th></th>
<th>(1) FE-IV excl.JPN</th>
<th>(2) FE-IV w/ adj OECD</th>
<th>(3) FE-IV OECD</th>
<th>(4) FE-IV w/ alt.FE OECD</th>
<th>(5) FE-IV w/ alt.FE</th>
<th>(6) FE-IV excl.JPN</th>
<th>(7) FE-IV excl.JPN</th>
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<tr>
<td>Dependent Variable:</td>
<td>Ln(1+FDI)</td>
<td>Ln(1+FDI)</td>
<td>Ln(1+FDI)</td>
<td>Ln(1+FDI)</td>
<td>Ln(1+FDI)</td>
<td>Ln(1+FDI)</td>
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</tr>
<tr>
<td>Robot/Emp</td>
<td>-0.017*** (0.004)</td>
<td>-0.012*** (0.004)</td>
<td>-0.009** (0.004)</td>
<td>-0.011*** (0.003)</td>
<td>-0.113** (0.053)</td>
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<td>Robot_Adj/Emp</td>
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<tr>
<td>Ln(1+Robot)</td>
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<td>15.16</td>
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<tr>
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<td>Source-Host FE</td>
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<tr>
<td>Year FE</td>
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<td>0</td>
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<td>0</td>
</tr>
</tbody>
</table>

Note: For (1) to (6), Source-Industry-Host clustered standard errors are in parentheses. For (7), Source-Host clustered standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors’ calculations based on estimation results.

Table 4 shows some results for robustness checks. We report results using the FE-IV method for clarity. Note that all relevance tests indicate that our IV is strongly related to robot intensity. First, we exclude Japan as a source country (column (1)). According to Jurkat (2022), the data collection standard for robots in Japan differs from other countries and impairs data comparability across countries. Based on their arguments, we exclude Japan and re-estimate the equation. The results show a slightly larger quantitative effect, but they remain consistent with the baseline findings.

Second, we adjust sectoral-level robot stock by accounting for “unspecified robots.” In the IFR database, certain robots in each country are classified as “unspecified,” indicating that the sector of their adoption is unknown. Following Acemoglu and Restrepo (2020), we reallocate these unspecified robots to industries in the same proportions as in the classified data. More specifically, we use the average share of classified data from 2004 to 2019. Using this reconstructed data, we estimate the equation. The result is shown in column (2) and is the same as the baseline results.

Third, we use a broader range of source countries. In column (3), we consider 14
additional OECD member countries where sectoral-level employment data are available. In column (4), we consider all OECD countries with available robot data. Due to the unavailability of sectoral-level employment data in certain countries, we use robot stock instead of robot intensity. The results in (3) and (4) show that an increase in robot adoption reduces FDI outflows.

Fourth, we consider alternative fixed effects. In the baseline models, we consider source-country-sector-host country fixed effects and year-fixed effects. These are useful to control unobserved time-invariant characteristics between two countries in each sector and global unobserved effects. Nevertheless, certain time-varying unobserved factors may matter. To consider those possibilities, we include industry-year fixed effects, source-host fixed effects, and year-fixed effects. The results are reported in column (5). Industry-year fixed effects are included for controlling some unobserved time-varying sectoral shocks. Source-host fixed effects help capture bilateral relationships such as geographical distances and historical relationships.

Additionally, we include industry-year fixed effects and source-host-year fixed effects following Artuc et al. (2018). This specification is useful for considering time-varying sectoral-specific shocks and time-varying bilateral shocks. The result is shown in column (6). The results in (5) and (6) are remarkably the same as those in the baseline model qualitatively and quantitatively.

Finally, we aggregate data across industries in each source country and construct country-level data. Compared with baseline results, results with country-level data (aggregated across industries) can mitigate zeros and skewness problems in FDI because the number of observations of zero FDI decrease, and skewness are less severe. The result is reported in column (7). The result indicates that FDI outflows are negatively affected by robotization.

In summary, our empirical findings strongly support that robotization in source countries decreases FDI outflows, aligning with the predictions of our stylized model in section 2. This finding is robust and confirmed by various analyses using different data transformations, specifications, estimation methods, instrumental variables, a broader range of source countries, and country-level data.

---

12 List of 14 additional countries: AUT, BEL, CZE, DNK, ESP, EST, FIN, GRC, HUN, NLD, NOR, POL, PRT, SVK.
5. Discussion

In this section, we discuss heterogeneous effects of robotization across different regions. Although our conceptual frameworks and empirical results reveal that robotization in source countries negatively affects FDI outflows, it can be interpreted as an average effect. Due to variations in economic structures and skill levels of labor, which are potential factors determining the effects of robotization, the impact of robotization in source countries on FDI can differ across regions and host countries. Following the discussion on the heterogeneous effects across regions in section 5.1, we present additional results that shed light on the interpretation of these regional differences in section 5.2.

5.1. Regional Heterogeneities

We categorize regions into seven groups following World Bank Classification: East Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, North America, South Asia, and Sub-Saharan Africa. To estimate regional heterogeneities, we use the following equation.

\[
\ln(1 + FDI_{ijkt}) = \sum_r \beta_r \left( \frac{\text{Robot employment}}{employment} \right)_{ijt} \times I_r + \alpha_{iit} + \alpha_t + \varepsilon_{ijkt}
\]  

(17)

where \(r=\{\text{East Asia and Pacific, Europe and Central Asia, Latin America and the Caribbean, Middle East and North Africa, North America, South Asia, and Sub-Saharan Africa}\}\) indicates each region and \(I_r\) is a dummy variable for each host country. \(I_r\) has the value of one when a host country is located in an indicated region; otherwise, it has zero value. Thus, \(\beta_r \left( \frac{\text{Robot employment}}{employment} \right)_{ijt} \times I_r\) can be interpreted as heterogeneous effects of robotization in source countries on FDI outflows to different regions. To estimate equation (17), we use the panel fixed effects and the IV approach with the panel fixed effects. We use IV-base as an instrumental variable. Table 5 shows the results.

The effects of robotization are different across regions. FE-IV results show that
host countries in East Asia, Europe, and South Asia are significantly affected by robotization in source countries. However, host countries in Latin America and North America are not significantly affected, or even FDI inflows to those regions increase.

Specifically, FDI outflows to East Asia decreased by 2.2% by an increase of one unit increase in robot intensity in G7 countries. FDI inflows to countries in Europe decreased by 1.4%, and those in South Asia decreased by 1.9%. All results are statistically significant at 1% or 5% level. However, FDI outflows to Latin America increased by 0.5%, though the estimated coefficient is not statistically significant. FDI outflows to North America increased by 6.5%, which is quite large. The results clearly reveal that the effects of robotization in source countries on FDI outflows depend on the characteristics of host countries.

### Table 5. Regional Heterogeneities

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<tr>
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</tr>
<tr>
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<td>Ln(1+FDI)</td>
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<td>-0.022***</td>
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<td>Robot/Emp x Europe and Central Asia</td>
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<td>-0.014***</td>
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<td>(0.001)</td>
<td>(0.004)</td>
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<td>Robot/Emp x Latin America</td>
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<td>0.005</td>
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<td>(0.005)</td>
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<tr>
<td>Robot/Emp x Middle East &amp; North Africa</td>
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<tr>
<td></td>
<td>(0.001)</td>
<td>(0.006)</td>
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<tr>
<td>Robot/Emp x North America</td>
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<td>(0.015)</td>
</tr>
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<td>Robot/Emp x South Asia</td>
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<td>-0.019**</td>
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<td>(0.002)</td>
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<td>Robot/Emp x Sub-Saharan Africa</td>
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</table>

Note: Source-Industry-Host clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors’ calculations based on estimation results.
5.2. Origin of Regional Heterogeneity: Role of Manufacturing and Education

In section 5.1, we demonstrate regional variations in the changes in FDI inflows resulting from robotization in source countries. Next, we examine key factors contributing to these heterogeneities. We consider two factors: the proportion of manufacturing output to GDP and the average years of schooling in host countries.

We consider the proportion of manufacturing output to GDP for two reasons. First, we focus on outward FDI in manufacturing sectors, so that share of manufacturing sectors in host countries can affect empirical results. Second, as we discussed, manufacturing sectors in source countries mainly adopt industrial robots more compared to service sectors. Consequently, from the perspective of the vertical FDI, host countries with a large share of manufacturing sectors are more profoundly affected by the robotization in source countries. Based on these considerations, we classify all host countries into two groups: those with a high proportion of manufacturing share (High M) and those with a low proportion of manufacturing share (Low M). More specifically, we compute the average proportion of manufacturing sector output to GDP during the sample periods for host countries. The data is obtained from World Bank World Development Indicator. Subsequently, we arrange the countries in descending order based on their average value of manufacturing output share, from the country with the highest share to the one with the lowest share. Then, we label the upper 50% of countries as High M and the remaining countries as Low M.

Furthermore, years of schooling can play a significant role. Previous literature, such as Graetz and Michaels (2018), claims that replaceability, a degree of how easily industrial robots replace human jobs, varies depending on labor skills. Based on their arguments, we consider educational attainment in each country. We use Barro and Lee (2013)’s educational attainment database. We categorize three groups for host countries: high years of schooling (High YRS), middle years of schooling (Middle YRS), and low years of schooling (Low YRS). Specifically, we compute average years of schooling using each country’s 2000, 2005, 2010, and 2015 data. After that, we order the country with the longest years of schooling to the country with the shortest years of schooling. Then, we label the upper 1/3 countries as High YRS, the next 1/3 countries as Middle YRS, and the remaining as Low YRS. Lastly, we categorize
host countries as six groups using cross-product of dummies for the share of manufacturing and years of schooling. We estimate the impact of robotization on outward FDI using the following equation:

\[
\ln(1 + FDI_{ijkt}) = \sum_{YRS} \sum_M \beta_r \left( \frac{Robot_{employment}}{} \right)_{ijt} \times I_M \times I_{YRS} + \alpha_{ijk} + \alpha_t + \epsilon_{ijkt} \quad (18)
\]

where \( I_M \) and \( I_{YRS} \) are indicator functions when it has value one if a host country is a member of \( M=\{High M, Low M\} \) and \( YRS=\{High YRS, Middle YRS, Low YRS\} \); otherwise, it has value zero.

<table>
<thead>
<tr>
<th>Table 6. Effects of Manufacturing Share and Years of Schooling</th>
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<tbody>
<tr>
<td>Estimator:</td>
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<tr>
<td>Dependent Variable:</td>
</tr>
<tr>
<td>Robot/Emp x Low M x Low YRS</td>
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<tr>
<td>(0.001)</td>
</tr>
<tr>
<td>Robot/Emp x Low M x Middle YRS</td>
</tr>
<tr>
<td>(0.001)</td>
</tr>
<tr>
<td>Robot/Emp x Low M x high YRS</td>
</tr>
<tr>
<td>(0.001)</td>
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<tr>
<td>Robot/Emp x High M x Low YRS</td>
</tr>
<tr>
<td>(0.002)</td>
</tr>
<tr>
<td>Robot/Emp x High M x Middle YRS</td>
</tr>
<tr>
<td>(0.001)</td>
</tr>
<tr>
<td>Robot/Emp x High M x High YRS</td>
</tr>
<tr>
<td>(0.001)</td>
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<tr>
<td>Number of ID</td>
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<tr>
<td>avg T</td>
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<tr>
<td>rk-F statistics</td>
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</tbody>
</table>

Note: Source-Industry-Host clustered standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors’ calculations based on estimation results.

Estimation results with the panel fixed effects and IV-base are shown in Table 6. Results reveal that Robot intensity significantly affects outward FDI to host countries with high manufacturing share. Regardless of their educational attainment level,
countries with a smaller share in the manufacturing sector are not significantly affected. This may be caused by two different channels. Firstly, our sample is limited to FDI outflow in manufacturing sectors. Thus, this result is driven by the sample. Secondly, industrial robots are more adept at replacing human jobs within manufacturing sectors. For example, Dauth et al. (2017) discuss the effects of robot adoption on human employment in Germany. They claim that introducing robots reduces human jobs in manufacturing sectors but increases human jobs in service sectors. Although they do not discuss international effects, it implies that the replaceability and effects of robotization can vary across different sectors. If this holds true in international dimensions, introducing robots in source countries negatively affects FDI to countries with high manufacturing shares but insignificantly or positively affects FDI to countries with high service sector shares.

In our sample, notable Latin American countries, such as Brazil and Argentina, have relatively low shares of manufacturing output, and therefore FDI outflows to countries in Latin America are not significantly affected by robot adoption in source countries. Notably, Canada and the U.S., the key countries in North America, are also grouped as low manufacturing share countries so that FDI outflows to those regions are not significantly affected and even positively affected by robot adoption in source countries.

Among countries with a higher share of manufacturing sectors, countries with higher years of schooling are more significantly affected by robotization. This outcome could be attributed to the fact that the replaceability can vary across a labor skill level. For instance, Graetz and Michaels (2018) argue that the effects of robotization are not uniformly distributed across different skill levels. Their results reveal that robotization negatively affects the low-education group, specifically high school dropouts. In our sample, the average years of schooling are 4.7 years for the lowest group, 8.8 years for the middle group, and 11.6 years for the highest group. Thus, our sample's middle and high groups correspond to the low-skill workers in Graetz and Michaels (2018). In this sense, workers' skills level in host countries can matter for changes in inward FDI caused by robotization in source countries.
6. Concluding Remarks

This study examines the impact of robotization in a source country on its outward FDI. A number of existing studies have mainly examined the effects of robot adoption on employment and trade patterns in developed countries and employment in their trading partners, mainly focusing on developing countries. In other words, very few studies investigate the relationship between robotization in the source country and outward FDI or offshoring to the host country.

This study employs both theoretical models and empirical analyses to address these research questions. The theoretical model focuses on vertical FDI and finds that an exogenous increase in robot adoption in the source country reduces its vertical FDI. That is, a rise in robot use reduces offshoring by decreasing the cost of production at home.

Although the FDI data from the fDi Markets used in this study does not distinguish between vertical and horizontal FDI, we found that an increase in robot intensity in G7 countries negatively affects outward FDI in these countries. Furthermore, the extent of the negative impact varies across host country regions. This heterogeneous effect could be attributed to varying characteristics of the host country, including factors such as the proportion of the manufacturing industry and the education level of the labor force.

One limitation of this study is the difficulty in distinguishing between vertical and horizontal FDI using the fDi Markets data. To address this limitation, it is necessary to develop a theoretical model for horizontal FDI and investigate whether an increase in robot use in the source country affects its horizontal FDI. We remain this task for future work.
References


Appendix

Appendix A. Results with control variables

<table>
<thead>
<tr>
<th>Estimator:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FE Ln(1+FDI)</td>
<td>0.238*** (0.038)</td>
<td>0.244*** (0.038)</td>
<td>0.591*** (0.185)</td>
<td>0.044 (0.543)</td>
<td>0.907 (0.621)</td>
</tr>
<tr>
<td>FE Ln(1+FDI)</td>
<td>-0.248*** (0.060)</td>
<td>-0.269*** (0.059)</td>
<td>0.320 (0.275)</td>
<td>-1.286** (0.568)</td>
<td>-1.096** (0.556)</td>
</tr>
<tr>
<td>PO FDI</td>
<td>-0.297*** (0.110)</td>
<td>-0.289*** (0.110)</td>
<td>0.251 (0.530)</td>
<td>-1.512*** (0.570)</td>
<td>-0.571 (0.680)</td>
</tr>
<tr>
<td>AB Ln(1+FDI)</td>
<td>-3.548 (2.514)</td>
<td>-2.659 (2.521)</td>
<td>-15.065* (8.064)</td>
<td>8.878 (11.487)</td>
<td>7.121 (9.767)</td>
</tr>
<tr>
<td>AB Ln(1+FDI)</td>
<td>0.001 (0.002)</td>
<td>0.001 (0.002)</td>
<td>0.007 (0.008)</td>
<td>0.005 (0.008)</td>
<td>-0.004 (0.008)</td>
</tr>
<tr>
<td>Source</td>
<td>Ln(output):</td>
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<td>0.331*** (0.056)</td>
<td>1.374*** (0.558)</td>
<td>2.768 (2.498)</td>
</tr>
<tr>
<td>Source</td>
<td>Ln(wage):</td>
<td>-0.154** (0.060)</td>
<td>-0.153** (0.060)</td>
<td>-0.638 (0.570)</td>
<td>-1.116 (1.158)</td>
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<tr>
<td>Source</td>
<td>Ln(gfcp):</td>
<td>-0.200 (0.150)</td>
<td>-0.199 (0.151)</td>
<td>-2.472*** (0.589)</td>
<td>-10.629 (10.658)</td>
</tr>
<tr>
<td>Source</td>
<td>ICT/Emp:</td>
<td>-0.027** (0.011)</td>
<td>-0.027** (0.011)</td>
<td>-0.176*** (0.047)</td>
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<tr>
<td>Source</td>
<td>Tax rate:</td>
<td>0.006*** (0.002)</td>
<td>0.006*** (0.002)</td>
<td>0.036** (0.014)</td>
<td>-0.016 (0.045)</td>
</tr>
<tr>
<td>Source</td>
<td>KAOPEN:</td>
<td>-0.000 (0.001)</td>
<td>-0.000 (0.001)</td>
<td>0.000 (0.010)</td>
<td>-0.012* (0.007)</td>
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<tr>
<td>Source</td>
<td>Share_M:</td>
<td>0.162** (0.068)</td>
<td>0.161** (0.068)</td>
<td>0.924** (0.468)</td>
<td>0.106 (0.332)</td>
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<tr>
<td>Source</td>
<td>Share_Adv.Labor:</td>
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<td>-0.002 (0.001)</td>
<td>-0.002 (0.007)</td>
<td>-0.028*** (0.010)</td>
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Annex Table 1. Continued

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<tr>
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Note: For (1), (2), (3), Source-Industry-Host clustered standard errors are in parentheses. For (4), (5), heteroskedasticity-autocorrelation consistent errors are reported. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors’ calculations based on the estimation results.

Annex Table 1 shows estimation results with various control variables. We consider sector-level output (output), wage (wage), price of capital goods (gfcp), ICT capital per employee (ICT/Emp), and national level of the statutory tax rate for source countries. All sectoral-level variables are obtained from the OECD STAN database. The tax rate is taken from Tax Foundation. Furthermore, we consider real GDP (RGDP), real GDP per capita (RGDPP), human capital index (Hindex), and trade openness, which is defined as the sum of export and import divided by GDP. All variables are taken from Penn World Table 10.0. We also consider financial openness (KAOPEN), measured by Chinn and Ito (2006). We also include the share of manufacturing output to GDP (Share_M) and the share of the labor force with advanced education (Share_adv.labor). Those variables are taken from World Development Indicators. Similar to source countries, we include the host country’s statutory corporate tax rate taken from Tax Foundation. Results reveal that an increase in robot adoption in source countries negatively affects outward FDI.
**Appendix B. Results with alternative IV:**

**Bartik-style Instrumental Variable**

### Annex Table 2. Results with Alternative IV

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<td>0.005* (0.003)</td>
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Note: For (1), (2), Source-Industry-Host clustered standard errors are in parentheses. For (3), Source-Industry-Host clustered bootstrap standard errors (500 replications) are reported. For (4), heteroskedasticity-autocorrelation consistent errors are reported. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors’ calculations based on the estimation results.

Annex Table 2 shows estimation results with IV-Bartik. Results reveal that an increase in robot intensity negatively affects outward FDI, which is consistent with the results in Table 3. Also, the findings in Annex Table 2 are very similar to the baseline results quantitatively. Results confirm that our baseline results are robust.
본 논문에서는 로봇화(robotization)가 외국인직접투자(FDI)에 미치는 영향을 분석하였다. 이를 위해 이론적 모델을 구축하여 로봇화가 외국인직접투자에 미치는 영향을 예측하고 이론 모형의 결과를 실증적으로 검증하였다. 구축한 이론 모형에 따르면, 산업 로봇의 외생적(exogenous) 증가는 로봇 대여가격(rental rate)과 직무 수행에 드는 국내 비용을 모두 감소시키는 것으로 나타났다. 따라서 국내에서 더 많은 작업을 수행하는 것이 수익성을 더욱 높여 결국 FDA가 감소하게 된다. 실증분석 결과는 이러한 이론적 결과를 뒷받침하고 있다. 실증분석 결과, 한 국가의 로봇화는 해당국가의 해외직접투자를 줄이지만, 이러한 부정적인 영향의 크기는 지역별로 다르게 나타났다.
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The Effects of Robotization on Foreign Direct Investment

Sungwoo Hong, Wongi Kim, and Yeo Joon Yoon

This paper investigates the impact of robotization on foreign direct investment (FDI) through a combination of theoretical and empirical analysis. Theoretical findings reveal that exogenously increased robot usage reduces both the rental rate of robots and domestic task costs, leading to decreased outward FDI as more tasks are performed domestically. Empirical results indicate that higher levels of robotization in source countries have a negative effect on outward FDI, although this impact varies across different global regions.