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ROBOT AND AUTOMATION: NEW INSIGHTS FROM MICRO DATA[‡]

Advanced Technology Adoption: Selection or Causal Effects?[†]

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Advanced technologies, including robotics, artificial intelligence (AI), and software systems, are thought to be spreading rapidly in industrialized economies. In Acemoglu, Aaron, et al. (2022), we used the 2019 Annual Business Survey (ABS) to provide a comprehensive overview of the adoption of AI, robotics, dedicated equipment, specialized software, and cloud computing for US firms in all sectors during 2016–2018.

Our work documented these facts:

(i) The share of adopting firms remains low for AI and robotics (3.2 percent and 2 percent of firms, respectively) and rises to 19.6 and 40.2 percent for equipment and software, respectively.

(ii) Adoption is concentrated in large firms.

(iii) As a result, a high share of workers is exposed to these technologies, especially in manufacturing. For example, 12–64 percent of US workers and 22–72 percent of US manufacturing workers are exposed to these technologies.

(iv) A significant share of adopters, ranging from 30 percent for specialized software to 65 percent for robotics by employment weight, report using these advanced technologies for automation. In total, 30.4 percent of US workers and 52 percent of manufacturing workers are employed at firms using these technologies for automation.

(v) Consistent with the use of these advanced technologies for automation, adopters have higher labor productivity and lower labor shares.

(vi) Firms report that these technologies increase their demand for skills but do not necessarily expand employment.

This paper revisits the second fact—the reasons why firms adopting advanced technologies are larger. In principle, this could be for two

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different reasons. Either adoption of advanced technologies *causally* expands employment, or *selection* leads larger firms to more adoption. For example, already-large firms may have a greater likelihood of adopting advanced technologies because of fixed costs, or firms that are growing fast for other reasons may also be better at adopting and using these technologies.

These two explanations have different implications. The former would suggest that advanced technologies contribute to employment growth, at least at the firm level (the industry-level implications could differ from the firm-level ones, as pointed out in Acemoglu, Lelarge, and Restrepo 2020 and Koch, Manuylov, and Smolka 2021). The latter would weigh in favor of limited employment gains even in adopting firms and would caution against firm-level explorations using ordinary least squares or event study strategies to uncover the effects of advanced technology adoption.

Our results favor the selection interpretation. Using data from the Longitudinal Business Database (LBD), we document that adopters were already large and growing faster before AI, robotics, cloud computing, and specialized software systems became broadly available.[1] We also find that employment trends at adopting firms remained largely unchanged after the widespread use of these technologies. Persistent size and growth differences between adopters and nonadopters imply that firm-level estimates of the effects of advanced technologies must be interpreted with caution.

I. Adoption and Firm Size

We first provide graphical evidence on the relationship between firm size and the adoption of AI and robotics. We focus on these technologies because they have received considerable attention in recent empirical work. Figure 1 plots adoption rates for firms in 36 size and age categories, defined in terms of employment and age percentiles within detailed six-digit industries.[2] The figure also reports the average adoption rate for firms in each size class.

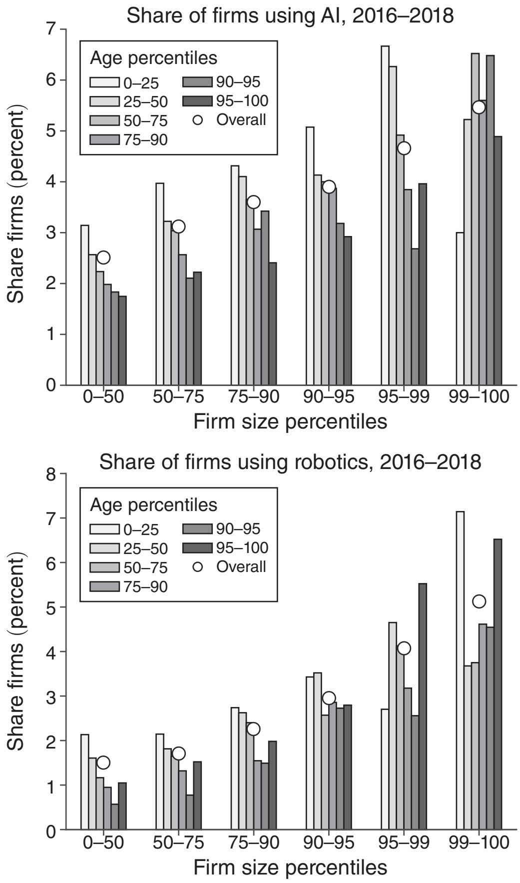

FIGURE 1. ADOPTION OF AI AND ROBOTICS FOR FIRMS IN DIFFERENT SIZE AND AGE CATEGORIES

Notes: The figure plots adoption rates for AI and robotics by firm age and size percentiles within detailed six-digit industries. See Acemoglu, Anderson, et al. (2022) for similar figures for the remaining technologies.

Source: 2019 ABS

[1] These statements refer to employment. We document in Acemoglu, Anderson, et al. (2022) that firms' adoption of advanced technologies is associated with an increase in sales and a reduction in their labor share. The same pattern for French manufacturing is documented in Acemoglu, Lelarge, and Restrepo (2020).

[2] We assign firms to their main six-digit North American Industry Classification System industry in terms of payroll across all its establishments. Employment percentiles are defined based on the employment distribution in each industry. By construction, Figure 1 isolates differences in adoption rates across firms of different size operating in the same narrowly defined industry and controls for size differences between manufacturing and nonmanufacturing firms.

Adoption rises with size for all technologies in the ABS: 5.5 percent of firms in the top percentile of their industries' employment distribution use AI, 5.1 percent use robots, 31.4 percent use dedicated equipment, 67.4 percent use specialized software, and 63.5 percent use cloud computing. In contrast, the adoption rate among firms in the fiftieth to seventy-fifth percentile of industries' employment distribution is much lower: 3.1 percent for AI, 1.7 percent for robots, 18.6 percent for dedicated equipment, 39.6 percent for specialized software, and 33.4 percent for cloud.

II. Firm Employment Histories

The previous section documented sizable differences in employment levels between adopting and nonadopting firms (for robotics and AI). We now explore whether employment histories, in terms of both levels and trends, differ between adopters and nonadapters.

Because LBD does not contain consistent information on firm-establishment histories, we create a pseudo–firm establishment panel that tracks employment in all establishments associated with each firm in the ABS technology module in 2018. We then conduct our empirical analysis at the level of these establishments between 1978 and 2018.[3]

Figure 2 focuses on the differential employment histories of adopters and nonadopters of robotics for illustration purposes. It plots the evolution of average employment by cohort for establishments in adopting and nonadopting firms.[4] The figure reveals three key patterns. First, establishments in adopting firms are initially larger (have higher employment) than establishments in nonadopting firms. These size differences are present at an early age and grow over time, especially for early cohorts. Second, differences in employment levels and growth rates precede the period of rapid robot adoption in the United States, which took place in the late 1990s and early 2000s. Third, employment dynamics of adopters' establishments seem unaffected by rising adoption of robots in recent decades.

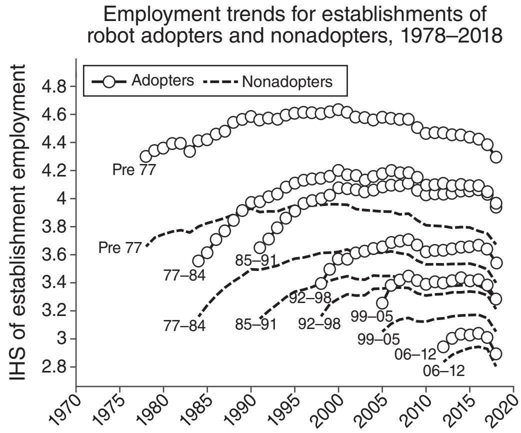

FIGURE 2. EMPLOYMENT TRENDS FOR ESTABLISHMENTS IN ROBOT-USING FIRMS AND OTHERS FOR 1978–2018

Notes: The figure plots the inverse hyperbolic sine of employment in establishments associated with firms using robots in the 2019 ABS (lines with circles) and those associated with nonrobot users in the 2019 ABS (dashed lines). For each cohort, we report employment numbers for the years following its entry into the LBD.

Sources: 2019 ABS and 1978–2018 LBD

To explore these patters for all technologies, we turn to the following regression model:

$$(1) \quad y_{j,i,c,t} = \alpha_c + \beta_{i,t} + \gamma_c \times Adopter_j + \delta_t \times Adopter_j + \epsilon_{j,i,c,t},$$

for an establishment j in industry i, cohort c, in year t. The left-hand-side variable is the inverse hyperbolic sine (IHS) of establishment employment, which allows us to include zeros in our analysis. The right-hand-side variables are cohort dummies α_c; industry-by-year dummies $\beta_{i,t}$, which account for differences in employment trends by four-digit industries; and cohort and growth effects depending on adopter status (as measured by the adopter dummy $Adopter_j$). These terms allow adopters to have different initial levels (differences by cohort) and different growth dynamics (different time effects).

[3] In particular, this pseudopanel follows the same establishments over time, even though some of these establishments may not have belonged to the firm in question in the past. See Foster et al. (2016) for more details on this strategy to track activity of firms back in time.

[4] The first year in the LBD is 1976. We do not observe the exact age of establishments that existed at this point and assign them to a "pre-77" cohort.

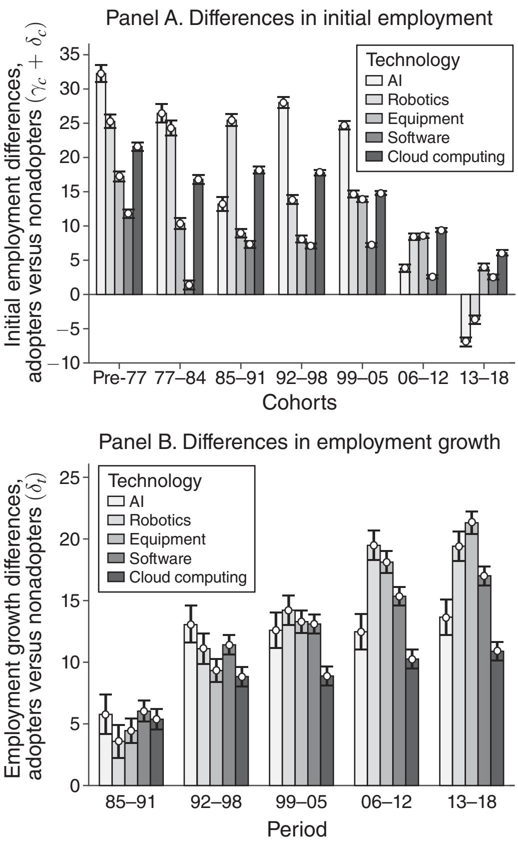

Figure 3. Differential Employment Dynamics for Establishments in Adopting Firms Relative to Others

Notes: Panel A plots estimates of $\gamma_c + \delta_c$ (from equation (1)), which measures the differential establishment employment size for adopter firms relative to nonadopters. Panel B plots δ_t, which measures the differential establishment employment growth for adopter firms relative to nonadopters.

Sources: 2019 ABS and 1978–2018 LBD

Figure 3 depicts estimates from equation (1) separately for the five technologies in the ABS. Panel A presents estimates of $\gamma_c + \delta_c$, which compare the initial establishment size of adopting firms of cohort c to the size of nonadopting firms at the time of entry.[5] The results in this panel show that, consistent with our discussion for robotics adoption in Figure 2, the initial size (in terms of establishment employment) of adopting firms is significantly greater than the size of nonadopters at the same point in time. For example, establishments at robot-adopting firms from the 1977–1984 cohort were initially 24.3 percent larger than establishments of firms not adopting robotics technology. The same difference is 14.7 percent for robot-adopting firms from the 1999–2005 cohort.

Panel B depicts the estimates of δ_t, which measures the differential (establishment) employment growth of adopting firms. It confirms that establishment employment for adopters grew more rapidly than it did for nonadopters. For example, from 1978–1984 to 1992–1998, establishments of robot-adopting firms expanded their employment by 11.1 percent more than nonadopters. Notably, for most technologies, these differential growth experiences long predated the periods of high adoption in the United States as a whole. Indeed, robotics, AI, specialized software systems, and cloud computing were not spreading rapidly before the late 1990s.[6] For example, the adoption of AI concentrates in the 2016–2018 period (see Acemoglu, Autor, et al. 2022), while robot adoption gained prominence in the late 1990s and the 2000s (see Acemoglu and Restrepo 2020). Yet, establishments of AI and robot-adopting firms were larger and grew more rapidly than those of nonadopters decades before these periods.

Panel B also shows that the differential employment growth of adopters relative to nonadopters is unaffected by the increased adoption of these technologies in recent years. If anything, establishments in adopting firms grew at more comparable rates to establishments in nonadopting firms in recent years. For example, our estimates in Panel B imply that the yearly growth differential for establishments in robot-adopting firms relative to nonadopters went from 0.8 percent per year in 1978–1998 to 0.4 percent in 1999–2018.

III. Discussion

Figures 2 and 3 show that establishments in adopting firms were initially larger and grew more rapidly than nonadopters, even before

[5] The interaction terms γ_c give employment differences at the base period. Adding $\gamma_c + \delta_c$ gives an estimate of employment differences in the first period each cohort enters the LBD.

[6] The exception is dedicated equipment, such as computer–numerically controlled machines, whose widespread adoption dates back to the early 1970s and is studied in detail in Boustan, Choi, and Clingingsmith (2022).

the adoption of advanced technologies intensified in recent years. These patterns support the view that adopters of advanced technologies are differentially selected and were already large and on differential growth trajectories.

The figures also document that the difference in employment dynamics between adopting firms' establishments and others has remained largely unchanged or become less pronounced in recent years as adoption intensifies. This is the opposite of what one would expect if advanced technologies caused adopting firms to expand their employment. Instead, it points to small or negative effects of automation technologies on firm employment trajectories.

The possibility that technology does not lead to large employment expansions at adopting firms aligns with the fact that a significant share of adopters report using advanced technologies for automation. In contrast to other applications of advanced technologies, automation reduces production cost by displacing workers from their roles, creating an ambiguous effect on firm-level employment. This possibility also aligns with firms' self-assessments on the effects of these technologies, which point to ambiguous effects of advanced technologies on employment levels (Acemoglu, Anderson et al. 2022).

One challenge when interpreting our findings is that we do not know the exact adoption date of these technologies. Currently, the ABS data only tell us whether a firm used a technology in 2016–2018. Future waves of the ABS technology module will measure year of adoption, providing a more accurate picture of how technology changes firm employment dynamics.

REFERENCES

Acemoglu, Daron, Gary W. Anderson, David N. Beede, Cathy Buffington, Eric E. Childress, Emin Dinlersoz, Lucia S. Foster, et al. 2022. "Automation and the Workforce: A Firm-Level View from the 2019 Annual Business Survey." NBER Working Paper 30659.

Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo. 2022. "Artificial Intelligence and Jobs: Evidence from Online Vacancies." *Journal of Labor Economics* 40 (S1): S293–340.

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

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy* 128 (6): 2188–244.

Boustan, Leah Platt, Jiwon Choi, and David Clingingsmith. 2022. "Automation after the Assembly Line: Computerized Machine Tools, Employment and Productivity in the United States." NBER Working Paper 30400.

Foster, Lucia, John Haltiwanger, Shawn Klimek, C.J. Krizan, and Scott Ohlmacher. 2016. "The Evolution of National Retail Chains: How We Got Here." In *Handbook on the Economics of Retailing and Distribution*, edited by Emek Basker, 7–37. Cheltenham, UK: Edward Elgar Publishing.

Koch, Michael, Ilya Manuylov, and Marcel Smolka. 2021. "Robots and Firms." *Economic Journal* 131 (638): 2553–84.