Are Robots Special? Empirical Evidence on Type-Specific Capital–Labor Interactions

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Abstract

Mainstream analyses of automation often treat capital as a homogeneous input or focus narrowly on specific capital classes, such as industrial robots. We use matched Swedish administrative microdata linking firms, workers, and imports to study how heterogeneous forms of capital interact with labor and firm performance. First, we replicate the main findings of Acemoglu et al. (2020) for Sweden and confirm that robot adoption has similar effects on firms' value added, employment, and workforce composition as in France. Second, we extend the empirical setting to capture heterogeneous effects by firm size and the value of robot adoption. Third, we apply the same framework to a broad range of disaggregated capital goods identified at the 8-digit product level. We find that several non-robot capital types have effects on labor and productivity comparable to those of robots, while aggregated capital measures tend to yield weak results. Our findings suggest that although robots have large and visible impacts on labor markets, they are not unique in their economic function, and their interaction patterns with labor resemble those of older and more conventional capital-embodied technologies.

I. Introduction

As Robinson (1953) noted, much of mainstream economic theory has long modeled the factors of production, such as labor and capital, as homogeneous inputs. This simplification can be problematic for understanding technological and distributional dynamics, since differences in how specific types of capital and labor interact may be central to explaining both productivity and inequality. Recent work has begun to incorporate heterogeneity in labor, distinguishing workers by skill, occupation, or task (see, e.g., Acemoglu and Autor (2011), Autor (2013), Autor et al. (2003), and Goos et al. (2014)). In contrast, the role of heterogeneous capital remains relatively underexplored. The interaction between different forms of capital and different types of labor is still poorly understood, even though it is

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likely central to explaining variation in firm performance and market dynamics. Partly this lack of analysis can be traced to limited data availability, as most of the studies of capital adoption use industry or country level data. With new capital-embodied technologies emerging continuously, understanding how heterogeneous labor and capital interact is especially relevant to the debate on automation. We ask: how do different types of capital, including but not limited to robots, interact with labor and firm outcomes?

Whether productivity gains or displacement effects dominate ultimately determines the impact of automation on employment and wages. Yet the literature remains divided on which mechanism prevails. While Acemoglu et al. (2020) find that displacement effects dominate for robot adoption in French data, Aghion et al. (2020) do not find similar results for automation capital more broadly. The way capital is classified as "automation capital" appears to influence these conclusions. This suggests that further empirical work explicitly accounting for the heterogeneous nature of capital is essential to understand the implications of automation.

In this project, we use rich Swedish administrative microdata that link firms, workers, and import records to study the effects of capital-embodied automation on firm and worker outcomes. In the first step, we replicate the main empirical specifications of Acemoglu et al. (2020) and Aghion et al. (2020). In the Swedish context, we find that robot adoption, coded as a binary variable at the firm level, is associated with an increase in value added of about 31%, a decline in the labor share by roughly 17 percentage points, and a rise in wage rate, defined as wage bill divided by the number of workers, and employment of around 9% and 13%, respectively. This means that even though the labor share is falling, the total wage bill actually increases, but value added increases more. This step assesses how robot adoption affects firm-level outcomes and serves as a benchmark result. For comparison, Acemoglu et al., 2020 find a 20% increase in value added, a 4 percentage point decline in the labor share, a 10% increase in hours worked, and a 1% increase in the hourly wage for the years 2010 to 2015. While Acemoglu et al., 2020 find an increase in TFPR, our results are not significant for this variable. For automation capital as the indepentend variable of interest, we do not find significant results either, except for the outcome of the wage rate. This is broadly in line with Aghion et al., 2020.

Next, we analyze the effects of other capital goods at a disaggregated level, defined by the 8-digit product code, to place the effects of robots in perspective and explore the broader heterogeneity of capital. This analysis reveals that many capital goods have effects similar to or even stronger than those of robots, including not only automation equipment but also older and more conventional types of machinery such as precision tools and transport equipment. The focus on robots alone therefore overlooks that they represent only one example of a broader set of capital inputs that can reshape production and employment patterns.

Additionally, we examine the results for the disaggregated capital goods included in *automation capital* in Aghion et al. (2020), and find that while the estimates on the aggregated level are small and statistically insignficant, some of the more granular results are sizable and statistically significant. The results from this analysis underline how aggregating heterogeneous capital into one indicator can 'average away' underlying significant effects.

Taken together, these results emphasize the importance of taking into account a wide array of granular capital classes in empirical work, both to put results into perspective, and to ensure existing effects do not get averaged out by aggregation.

II. Conceptual background and related literature

A. Capital heterogeneity and skill complementarity

Capital is heterogeneous in many dimensions, including its technological characteristics, purpose in production, and the ways it interacts with labor. Understanding this heterogeneity is crucial, as different types of capital can have very different implications for employment, wages, and inequality. In particular, capital may substitute for certain kinds of labor while complementing others, which shapes both firm dynamics and the distribution of income across workers. This question lies at the core of debates on technological change: when new capital is introduced, do workers gain through firm expansion and productivity growth, or are they displaced as certain tasks become automated?

Hötte et al. (2023) review the literature on technological change and its effects on labor and find that across various categories of technology, labor-displacing effects are often offset by scale effects. O'Mahony et al. (2021) show in a theoretical model that capital heterogeneity is central to understanding the decline in the labor share, and using industry-level OECD data, they demonstrate that different types of capital assets affect the labor share in opposite directions. Aghion et al. (2019) emphasize the role of institutions and policies in shaping the effects of automation, finding that robot adoption in France between 1994 and 2014 reduced aggregate employment, with less educated workers being more negatively affected. Chen (2020) highlight the importance of capital-skill complementarity and rising capital intensity in the goods sector for understanding structural transformation in the United States since the 1950s. Their analysis supports the view that capital tends to substitute for less educated workers while complementing those with higher education.

Taken together, these studies show that both the type of capital and the composition of the workforce matter for understanding the consequences of technological change. In this context, it remains an open question whether industrial robots and other forms of automation represent a fundamentally new challenge for labor, or whether their effects resemble those of earlier generations of capital accumulation. This question is central to assessing the long-run implications of technical change for wage levels and inequality.

B. Robots and automation

Much of the recent empirical literature on automation has focused on industrial robots as a benchmark for studying technology adoption and its labor market consequences. Graetz and Michaels (2018) use industry-level data from 17 countries spanning 1993 to 2007 to examine the impact of robot adoption. They find that industrial robots are associated with higher labor productivity and estimate that they account for about 15 percent of aggregate productivity growth during this period. They also report higher wages and lower output prices in industries with greater robot use, while overall employment remains largely unaffected, though the share of workers with lower education declines.

Building on this work, Acemoglu et al. (2020) study French firm-level data and find that robot adoption increases productivity but reduces employment and the labor share, suggesting that displacement effects dominate over productivity-driven scale effects. In contrast, Aghion et al. (2020) examine a broader set of automation-related capital assets and find no such aggregate displacement effect once a wider definition of automation capital is considered. They argue that access to international markets may moderate the labor market consequences of automation.

These contrasting findings point to a broader question about what kinds of capital should be considered "automation." While robots have become a symbol of technological change, they represent only a narrow segment of production capital. Aggregating many different automation goods may obscure important heterogeneity across technologies and their interactions with labor. In this study, we address this issue by first replicating the results for robots in the Swedish context and then extending the analysis to a wider range of capital goods. By examining capital at a disaggregated level, we assess whether robots differ meaningfully from other forms of capital, or whether their effects reflect a more general pattern of capital–labor interaction.

C. Firm-level adoption patterns

Dinlersoz and Wolf, 2024 use a the Survey of Manufacturing Technology (SMT) from 1991 to examine the implications of skill biased technical change as an explanation for the labor share decline. They find that in more automated establishments, labor share is lower, and there is a lower fraction of production workers, while workers are more productive and receive higher wages. While they emphasize the importance of directed technical change, the survey also reveals that the most common motivator for automation is a quality increase. Finally, they estimate TFP using a CES setting where firms endogenously set the weights of different production inputs by investing in technology. This estimation shows that CD estimates underestimate TFP by not taking into account endogenous technology choice.

Dixon et al., 2020 provide additional evidence for robot adoption being motivated by product improvement rather than saving labor costs using data on Canadian firms between 2000 and 2015. They also find that robots increased worker turnover and total employment, and displaced managerial work. They also found outside-hiring of managers and additional training of employees when robots are adopted. Wang et al., 2025 us data from Chinese listed firms and confirm the finding that robot-using companies have higher product quality. They find that one channel for this effect is replacing low-skilled labor with a bundle of complex robots and high-skilled labor.

Deng et al., 2024 use plant-level data on robotization in Germany between 2014 and 2018, and establish a number of stylized facts. They find that robot use is relatively rare, even within manufacturing (8.2% of plants). Moreover, plants that use robots are larger and more productive and the distribution of the stock of robots is highly skewed. Ex-ante, plant size predicts robot adoption, as is the share of low-skill labor.

Leone, 2023 connects the acquisition of manufacturing firms by multinationals to robot adoption, and a subsequent decline in the labor share. Using Spanish manufacturing firm data from 1990 to 2017, this channel is estimated to have contributed about 8% of the decline in the manufacturing labor share over the sample period.

While much of the recent empirical literature on automation has focused on robots, there is little evidence to suggest the effects of robots on the labor share, wages, and productivity, are vastly different to the effects of other types of automation capital. One reason for the prevalence of studies on robots is data availability, thanks to industry-level data provided by the International Federation of Robotics (IFR). As presented above, some estimates exist using establishment or plant level data from TODO. We add to this literature by estimating the effects of robot adoption in Swedish establishment-level data and broadening the horizon of analysis to a wide range of capital inputs. The aim of this exercise is to (i) put into perspective the magnitude of robot estimates and (ii) understand more deeply the heterogeneity of directed technical change.

III. Data and variable construction

The underlying data set is provided by Statistic Sweden (SCB) and includes matched data on firms, workers, and imports. Following Acemoglu et al. (2020), we use five years of data in our main specification. For the years 2012 to 2016 which we use, consistent definitions of occupations, industry, and import goods codes are available. In the following, we will describe the data sources, processing, and variable construction.

A. *Firm data*

FEK The registry FEK (företagens ekonomi) contains firms' financial data. It comes from tax records and includes information on capital, labor, the wage bill, profits, revenue, and value added. All active Swedish firms except those in the financial sector are are included. The data is filtered to only include manufacturing firms, which corresponds to SNI codes 10 – 33.[1] We further restrict the sample to firms that show up in both years 2012 and 2016 with positive revenue, paying wages, and a positive number of employees.

The register also includes information at the establishment level (LVE). This is used to add the commuting zone of the biggest establishment as a variable, relying on SCB's classification of commuting zones. This measure is based on information on workers' home location and location of their main employment.[2]

A corporate dummy is added from the corporation register KCR. We classify a firm as part of a corporation if the firm id shows up in that register. The measure the change in log TFPR, which is one of the outcome variables in the regressions, following Acemoglu et al., 2020. It is defined as:

$$\Delta TFPR = \Delta \log y - \lambda_l \Delta \log l - \lambda_m \Delta \log m - (1 - \lambda_l - \lambda_m) \Delta \log k,$$

where λ_l and λ_m are defined as the 2012 expenditure shares of labor and intermediates in revenue, respectively, y is total revenue, and k is the capital stock.

Value added is constructed as revenue minus intermediate inputs. There is an alternative measure for value added available from statistics Sweden, which adjusts for changes in inventories, capitalized production, and some production expenses not included in intermediates. We choose to use the 'unadjusted' measure in accordance with how Acemoglu et al., 2020 construct value added. Similarly, we follow Acemoglu et al., 2020 and define labor productivity as value added divided by the number of workers, and the labor share as the share of the wage bill in value added.

B. Worker Data

LISA The SCB registry LISA, or *longitudinell integrationsdatabas*, contains employment-related administrative data for individuals aged 16 and older[3]. This data includes information on individuals and matches them to their main employer. We use this individual level information about gender, age, and occupation, to construct variables capturing the workforce structure at the firm level. More specifically, we calculate the number of workers, female workers, skilled workers, and the average age of employees. Skilled workers in this context are defined as those with an occupation that requires

[1] From 2008 onwards, the Swedish Statistical Office uses SNI2007 to classify industries. Documentation is available via https://www.scb.se/en/documentation/classifications-and-standards/swedish-standard-industrial-classification-sni/

[2] For documentation, see https://www.scb.se/hitta-statistik/statistik-efter-amne/arbetsmarknad/utbud-av-arbetskraft/befolkningens-arbetsmarknadsstatus/produktrelaterat/fordjupad-information/lokala-arbetsmarknader-la/ and https://www.scb.se/hitta-statistik/statistik-efter-amne/arbetsmarknad/utbud-av-arbetskraft/registerbaserad-arbetsmarknadsstatistik-rams/produktrelaterat/Fordjupad-information/lokala-arbetsmarknader-la/

[3] From 2016, the minimum age to be included in LISA is 15.

at least a 2-year education after graduating from a *gymnasium*, the Swedish equivalent of high school. This corresponds to occupation codes starting with one, two, or three according to the Swedish classification system for occupations (SSYK)[4]. Note that the classification system was revised in 2012, effective from 2014, which did not affect the logic by which we classify 'skilled' and 'unskilled' labor.

C. Import Data

UHV The UHV, which stands for *utrikeshandel med varor*, contains information on both imports and exports at the country-firm-good level. Goods are classified according to the Combined Nomenclature (CN) of the EU with 8-digit identifiers[5]. The data is complete for imports from countries outside the EU, and are reported above a certain threshold for within EU imports, which has increased over time.

For identifying capital imports, we utilize the Broad Economic Categories (BEC) introduced by the UN. The BEC classification label different products as "Consumption", "Intermediate" or "Capital". Within the group "Capital", products are further divided into "Generic" and "Specific" since 2012. Where robots are referred to, we use the HS code "84795000 - Industrial robots, n.e.s.". *Automation capital* follows the definition in Aghion et al., 2019[6].

From the import data, which we merge to the firm dataset, we construct dummies for whether a company imported any capital between 2012 and 2016, whether it imported robots or automation capital, as well as each 8-digit product code within the class of capital goods. In the main regressions, the sample is restricted to capital importers.

D. Descriptives

This matched dataset allows us to trace how the acquisition of specific capital goods, identified at the 8-digit CN level, relates to changes in firm performance and workforce composition over time. We refer to the groups of capital analyzed by Aghion et al., 2020 as *automation capital*, and the one in Acemoglu et al., 2020 as *robots*. Descriptive statistics are summarized in table 1.

There are 16,265 manufacturing firms in our sample, of which 7,429 imported any type of capital goods between 2012 and 2016. About 0.9% of these imported robots, and 19.8% imported automation capital. Note that there is some overlap between firms that automate and firms that imported robots.

Comparing the characteristics of the firms in these groups at baseline, it is clear that

[4] Documentation can be found here: https://www.scb.se/dokumentation/klassifikationer-och-standarder/standard-for-svensk-yrkesklassificering-ssyk/

[5] CN codes can be looked up here https://cnwebb.scb.se/?languageId=GB

[6] A list of Automation Technologies https://www.openicpsr.org/openicpsr/project/184641/version/V1/view?path=/openicpsr/184641/fcr:versions/V1/replication_AEAPP-2023-1039/data/other

firms that import any type of capital are larger, whether measured in of revenue, value added, or the number of workers. They also generate more value added per worker and pay higher wages. Similarly, firms that automate are on average approx. 3.5 times larger than capital importers in terms of revenue, while robot adopters are more than 26 times the size of the average capital importer. Value added per worker and wages are higher among firms who automate, and even higher for robot adopters.

Turning to the workforce composition, capital importers have a slightly higher share of female workers than the average among all manufacturing firms. Robot adopters employ 23.9% women on average, while capital importers in general only have 21.8%. More sizable differences can be observed when looking at the skill share of the labor force, where the average among manufacturing firms is 19.2%, which increases to 29.3% among capital importers and is 36.6% for those who purchased robots. Firms that automate are more similar in terms of these work force characteristics to the overall group of capital importers. Finally, it is worth noting that robot adopters have a much lower labor share, at 51.5%, than the average manufacturing firm, which has a labor share of 70.5%.

	All manufacturing	Capital importers	Automation	Robots
n	16,265	4,667	549	68
Sales y (*)	13.966	326.608	1140.692	5743.977
Value added va (*)	5.068	125.415	469.099	2662.568
Workers l	7.772	82.204	284.313	1156.559
va per l	596,995	920,497	951,491	1,248,167
Wage	287,721	354,686	373,252	392,321
Labor share	0.676	0.561	0.549	0.515
Skill share	0.206	0.319	0.305	0.366
Female share in l	0.201	0.227	0.211	0.239
Robot adoption	-	0.015	0.042	-
Automation	-	0.118	-	-

(*) In 1 million SEK.

Table 1: Summary statistics by group at baseline

While the overall adoption rate of robots among capital importers is less than one percent, it is much higher within some industries. Motor vehicle manufacturing, production of iron and steel and ferroalloys, manufacture of optical instruments and photographic equipment, manufacture of consumer electronics, and manufacture of pipes, tubes, hollow profiles and accessories of steel all have robot adoption rates above 4%.

Examining instead the value of robots imported per firm, the highest variation is found in the same industries, with the exception of pipes, tubes, hollow profiles and accessories. Instead, production of communication equipment is more varied in the value of robots imported.

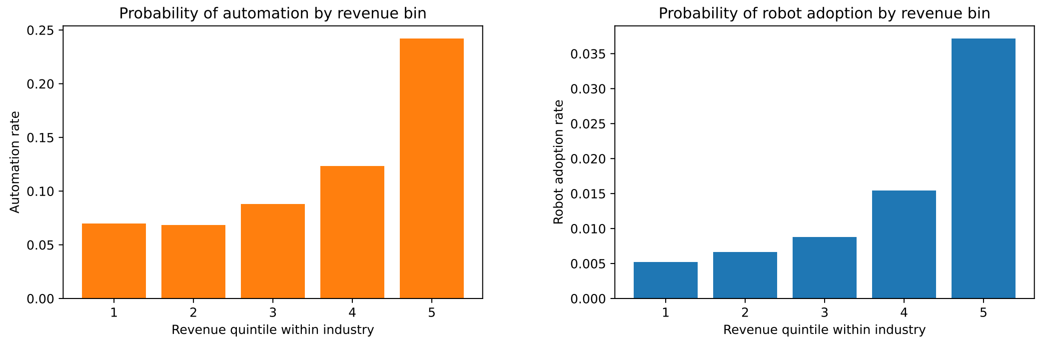

Figure 1: Adoption rates of automation capital and robots by size decile within an industry.

While robot adopters make up for a small share of firms, they make up for approximately 14% of employment, 28% of value added, and 23% of revenue in the manufacturing sector. Similarly, This concentration of adoption of automation capital in large firms is visualized further in Figure 1. The graphs show the average rate of adopting automation capital and robots, respectively, by the revenue size quintile within an industry. While the probability of importing and automation capital increases in firm size, the concentration of robot adoption in the top quintile is much more pronounced.

In the following sections we will turn to how firms evolve over time, depending on the type of production capital that they import.

IV. Replication: Robots and automation capital

In this section, we present results replicating the main specification in Acemoglu et al., 2020 in Sweden. We also run these regressions on an indicator for importing any type of automation capital. The results are summarized in Table 2. We regress the change in various firm characteristics between 2012 and 2016 on a dummy indicating whether the firm has adopted either robots or automation capital, and a number of controls. The controls include the logs of labor, value added, whether the firm is part of a larger corporation, and fixed effects for industry (at the 3-digit level) and commuting zone of the largest establishment:

$$\Delta Y_f = \alpha + \beta \text{Adopt}_f + X_f'\gamma + \mu_i + \lambda_z + \varepsilon_f, \tag{1}$$

where ΔY_f denotes the change in a given firm outcome between 2012 and 2016, and Adopt_f is an indicator equal to one if firm f imported robots (Panel A) or automation capital (Panel B) during this period. The vector X_f includes controls for initial firm size (log employment) and log value added, as well as a dummy for whether the firm is part of a larger corporate group. μ_i and λ_z represent fixed effects for industry (at the 3-digit NACE level) and commuting zone of the largest establishment, respectively.

Standard errors are clustered at the industry level. We also present employment-weighted specifications to account for firm size heterogeneity. The coefficient of interest, β, captures the average difference in growth of the outcome variable between adopters and non-adopters, conditional on baseline firm characteristics.

$\Delta \log(va)$	Δlabshare	Δskillshare	$\Delta \log(va/l)$	$\Delta \log(TFPR)$	$\Delta \log(l)$	$\Delta \log(w)$	n
A. Robots							
Baseline (unweighted)							
0.312	-0.174	-0.021	0.180	-0.054	0.131	0.091	68.0
**	*		**		*	***	
Employment weighted							
0.226	-0.120	-0.022	0.103	-0.032	0.122	0.062	68.0
***	*		*		***	*	
B. Automation							
Baseline (unweighted)							
0.055	-0.032	-0.013	0.023	-0.000	0.031	0.025	549.0
						*	
Employment weighted							
0.019	-0.025	-0.008	-0.018	-0.030	0.037	0.027	549.0

Notes: The table reports coefficients from regressions of changes in firm outcomes between 2012 and 2016 on an indicator for whether the firm adopted either robots (Panel A) or automation capital (Panel B). The dependent variables are: $\Delta \log(va)$ change in log value added; Δlabshare change in the labor share; Δskillshare change in the share of skilled workers; $\Delta \log(va/l)$ change in log value added per worker (labor productivity); $\Delta \log(TFPR)$ change in log revenue productivity; $\Delta \log(l)$ change in log employment; and $\Delta \log(w)$ change in log average wages. All regressions include controls for the logs of labor and value added (in 2012), an indicator for group affiliation (whether the firm is part of a larger corporation), and fixed effects for industry (at the 3-digit NACE level) and commuting zone of the largest establishment. Employment-weighted regressions weight each firm by its initial employment. Standard errors are clustered at the industry level.
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2: Robot and Automation Effects (final)

Comparing Panel A of Table 2 to the coefficients found in Acemoglu et al., 2020, we find overall similar effects using the Swedish data. The effects on value added, the labor share, value added per worker, employment, and wages go in the same direction and are significant. Quantitatively however, the effects are much more pronounced in the Swedish data. For comparison, the coefficient for the change in value added is .204 in the French data, while we arrive at a value of .312. Two notable departures are worth pointing out: the skill share and the change in TFPR. For both, our results have opposite signs compared to the French results, and they are not significant at the 95% confidence level. We see a similar pattern after using employment weights.

In Panel B of Table 2, we apply the same method to the adoption of automation capital. The results for value added, the labor share, and value added per worker have the same sign but are more muted. The other results are not significant. We interpret this as the bundling of multiple types of heterogeneous production capital partially netting out the aggregate effects. While they still seem to have a positive effect on scale in terms of value added, and value added per worker, the effect on employment and wages is no longer clear. We will come back to this point in Section B, where we run the same specification on disaggregated categories of automation capital.

Note that adding more digits to the industry FE does not change results much, but some cells have a very low number of observations with more FEs, affecting significance.

One key takeaway from this replication is that most of the main results are similar to those in the French data, but stronger. This also serves as a helpful benchmark for the following sections of this paper. At the same time, bundling multiple capital goods into one adoption indicator seems to mute effects, possibly because of heterogeneity among asset types within the bundle canceling each other out. This emphasizes the importance of taking capital heterogeneity into account in this type of analysis.

V. Heterogeneous capital extension

In this section, we present results from estimating the same specifications as above for all 8-digit capital goods. Note that for some figures, we only include results where both the effect on value added and on the labor share in value added are significant. We comment on this in the text and in the caption of each figure. We mainly focus on the results for value added and the labor share of value added for two reasons. First, they summarize neatly the effect on scale and the input mix between capital and labor. Second, these benchmark results are most clearly comparable across datasets.

A. Robot-like capital classes

Figure 2 illustrates which categories of capital goods display effects on firm outcomes that are most similar to those of robots. Each point represents an 8-digit capital product class, with the estimated effect on value added on the horizontal axis and the effect on the labor share on the vertical axis. The figure highlights a group of capital goods, such as precision machinery, industrial control equipment, and material-handling systems, that exhibit a similar pattern of increasing value added and reducing the labor share in quantitatively similar magnitudes as robots. Notably, several of these goods are not directly related to automation, including conventional machinery and transport equipment, yet they show effects comparable to those of robots. This similarity could indicate that such capital either plays a complementary role in automation or affects production in comparable ways. This underscores that robots are part of a broader set of capital inputs that jointly shape firm performance and workforce composition.

This interpretation of the results is further strengthened when inspecting those capital

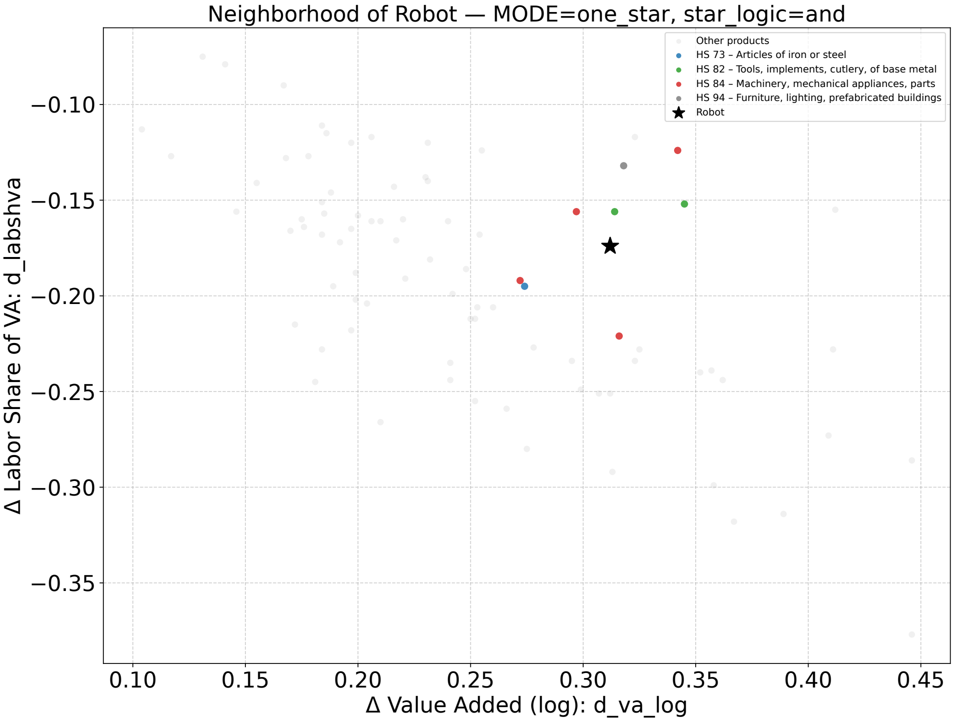

Figure 2: Capital classes similar to robots, significant (95% level) for both results.

goods that have a stronger effect on value added and the labor share than robots. Among these are diesel or semi-diesel engines[7], various types of pumps[8], ultrasound scanners, as well as other instruments used for physical and chemical analysis[9].

Taking a step back, it is also worth mentioning that all capital classes with significant results have a negative effect on the labor share, while increasing value added. This observation is in line with the interpretation that capital in general increases production scale in terms of output, while displacing labor in relative terms. Whether scale or displacement effects prevail is not immediately clear, and neither is the effect on different types of workers. Within the group of capital goods with the strongest effects on value added and the labor share, all significant estimated for the effect on the number of workers and wages per worker are positive. This means that a lower labor share that goes hand in hand with capital adoption does not necessarily imply negative effects for workers.

Overall, we find that robots do not seem to be linked to stronger effects on firm scale and labor shares than other, more traditional types of capital classes and lab equipment.

B. Disaggregating automation capital

Turning to the effects of *automation capital.* Recall that the effects of this aggregated class of capital products where not significant at the 95% level. To understand how this result

[7]Specifically, those not used for the propulsion of motorized vehicles or ships, between 50 and 300 kW, KN2012 codes 84089047, 84089061, 84089065.

[8]KN2012 codes 84134000, 84136069, 84141081, 84143081

[9]KN2012 codes 90278011, 90278091

is generated, Figure 3 depicts the estimates for value added and the labor share of all the disaggregated capital classes included in automation capital. The aggregate estimate is marked with a yellow star. It is somewhat centered and close to zero on both axes, which is as expected. The estimate is both economically and statistically insignificant.

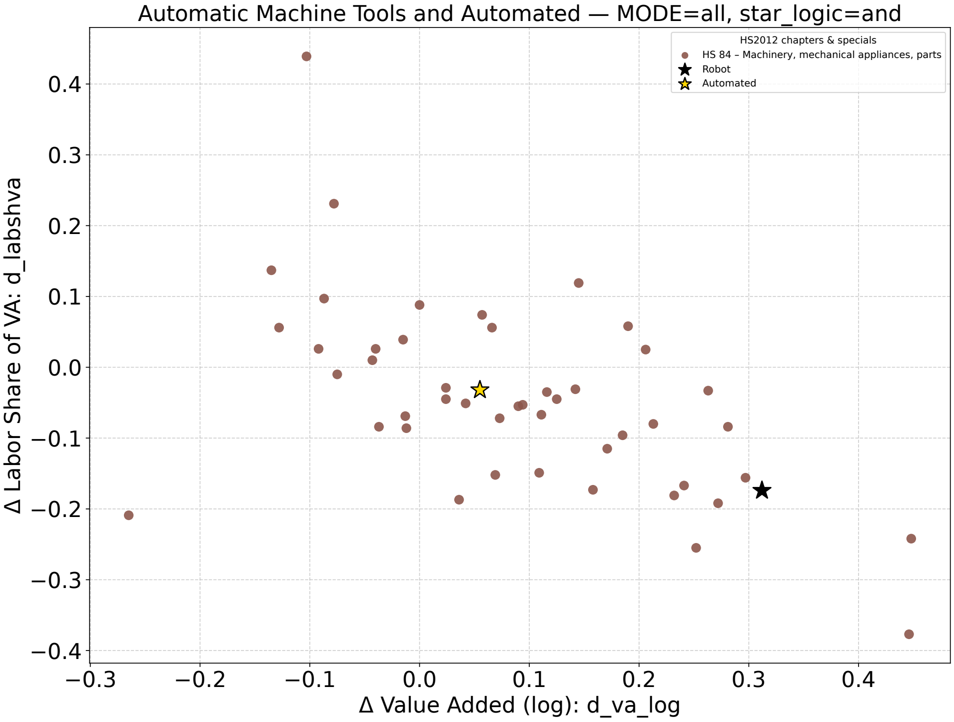

Figure 3: Capital classes included in *automation capital*, regardless of significance.

Within automation capital, there are a few capital classes that generate significant estimated for both outcomes, pictured in Figure 4. All of these have similar estimates as robots, with one exception that has far stronger effects.[10]

This illustrates how aggregating a number of capital classes into one broad group of *automation capital* affects the interpretation of results in two ways. First, if capital goods within the group have heterogeneous effects, with potentially different signs, then the aggregate effect can be centered around a near-zero effect size, even if the underlying capital goods have potentially significant and interesting effects. Second, the aggregation can lead to insignificant results even if (some of) the underlying estimates would be significant. Summarizing, the level of aggregation matters for both the effect size and its significance, which in turn plays a role in interpreting the interaction between capital and labor.

[10]This capital good is KN2012 No 84642080: "Grinding and polishing machines for working stone, concrete, asbestos cement or similar mineral materials".

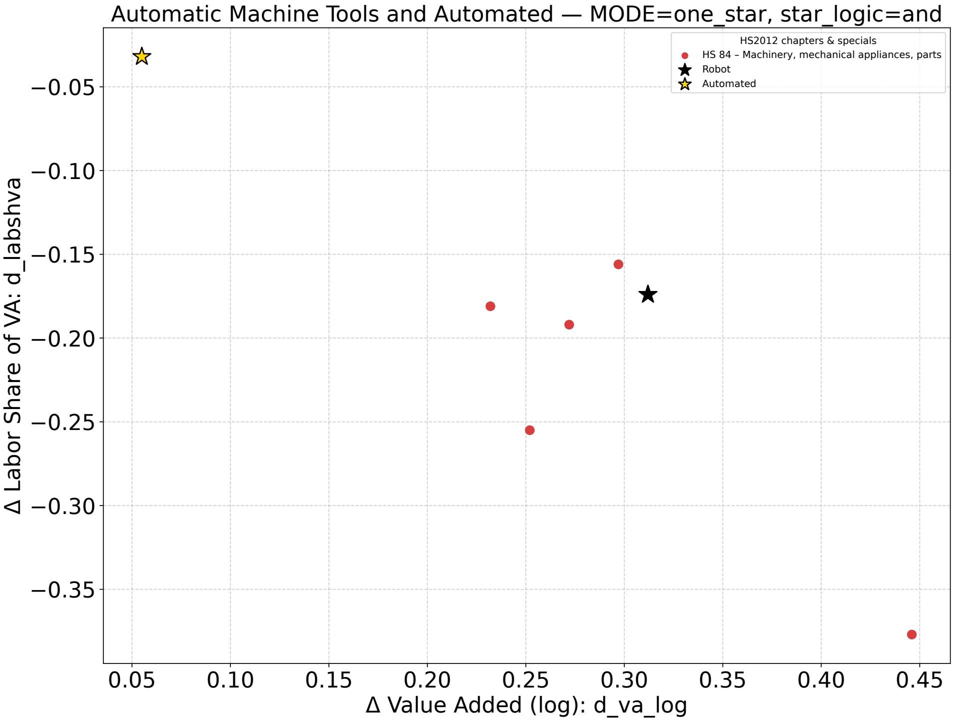

Figure 4: Capital classes included in *automation capital*, significant (95% level) for both results.

C. *Interpretation*

In this section, we extend the previous analyses by taking a closer look at the estimated effects of disaggregated capital classes, with two main takeaways emphasizing the importance of taking into account heterogeneity in capital. On the one hand, zooming in to one particular capital class, like *robots*, can lead to a lack of context for the interpretation of effect sizes, and an unproportionate weight being placed on that particular technology. On the other hand, aggregating a number of capital classes into one indicator as is the case with *automation capital*, can cloak significant and sizable effects going on within the aggregated class. Both of these observations emphasize the importance of capital heterogeneity, not just in theory, but also empirically.

VI. Conclusion

This paper contributes to the growing literature on automation and technological change by examining how different forms of capital interact with heterogeneous labor. Using matched Swedish administrative data, we replicate established findings on robot adoption and extend the analysis to a broader set of capital goods. Our results show that robots have sizable effects on firms' value added, employment, and labor composition, but they are not unique in this regard. Several other types of capital, including older and more conventional machinery, display similar or even stronger effects on firm outcomes and workforce structure.

By analyzing capital goods at a highly disaggregated level and relating them to labor outcomes by educational level, gender, and age, we show that automation is part of a broader pattern of capital and labor interactions. The effects of technological change on employment therefore depend not only on the introduction of new technologies but also on the composition of existing capital in production.

These results can inform both research and policy. For researchers, our findings highlight the importance of accounting for heterogeneity in capital when studying technology adoption and labor market outcomes. For policymakers, the evidence suggests that policies promoting skill development or supporting workers affected by automation should consider the wide range of technologies that shape firms' demand for labor, not just industrial robots.

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Appendix

A. *Additional regression results*

$\Delta \log(y)$	Δlabshare(y)	$\Delta \log(y/l)$	$\Delta \log(l)$	Δskillshare	$\Delta \log(l^f)$	$\Delta \log(age)$	n
A. Robots							
Baseline (unweighted)							
0.195	0.000	0.064	0.131	-0.000	0.088	-0.011	68.0
**			*				
Employment weighted							
0.149	0.004	0.026	0.122	-0.012	0.102	0.001	68.0
*			***		*		
B. Automation							
Baseline (unweighted)							
0.044	-0.002	0.013	0.031	0.065	0.002	0.003	549.0
				**			
Employment weighted							
0.023	0.002	-0.014	0.037	0.051	0.026	-0.002	549.0
				*			

Notes: The table reports coefficients from regressions of changes in firm outcomes between 2012 and 2016 on an indicator for whether the firm adopted either robots (Panel A) or automation capital (Panel B). The dependent variables are: $\Delta \log(y)$ — change in log sales; $\Delta labshare(y)$ — change in the labor share of sales; $\Delta \log(y/l)$ — change in log sales per worker (labor productivity); $\Delta \log(l)$ — change in log employment; Δskillshare — change in the share of skilled workers; $\Delta \log(l^f)$ — change in log number of female employees; and $\Delta \log(age)$ — change in log firm age. All regressions include controls for the logs of labor and value added (in 2012), an indicator for group affiliation (whether the firm is part of a larger corporation), and fixed effects for industry (at the 3-digit NACE level) and commuting zone of the largest establishment. Employment-weighted regressions weight each firm by its initial employment. Standard errors are clustered at the industry level.
Significance levels: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3: Robot and Automation Effects (additional outcomes)

B. *Additional Figures 8-Digit Capital Product Results*

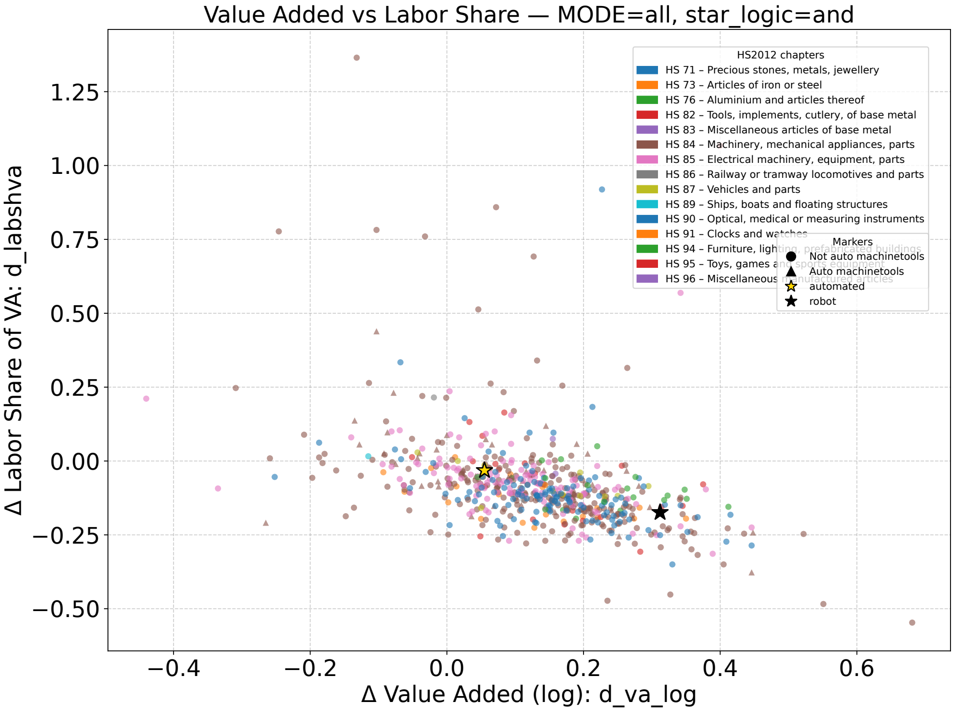

Figure 5: All types of capital, all results.

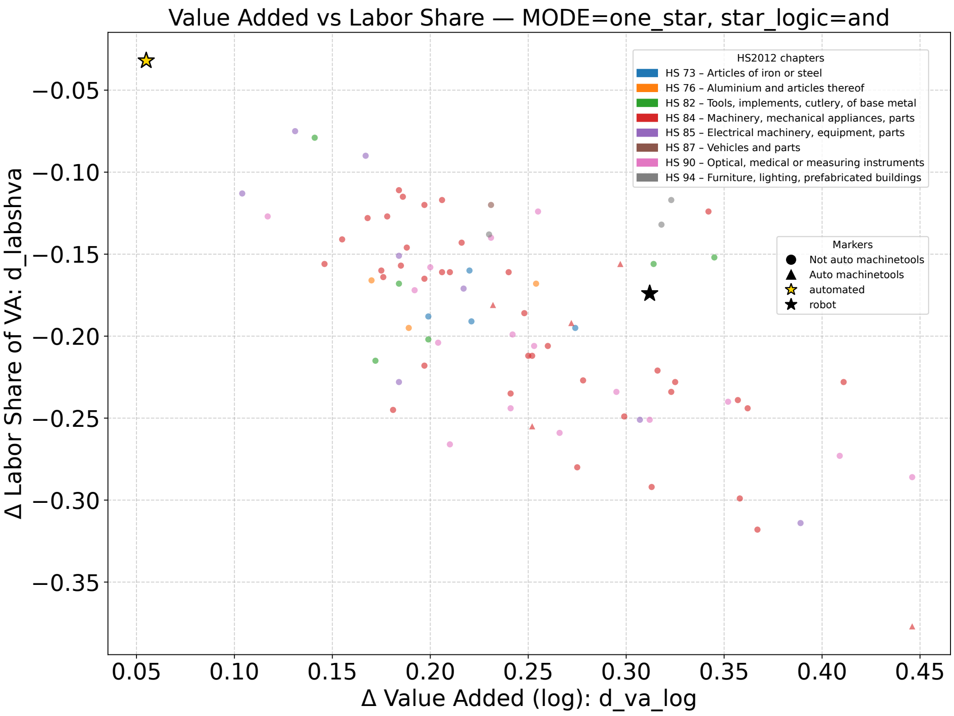

Figure 6: All types of capital, only significant results.

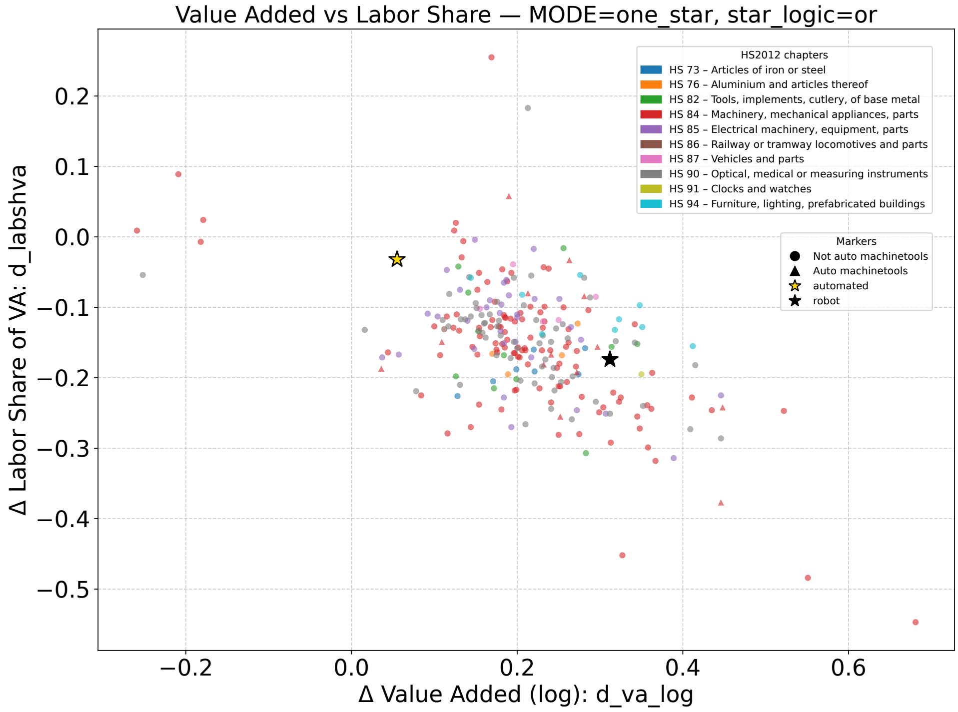

Figure 7: All types of capital, at least one significant result (labor share or value added).

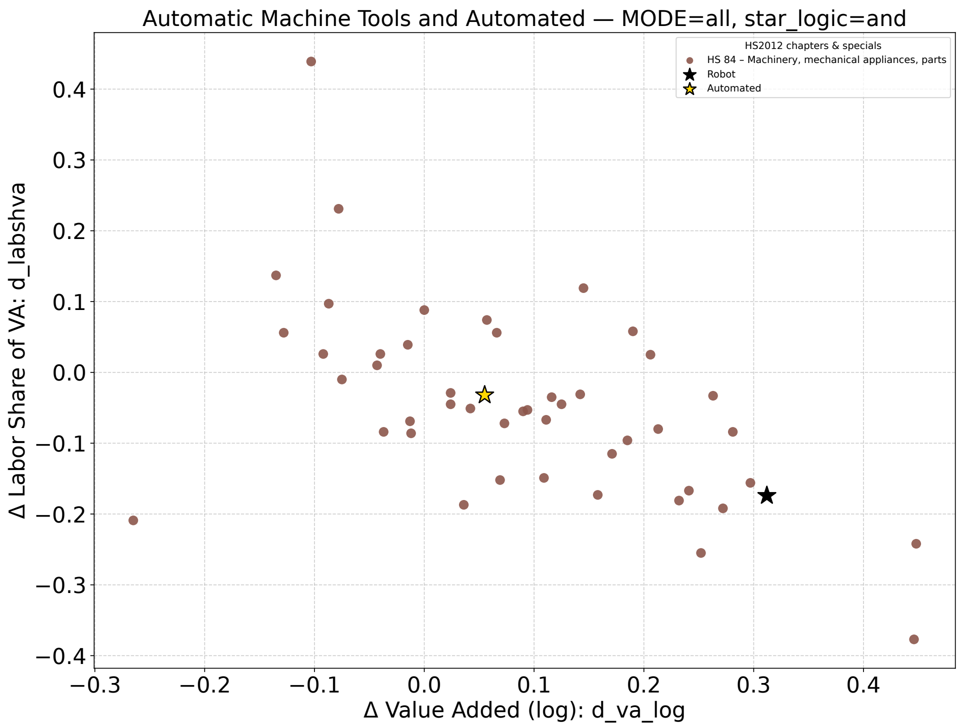

Figure 8: Automation capital, all results.

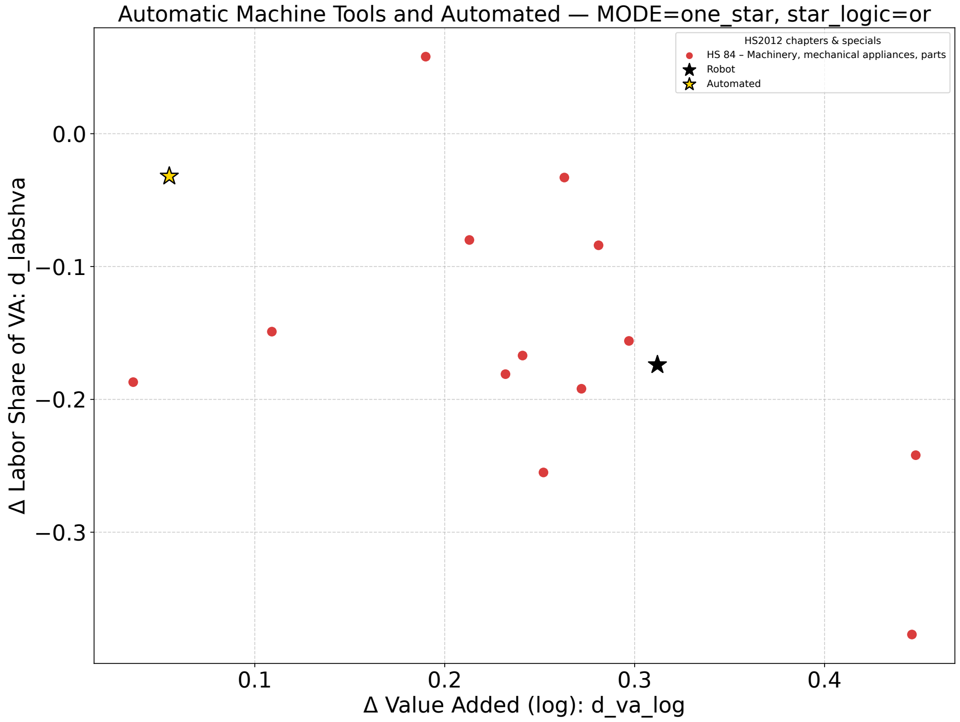

Figure 9: Automation capital, at least one significant result.